

Kudic, Muhamed; Guhr, Katja

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Cooperation Events, Ego-Network Characteristics and Firm Innovativeness – Empirical Evidence from the German Laser Industry

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**Cooperation Events, Ego-Network Characteristics
and Firm Innovativeness**
– Empirical Evidence from the German Laser Industry –

Muhamed Kudic
Katja Guhr

February 2013

No. 6

Authors: *Muhamed Kudic*
Department of Structural Change
E-mail: muhamed.kudic@iwh-halle.de
Phone: +49 345 7753 839

Katja Guhr
Department of Structural Change
E-mail: katja.guhr@iwh-halle.de
Phone: +49 345 7753 840

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Address: Kleine Maerkerstrasse 8, D-06108 Halle (Saale), Germany
Postal Address: P.O. Box 11 03 61, D-06017 Halle (Saale), Germany
Phone: +49 345 7753 60
Fax: +49 345 7753 820
Internet: <http://www.iwh-halle.de>

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Abstract

We study how firm innovativeness is related to individual cooperation events and the structure and dynamics of firms' ego-networks employing a unique panel dataset for the full population of 233 German laser source manufactures between 1990 and 2010. Firm innovativeness is measured by yearly patent applications as well as patent grants with a two year time-lag. Network measures are calculated on the basis of 570 knowledge-related publicly funded R&D alliances. Estimation results from a panel data count model with fixed effects are suggestive of direct innovation effects due to individual cooperation events, but only as long as structural ego-network characteristics are neglected. Innovativeness is robustly related to ego-network size and ego-network brokerage whereas ego-network density reveals some surprising results.

Keywords: R&D cooperation, ego-networks, firm innovativeness

JEL Classification: L25, O32, D85

Kooperationsereignisse, Ego-Netzwerkstrukturen und Innovationserfolg

**– Eine empirische Untersuchung
am Beispiel der deutschen Laserindustrie –**

Zusammenfassung

Die vorliegende Studie untersucht den Zusammenhang zwischen dem Innovationserfolg auf Firmenebene, Einzelkooperationsereignissen und der strukturellen Evolution von firmenspezifischen Egonetzwerken unter Verwendung eines Paneldatensatzes, der die gesamte Population deutscher Laserstahlquellenhersteller zwischen 1990 und 2010 umfasst. Zur Messung des Innovationserfolges wurden Informationen über die jährliche Anzahl von Patentanmeldungen und -erteilungen ausgewertet. Netzwerkmaße wurden auf Basis von 570 öffentlich geförderten FuE-Verbundprojekten ermittelt. Die Schätzergebnisse eines Zählmodells für Paneldaten mit fixen Effekten und unter Berücksichtigung einer zeitlichen Verzögerung der abhängigen Variable um zwei Jahre deuten darauf hin, dass Einzelkooperationen einen unmittelbaren Innovationseffekt haben; dies gilt jedoch nur, solange firmenspezifische Ego-Netzwerkstrukturen keine explizite Berücksichtigung finden. Die Ergebnisse deuten darauf hin, dass ein signifikanter und robuster Zusammenhang zwischen Ego-Netzwerkgröße sowie der strukturellen Ego-Netzwerkpositionierung einer Firma und dem Innovationserfolg auf Firmenebene besteht. Die Untersuchung der Ego-Netzwerkdichte liefert einige unerwartete, jedoch hochinteressante Ergebnisse.

Schlagwörter: FuE-Kooperation, Ego-Netzwerk, Innovationserfolg

JEL-Klassifikation: L25, O32, D85

1 Introduction¹

The generation of new knowledge in innovation processes mostly precedes through the recombination of existing knowledge contents. From the firm perspective, the recombination may be achieved either through internal learning processes within the boundaries of the firm or through interaction with other economic actors (Graf & Krueger, 2011, p. 69). Long-term cooperation projects provide a particularly important vehicle for firms to reach beyond the own firm boundaries (Alic, 1990). These projects often take the form of strategic alliances (Grunwald & Kieser, 2007, p. 369) which can be defined as “[...] voluntary arrangements between firms involving exchange, sharing, or co-development of products, technologies, or services” (Gulati, 1998, p. 293). There is a large variety of strategic alliances in terms of motivations, goals and organizational forms (Osborn & Hagedoorn, 1997; Mowery, et al. 1996). Especially in high-tech industries the number of R&D partnerships has increased considerably since the 1980s (Hagedoorn, 2002). Thus, firms increasingly face the challenge to manage and control a portfolio of national and international alliances simultaneously.

In this study we apply an ego-network perspective in order to capture the firm specific cooperation patterns and subsequent innovation outcomes over time.² Ego-networks are constructed on the basis of a specific type of cooperative relationship: knowledge-related publicly funded R&D alliances that aim at increasing the innovativeness of the involved organizations. Subject of our analysis are various types of individual cooperation events as well as yearly firm-specific R&D cooperation project portfolios which are defined from the focal actor’s perspective and consist of a set of direct, dyadic ties between the focal actor and its alters as well as indirect ties between the alters (Ahuja, 2000). They do not include second-tier ties or second-step ties to which the focal actor is not directly connected (Hite & Hesterly, 2001).

Prior related work has analyzed the relationship between knowledge-intensive R&D alliances and firm innovativeness (Narula & Hagedoorn, 1999; Stuart, 1999; Stuart, 2000) and introduced concepts explaining identification and commercial utilization of knowledge (Cohen & Levinthal, 1990) as well as disturbances in interorganizational knowledge transfer and learning processes (Simonin, 1999). Scholars from various disciplines have moreover analyzed how various dimensions of structural embeddedness

¹ This paper draws upon a joint research project conducted together with Guido Buenstorf, University of Kassel, Institute of Economics and International Center of Higher Education Research (INCHER-Kassel) and Katja Guhr, Department for Structural Economic at the Halle Institute for Economic Research. We have presented draft versions of the paper at the 7th EMAEE conference in 2011 in Pisa, Italy, the IIDEOS Ph.D. colloquium in 2011 in Marburg, Germany and the 5th EMNET Conference in 2011 in Limassol, Cyprus (cf. Kudic, et al., 2011a; 2011b). We have greatly benefited from comments by the audience. The latest version of this paper is an extract from the first author’s Ph.D. thesis (Kudic 2013).

² These terms “ego-networks”, “alliance portfolio” and “alliance constellation” are used in this paper interchangeably, for an overview and comparison of definitions and concepts see (Wassmer, 2010).

in interorganizational networks (Powell et al. 1996; Rodan & Galunic, 2004; Capaldo, 2007) or the overall network structure itself (Schilling & Phelps, 2007) affect innovativeness of involved firms. In contrast, longitudinal empirical studies that explicitly analyze the relationship between ego-network characteristics and firm innovativeness are comparably rare.³

One essential question that arises in this context is whether innovativeness of firms in high-tech industries is affected directly by individual R&D cooperation events or rather indirectly by structure and structural change of firm specific ego-network characteristics over time. In other words, through which transmission channels do cooperation events affect firm's innovative performance in subsequent time periods. On the one hand it is plausible to assume that individual cooperation events directly affect the firm innovativeness. On the other hand, past as well as present cooperation events determine the configuration of the focal actor's individual ego-network structure over time which by itself is likely to affect the firm's innovativeness. The explicit consideration of structural consequences of firm-level cooperation events raises the awareness for the existence of direct as well as indirect cooperation related innovation effects. In addition, Wassmer (2010, p. 162) concludes in his comprehensive review on alliance portfolios that further research based on longitudinal studies is needed to understand how and why firms change the configuration of their alliance portfolios over time and how that affects firm performance. This dual character of individual cooperation events has been widely neglected in previous research on ego-networks and constitutes the core of this study.

Consequently, we seek to answer the following research questions: (I) Do individual cooperation events – direct effects – or rather structural ego-network characteristics – indirect effects – affect firm innovativeness over time? (II) How do individual cooperation events affect the structural configuration of focal actor ego-network and which structural features affect innovation output?

To answer these questions, we apply a unique longitudinal dataset covering a broad range of firm-level variables, innovation indicators and cooperation measures for the full population of 233 German laser source manufactures active between 1990 and 2010. Relational variables encompass all officially listed of 570 R&D cooperation projects funded by the German Federal State and the European Commission. Both data sources allow for an exact identification of tie-formation as well as tie-termination events for all firms in the sample and provide the basis to consider evolutionary network change processes at the micro-level. Information on type, content and funding of cooperation projects provide a solid basis for a fine grained analysis of direct innovation effects. Structural ego-network measures are calculated on a yearly basis by applying of full network data and quantitative network analysis methods (Wasserman & Faust, 1994). Network boundaries are specified on a yearly basis using a comprehensive Ger-

³ Most notable exceptions are: (Ahuja, 2000; Baum et al. 2000; Wuyts et al. 2004).

man laser industry dataset (Buenstorf, 2007). Firm innovativeness is measured by yearly patent applications and patent grants with a two year time-lag.

The paper is organized as follows: In section 2, we provide a theoretical foundation, present our conceptual framework and derive a set of testable hypotheses. A description of the main characteristics of the German laser industry follows in Section 3, together with a brief presentation of the data. Section 4 discusses methodological issues and specifies the dependent and independent variables. Thereafter, focusing on some econometric issues we provide summary statistics and econometric estimation results. After discussing the results and key findings the paper closes with a short conclusion and outlines fruitful avenues for further research.

2 Theoretical Considerations, Conceptual Framework and Hypotheses

2.1 R&D Alliances, Networks and Innovation Output

Numerous theoretical contributions have sought to explain the nature of hybrid organizational forms and the motives of firms cooperate in their innovation efforts (Hagedoorn, 1993; Osborn & Hagedoorn, 1997; Gulati, 1998). Some early explanations adopted the perspective of transaction cost economics (Jarillo, 1988; Thorelli, 1986; Williamson, 1991). They interpret hybrid arrangements as strategic alliances (Borys & Jemison, 1989) which are positioned between markets and hierarchies and reduce transactions costs under moderate asset specificity and frequency of disturbances (Williamson, 1991, p. 292). Other scholars have argued that hybrids have to be regarded as a unique organizational form that can be not classified as an intermediate between markets and hierarchies (Powell, 1990; Podolny & Page, 1998). However, the structural forms behind these hybrids are manifold ranging from short-term supply contracts, licensing and franchise agreements, consultancy contracts to consortia, long-term partnerships and joint ventures (Podolny & Page, 1998; Mowery et al. 1996). Previous studies on the motives for strategic alliances show that especially R&D alliances provide significant cost saving potentials (Harrigan, 1988; Hagedoorn, 2002) and allow firms to reduce the risk inherent in R&D processes (Ohmae, 1989; Hagedoorn, 1993; Sivadas & Dwyer, 2000). Furthermore, R&D alliances provide access to new products and markets (Kogut, 1991; Hagedoorn, 1993), allow for time savings by shortening the time-span between invention and market introduction (Mowery et al. 1996) and provide the opportunities to internationalize business and penetrate markets abroad (Johanson & Mattson, 1988; Hakansson & Johanson, 1988; Narula & Hagedoorn, 1999). With the emergence of the knowledge-based approach in organization science (Kogut & Zander, 1992; Spender & Grant, 1996; Grant, 1996) scholars realized the strategic importance of firm-specific knowledge resources for the competitive advantage of firms (Coff, 2003). Knowledge related cooperation motives as well as several aspects related to

interorganizational learning (Hamel et al. 1989; Hamel, 1991; Khanna et al. 1998; Kale et al. 2000) and knowledge exchange processes (Rothaermel, 2001; Grant & Baden-Fuller, 2004; Buckley et al. 2009) have been analyzed in the field of alliance and network research. However, scholars have argued that “among the various motivations for partnering, innovation is said to be a rationale of singular importance” (Bidault & Cummings, 1994, p. 33). Since then the relationship between knowledge transfer, R&D cooperation and firm innovativeness has been subject to numerous case studies (Dyer & Nobeoka, 2000; Ciesa & Toletti, 2004; Eraydin & Aematli-Köroglu, 2005; Capaldo, 2007) as well as several survey-based studies. For instance, De Propriis (2000) has studied the link between innovation performance and upstream as well as downstream interfirm partnerships drawing upon a unique dataset comprised of 435 firms located in the West Midlands. Estimation results substantiate the importance R&D cooperation as an important driver to innovation of firms. Harabi (2002) found statistically significant support for the impact of vertical R&D cooperation on firm-level innovation outcomes based on a sample of 370 small and medium sized German firms whereas the results indicate that informal cooperation modes seem to be of prior importance compared to formal ones. In a similar vein, Freel & Harrison (2006) investigated the impact of cooperation on innovation based on a survey of 1347 small sized firms in North Britain in both manufacturing and services. They report a positive relatedness between product innovation success and cooperation with customers and public sector. Even though these studies provide us with important insights on the relationship between R&D partnerships and firm’s efforts to innovate they suffer from at least three serious limitations. Firstly, the majority of survey based cooperation studies focus on dyadic partnerships and neglects the structural dimension of the overall innovation network in which the firms under investigation are embedded. Secondly, network studies are quite sensitive with regard to network boundary misspecification and missing cooperation data. Empirical studies employing full network data are quite rare. Finally, majority of survey based cooperation studies draws upon cross-sectional data and neglect the dynamic nature of cooperation activities and the subsequent innovation consequences. In response to these issues researchers have started quit recently to analyze the relationship between firm positioning in complex interorganizational networks and firm innovativeness based on longitudinal large-scale databases⁴ (Stuart, 2000; Lee, 2010; Fornahl et al. 2011).

2.2 Ego-network Structure and Innovation Output

Over the past years the number of R&D collaborations increases rapidly, especially in high-tech industries, (Hagedoorn, 2002) and firms increasingly face the challenge of managing a portfolio of multiple collaborations simultaneously. This empirically observable fact turns the attention on firm specific cooperation networks and raises several interesting and still widely unanswered research questions (Wassmer, 2010).

⁴ Schilling (2009) provides a comprehensive overview of large scale alliance and network data databases such as “SDC”, “MERIT-CATI”, “CORE”, “RECAP”, and “BIOSCAN”.

In economics, management and organization science surprisingly less research has been conducted on “alliance network compositions” (Baum, Calabrese, & Silverman, 2000), “ego-networks” (Ahuja, 2000; Hite & Hesterly, 2001; Jarvenpaa & Majchrzak, 2008), “alliance constellations” (Das & Teng, 2002; Gomes-Casseres, 2003), “alliance portfolios” (Parise & Casher, 2003; Hoffmann, 2005; Hoffmann, 2007; Lavie, 2007; Lavie & Miller, 2008) or “portfolios of interfirm agreements” (Wuyts et al. 2004). Our main interest is in the existence and extent of additional ego-network effects shaping the focal actor’s innovative performance. Previous research (Ahuja, 2000) has analyzed the relationship between three aspects of firms ego-network characteristics – direct ties, indirect ties as well as structural holes – and subsequent firm level innovation outcomes and raises awareness for the negative innovation effects of structural holes at the network level. Baum and his colleagues (2000) have shown that the early innovative performance of Canadian biotech startups’ – measured by patent grant counts and R&D spending growth – is strongly affected by the alliance network composition of these firms at founding. Wuyts and his colleagues (2004) have analyzed the impact of different types of alliance portfolio descriptors on firms’ incremental and radical innovations as well as on firm profitability. Evidence to explain overall benefits of alliance portfolios compared to dyadic cooperation linkages can be drawn from three lines of argument. Firstly, ego-networks provide a risk reduction effect which goes beyond the dyadic level (Hoffmann, 2007). By actively managing and controlling a portfolio of alliances, risk can be reduced by realizing risk diversification effects (Markowitz, 1952). Given potentially high rates of failure in achieving risk reduction in dyadic alliances (Bleeke & Ernst 1991; Sivadas & Dwyer 2000), spreading risks over a portfolio of alliances helps firms reduce the variances in expected returns. Secondly, firms can gain cost savings through the realization of synergy effects in a portfolio of alliances (White, 2005; Hoffmann, 2005). Cooperation routines and standardized cooperation interfaces (Goerzen, 2005) as well as alliance experience (Anand & Khanna, 2000) and alliance management capabilities (Schilke & Goerzen, 2010) save cooperation costs and increase the overall efficiency of a focal actor’s ego-network. For instance, Rothaermel & Deeds (2006) report a moderating effect of alliance experience on the relationship between high-technology venture’s R&D alliances and its new product development. Third, an alliance portfolio enhances the scope of potential learning and knowledge access opportunities by providing access to multiple stocks of knowledge (Grant & Baden-Fuller, 2004). Due to the heterogeneity of directly connected partners the range of potentially accessible knowledge stocks increases. In addition, the interconnectedness of direct partners facilitates the flow of information in the narrower surroundings of the focal actor. The broader range of knowledge accessing and learning opportunities and the enhanced flow of information across partners are likely to have a positive impact on firm’s ability to innovate and gain competitive advantages (Gomes-Casseres, 2003).

Most the previously discussed arguments reflect directly the structural configuration of a focal actor’s ego-network. In other words, a focal actor’s cooperative path reflects in his past as well as present cooperation activities. Thus a closer look at the structural fea-

tures of firm specific cooperation patterns over time is worthwhile to answer the initially raised research questions. Basically two distinct structural ego-network dimensions can be distinguished in this context. On the one hand, we can analyze the firm's ego-network structure with regard to node-level related features. This perspective refers for instance to the number of directly connected partners or to the heterogeneity of partners in an ego-network. On the other hand, we can focus on the connectedness of partners in an ego-network in order to characterize its structural features. From this point of view the various types and configurations of linkages between the actors in an ego-network becomes relevant. In addition, ego-networks are not static; they change continuously over time and shape the structural configuration of the focal actor's portfolio as well as focal actor's subsequent innovative performance. This requires a dynamic view on networks which is provided in the following section.

2.3 An Evolutionary Perspective on Ego-networks

Recent reviews on overall networks (Provan et al. 2007; Bergenholtz & Waldstrom, 2011) and innovation networks (Pittaway et al. 2004; Ozman, 2009) agree that the dynamic character of networks is still not sufficiently well understood. 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 (Doreian & Stokman, 2005; Glueckler, 2007). This means that 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. 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 & Stokman, 2005, p. 5). Scholars from various scientific disciplines such as physics (Albert & Barabasi, 2000; Jeong et al. 2003), biology (Nowak et al. 2010), sociology (Doreian & Stokman, 2005; Snijders, 2004; Powell et al. 2005), organization & management science (Walker et al. 1997; Gulati & Gargiulo, 1999; Koka et al. 2006; Zaheer & Soda, 2009) and economics (Jackson & Watts, 2002; Cowan et al. 2006; Jun & Sethi, 2009) have started to analyze the determinants and mechanisms of structural network change processes in order to widen our understanding of how complex networks evolve over time. The majority of previous empirical studies on network evolution focus on the overall network level whereas research from the focal actors' perspective is rare (Hite & Hesterly, 2001). To date, only a small number of case studies (Dyer & Nobeoka, 2000; Dittrich et al. 2007) have addressed the issue of how portfolios of collaborations change over time. Wassmer (2010, p. 165) accordingly concludes that “[...] little is still known on how alliance portfolio configurations change over time and what drives this evolution”. In the present study we explicitly consider how tie-formations as well as tie-terminations of both focal

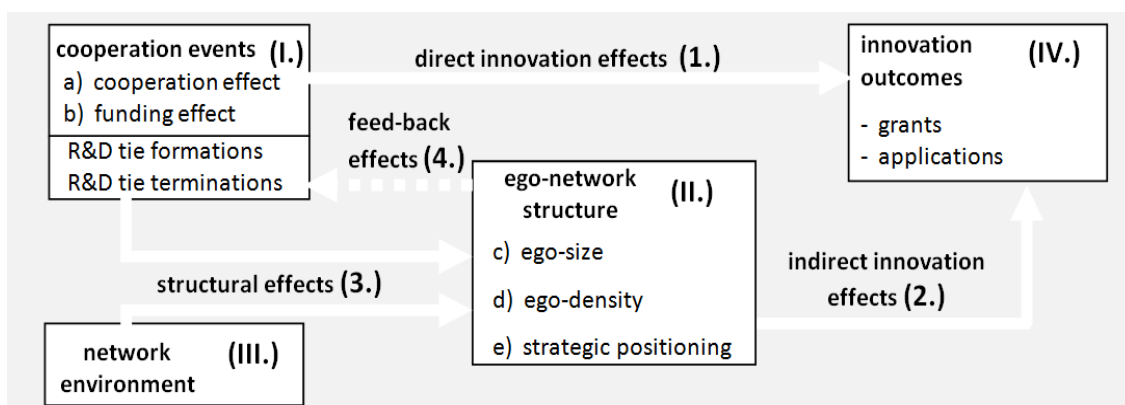
actors cooperation activities itself as well as network neighbors affect the structural configuration of ego-networks and subsequent innovation outcomes.

2.4 Conceptual Framework – Direct and Indirect Innovation Effects

Our conceptual framework (cf. Figure 1) refers to the previous theoretical underpinnings and substantiates the relationship between evolutionary micro-level networks change processes, changes in ego-network structure and firm-level innovation outcomes. The framework consists of four elements – (I.) cooperation events, (II.) ego-network structure, (III.) network environment, (IV.) innovation outcomes – and illustrates three cooperation-related effects – (1.) direct innovation, (2.) indirect innovation effect, (3.) structural effect, (4.) feed-back effect – from a focal actor's perspective.

Figure 1:

Conceptual framework –network change processes, ego-network configuration and firm level innovation output



Source: authors own illustration.

We start our argumentation by focusing on individual cooperation events (I.). Individual cooperation events encompass all tie-formations and tie-terminations on the micro-level which affect the structural configuration of the focal actor's ego-network. These structural effects (3.) can arise from the focal actor's cooperation activities itself as well as from the cooperation activities of the focal actor's direct partners. In the first case, the size of the ego-network is affected whereas in the second case the density of the focal actor's ego-network is affected. In addition, the network environment (III.) affects a focal actor's ego-network in at least two additional ways. First, a focal actor's cooperation decisions are strongly influenced by the cooperation opportunities and restraints provided by the broader network environment. Second, even if an ego and its alters do not conduct any cooperation activities in a given period of time the relative importance of its ego-network changes continuously due to cooperation activities of other network actors in the broader network environment. This means that structural ego-network features have to be analyzed in the context of the focal actor's network environment (III).

Now we turn the attention on the relationship between individual cooperation events (I.) and firm level innovation outcomes (IV.). As outlined above, this direct innovation effect (1.) has been subject to a large number of empirical studies. The findings of the studies substantiate the assumption that cooperation events are positively related to firm-level innovation outcomes. However, especially in case of publicly funded R&D cooperation projects it is unclear whether the cooperation itself or rather the received amount of funding affect firm innovativeness in subsequent time periods. To account for this issue we separate the direct cooperation related drivers of firm innovativeness into a “cooperation effect” (a) and a “funding effect” (b).

Firm specific cooperation activities have an additional, more indirect innovation effect, by shaping the focal actor ego-network structure. Theoretical arguments on risk diversification, synergy and cost-saving effects in alliance portfolios substantiate the assumption that an alliance portfolio is more than the sum of its parts. Thus, we argue that each cooperation event (I.) affects the structural configuration of a focal actors ego-network structure (II.) and exerts an indirect innovation effect (2.) which is assumed to affect firm-level innovation outcomes (IV.) in subsequent time periods. We include three structural ego-network dimensions – “ego-size” (c), “ego-density” (d) and “strategic positioning” (e) – in our conceptual framework in order to capture a broad range of portfolio characteristics. Ego-network size refers to the number of directly connected partners of a focal actor whereas ego-network density captures the connectedness of involved partners. In addition, firms act strategically in constructing their network (Dyer & Singh, 1998; Gulati, Nohria, & Zaheer, Strategic Networks, 2000) and choose those network partners which characteristics comply with their specific innovation process requirements. Consequently we include a structural component (“ego-density”) and strategic component (“strategic positioning”) in our framework.

Finally, the dotted feed-back line (4.) illustrates the intertemporal relationship between past and current cooperation events. The sum of all previously conducted tie-formations and tie-terminations of a focal actor itself and its closer network environment constitutes its individual ego-network structure. New cooperation decisions are based on previous cooperation experiences and determined by considerations of how new linkages fit to existing linkages. In other words, cooperation decisions are path-dependent and existing structures are resistant to change. Kim and his colleagues (2006) refer to this issue by providing a theoretical “network inertia” framework which explains the organizational resistance to changing interorganizational network ties as well as difficulties that an organization faces when it attempts to dissolve old relationships and form new network ties. Thus, a longitudinal setting is appropriate to account for the intertemporal dimension of structural ego-network change patterns appropriately.

The deduction of testable hypotheses in the following section concentrates on the drivers as well as interrelationships between direct innovation effects (1.) and indirect innovation effects (2.) in our framework.

2.5 Hypotheses on Direct & Indirect Cooperation-related Innovation Effects

Does R&D cooperation affect firm innovativeness, and if so, what are the rationales behind this assumption? The answer for at least the second part of this question was provided quite early by scholars (Alic, 1990; Hagedoorn, 1993). Due to the science-based character of the German laser industry (Grupp, 2000) we refer to knowledge related arguments to substantiate our first set of hypotheses. Two streams of literature – “knowledge acquiring approach” & “knowledge accessing approach” can be distinguished in this context (Al-Laham & Kudic, 2008). The distinction builds upon the underlying processes of knowledge generation (or “exploration”) and knowledge application (or “exploitation”) among partners in strategic alliances (Grant & Baden-Fuller, 2004, p. 61).

According to the first approach alliances can be regarded as “vehicle of learning” (Grant & Baden-Fuller, 2004, p. 64) which allow firm to share a particular part of its knowledge bases and exchange implicit stock of knowledge across firm boundaries. The firm’s ability to “[...] recognize the value of new, external information, assimilate it, and apply it to commercial ends [...]” (Cohen & Levinthal, 1990, p. 128) is of prior importance for organizational as well as interorganizational learning processes. Since the initial concept of “absorptive capacity” has been introduced several scholars have contributed to a concretization of the concept itself (Van Den Bosch et al. 1999; Zahra & George, 2002) and reconceptualization form a firm-level construct to a learning dyad-level concept (Lane & Lubatkin, 1998; Lane et al. 2001). In addition, the establishment of mutual trust between partners (Lui, 2009) has been recognized as a key factor of successful interorganizational learning processes in order to avoid learning races (Amburgey et al. 1996) or tensions between alliance partners (Das & Teng, 2000) which can result in alliance instabilities or terminations (Park & Russo, 1996; Inkpen & Beamish, 1997).

The second approach suggests that firms cooperate to get access to complementary stocks of knowledge (Grant & Baden-Fuller, 2004) without necessarily internalizing the partner’s skills (Doz & Hamel, 1997). In other words, a knowledge accessing strategy focuses on the use of the partner’s rich experience without acquiring any specific skills (Lui, 2009). Grant and Baden-Fuller (2004, p. 69) argue in their “knowledge accessing” framework that the efficiency of knowledge integration via alliances can be superior compared to markets or hierarchies where products require a broad range of different types of knowledge. Firms do not necessarily have to generate new stocks of explicitly 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. However, during interorganizational knowledge transfer processes several problems can occur. Simonin (1999) has introduced the concept of “causal ambiguity” and empirically analyzed the determinants affecting knowledge transfer processes in strategic alliances.

In summary, both knowledge acquiring as well as knowledge assessing strategies can significantly flexibilize and improve the firm's knowledge base; a necessary precondition for subsequent innovation processes. Broekel and Graf (2011, p. 6) argue that publicly funded R&D projects provide strong incentives to share knowledge and innovate due to the regulative framework on which all involved cooperation partners have to agree. To test the empirical relationship between direct cooperation events and innovation output, we separately look at the two types of publicly funded R&D cooperation projects. Based on our previous considerations we formulate the following two hypotheses:

- H-1a:** The yearly number of **national** cooperation projects ("Foerderkatalog") is positively related to firm's innovative performance in subsequent time periods.
- H-1b:** The yearly number of **supranational** cooperation projects ("CORDIS") is positively related to firm's innovative performance in subsequent time periods.

Next, we turn the attention on the structural dimension of individual cooperation events. The appropriate choice and establishment of R&D cooperation projects can increase the structural efficiency of an existing ego-network. Firms choose new partners under strategic considerations (Dyer & Singh, 1998; Gulati et al. 2000) which comply with their specific innovation process requirements. The rationale for the establishment of a cooperative relationship is not necessarily the direct access to the partner's recourse pool. Instead the focal actor's intention may be to reduce the dependence on brokers by establishing redundant linkages to strategically relevant actors or groups of actors. In other words, focal actors choose cooperation partners under strategic considerations in order to complement their existing ego-network structures and increase its efficiency. Consequently, tie-formations and tie-terminations may induce an additional structural effect (indirect innovation effect) by reshaping the ego-network configuration. These individual cooperation events thus contribute to firm specific innovation processes by filling "structural gaps" in existing ego-networks. Thus, not only the "cooperation project specific" effect but also the superior "ego-network specific" is likely to determine firm innovativeness. In other words, it is plausible to assume that an additional innovation effect occurs which is caused by the focal actor's ego-network structure. This implies that the several facets of focal firm's ego-network structure potentially affect the firm's innovativeness.

To test the empirical relationship between network structure and innovation output, we separately look at the individual structural dimensions characterizing networks. The size of an ego-network may affect focal actor's innovativeness for a variety of reasons. As outlined above collaborative arrangements provide access to new and complementary stocks of knowledge (Rothaermel, 2001; Grant & Baden-Fuller, 2004). With the number of direct linkages in a portfolio setting the range of potentially accessible to comple-

mentary knowledge stocks of partners increase. 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). Basically the same argument holds for knowledge acquiring strategies. In addition, in science based industries time-savings which can be realized through cooperation become increasingly important. Mowery and his colleagues (1996, p. 79) argue that the perceived shortening of product life cycles increases the competitive pressure on firms 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. These arguments becomes especially in an alliance portfolio context important as multiple collaborative R&D endeavors with diverse heterogeneous partners increases the accessibility to various types of knowledge stocks or learning opportunities and accelerates the development of new ideas and products. These arguments inform our second hypothesis:

H-2a: The greater the size of a focal actor's ego-network, the higher its subsequent innovative performance.

As outlined before, in addition to size, we can distinguish a structural and strategic oriented dimension in an ego-network context: degree of connectedness and brokerage positions. The degree of connectedness in an ego-network is related to the extent to which firms gain innovation experience of being well connected to other firms or public research organizations. According to closure theory a high degree of connectedness increases the visibility of network actors (Coleman, 1988). Furthermore, a high number of linkages in a densely connected ego-network lowers the risk of dependence on other organizations due to the existence of redundant ties and optional knowledge channels to relevant partners. In addition, in highly connected networks firms get access to various types of potentially decisive stocks of explicit as well as tacit knowledge. This increases the scope of firm potentially available complementary knowledge stock and increases firms' flexibility. These considerations lead to the following prediction:⁵

H-2b: The higher the degree of connectedness in a focal actor's ego-network, the greater its subsequent innovative performance.

A central debate in alliance and network literature occurs around Coleman's "closure theory". Burt (1992) highlights in his "structural hole" theory the importance of strategic positions and brokerage activities of actors in sparsely connected networks. Recent studies (Rowley et al. 2000; Burt, 2005) indicate that these two perspectives are not mutually exclusive. With regard to our last hypothesis we follow Burt's line of argument. According to this perspective it is not so much a high degree of connectedness but ra-

5 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) proposes that effects of network embeddedness may turn negative at high levels of connectedness.

ther the occupation of strategically relevant positions that is relevant to the effects of networks. Actors connecting a large number of otherwise unconnected actors – so called brokers – occupy such positions. Referring to this argument and keeping in mind our ego-network perspective, we put forward the following argument. Comparable to brokers in overall networks we can identify strategically decisive actors in ego-networks. “When an “ego” is tied to a large number of “alters” who themselves are not tied to one another, then ego has a network rich of structural holes.” (Podolny, 2001, p. 34). These positions are beneficial for several reasons. Broker can control, facilitate or prevent the flow of knowledge in an ego-network to a large extent by bridging structural holes in existing network structures. They are in a position which allows them bringing together firms as well as other organizations. Consequently we formulate our last hypothesis as follows:

H-2c: Focal actors that occupy a brokerage position in ego-networks show a higher innovative performance in subsequent time periods.

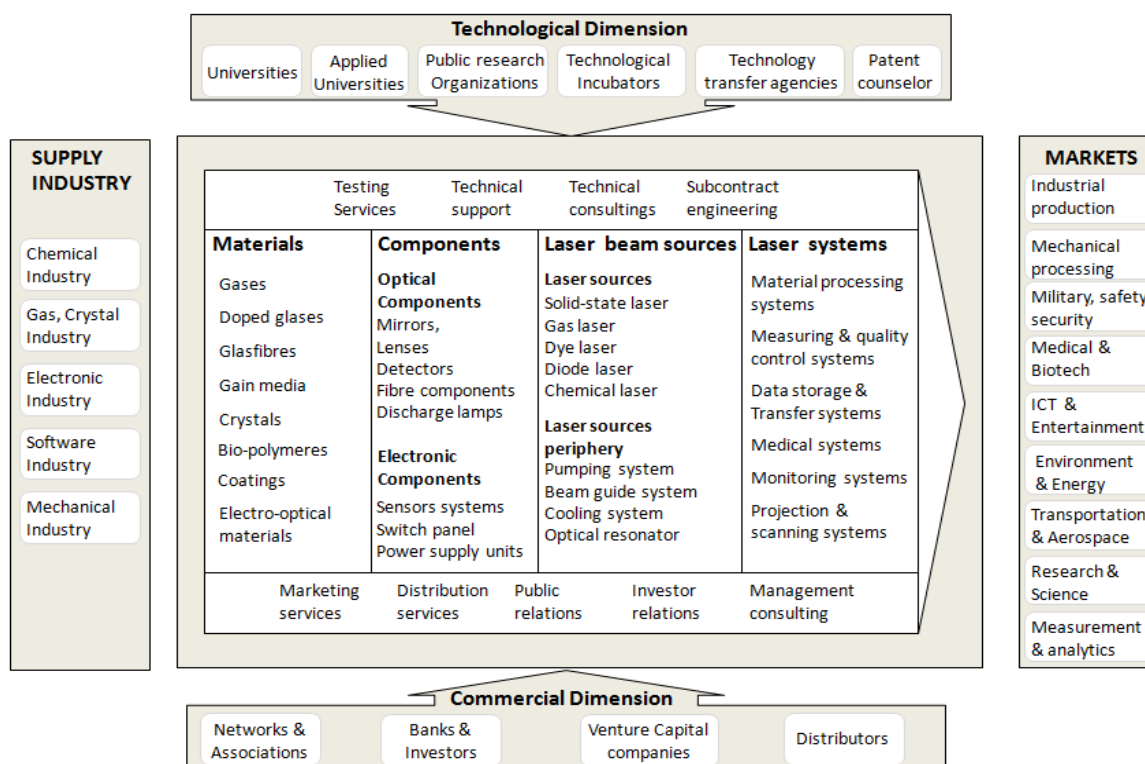
3 Industry Setting – Introducing the German Laser Industries

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 majority of contemporary network studies on knowledge and innovation focus on the biotech industry (Fornahl et al. 2011; Owen-Smith & Powell, 2004). The analysis of network structures and consequences of network embeddedness for other industries is clearly underrepresented but urgently needed to question previous empirical results. Second, the laser industry is a small but interesting part of the German optical technologies can be characterized as a science-driven industry (Grupp, 2000) in which firms’ ability to innovate is a key factor of firm performance and success. In addition, Germany has developed over the past decades into a world market leader in many fields of laser technology. For instance, Mayer (2004) reports that 40 % of all worldwide purchased laser beam sources in 2003 are produced by German laser source manufacturers. The world market share for laser sources implemented in laser processing systems is even higher and amounts in the same year for 50%. Finally, laser technology requires knowledge from various academic disciplines such as physics, optics and electrical engineering (Fritsch & Medrano 2010). The science-based and interdisciplinary character of the industry reflects high cooperation activities of German laser source manufacturers among each other and laser-related publicly funded research organizations (Kudic et al. 2011c). In sum, the German laser industry provides a rich opportunity to study knowledge transfer, learning and innovation processes in interorganizational R&D networks.

The diagram below (cf. Figure 2) illustrates the value chain of the laser industry and its linkages to the supply and market side as well as the contact points to technological and commercial partners. The laser industry value chain itself consists of the four main ele-

ments “materials”, “components”, “laser beam sources and periphery” and “laser systems” accompanied by cross sectional services that provide these four elements with certain technical and commercial advice. As part of the third main element the laser source manufacturers are considered as the heart of the industry’s value chain, because they produce the key component of any laser-based machine or system. Since the first stable operating solid-state ruby laser was presented early 1960s by (Maiman, 1960) a broad variety of novel laser beam sources has been invented.⁶ This implies a high degree of R&D collaborations, not only amongst laser source manufacturers, but also with universities and publicly funded research organizations.

Figure 2:
Laser industry value chain



Source: authors own illustration, based on: Laser Technology Report (2010). TSB Innovationsagentur Berlin GmbH / NRC Network Research & Consulting UG 2010.⁷

⁶ For an overview of technological developments on beam source sources over the past half century see: (Hecht, 2005; Hecht, 2010; Bertolotti, 2005).

⁷ www.tsb-optik.de (accessed: Sept 2011).

4 Data, Methods and Variable Specification

4.1 Applied Data Sources

The analytic part of the paper is based on three main data sources: patent data, industry data and network data.

We use *patent data* to construct indicators reflecting the innovative performance at the firm-level. Raw data stem from EPO Worldwide Statistical Database (*PatStat*-database, version 2010). Patents provide firms with a time-limited monopoly on the use of their innovative products and services (Brenner & Broekel, 2011, p. 12). Despite of the widespread use of patent data in empirical studies as proxy for firm innovativeness these indicators suffer from some notable limitations Fritsch and Slavtshev (2007, p. 204). On the one hand, patents reflect inventions which are not necessarily transformed into innovations and on the other hand innovators have several other possibilities to appropriate the benefits of an invention which not reflect in patent data (ibid.). Nonetheless, patent data are frequently used, especially in longitudinal settings, simply because no better innovation indicators are available over long time periods (Brenner & Broekel, 2011, p. 13). Our database on patent counts includes patent applications as well as granted patents from the German Patent Office and from the European Patent Office (including Euro-PCT patents). The German Patent and Trade Mark Office's DATABASE - DEPATISnet - was used to check results for integrity and consistence.

Industry data stem from a proprietary dataset containing the full population of German laser source manufacturers between 1969 and 2005 (Buenstorf, 2007). Based on this initial data set we use additional data sources to gather information on firm entries and exits after 2005.⁸ For the purpose of this paper we choose the business-unit or firm-level. We decompose the internal organizational structure of all laser source manufacturers in the dataset 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 233 laser source manufacturers in the period under observation. In addition, we identify 145 laser-related universities and public research organization by using the methodical procedure described below.

Network data stem from two official data base on publicly funded R&D collaboration projects. The first database is the *Foerderkatalog* provided by the German Federal State⁹, which encompasses in sum information on more than 110,000 completed and

⁸ 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.

⁹ <http://foerderportal.bund.de/foekat/jsp/StartAction.do> (accessed from May to September 2011).

still ongoing subsidized research projects and provide detailed information on starting point, duration, funding and characteristic features of involved project partners. This data source has quite recently been used by other researchers to gather network data (Fornahl et al. 2011; Broeckel & Graf, 2011). The publicly funded research projects are subsidized by five German federal ministries.¹⁰ In sum, we were able to identify for the full population of 233 German laser source manufacturers 416 R&D projects with up to 33 project partners from various industry sectors, non-profit research organizations and universities. The second raw data source is an extract of the CORDIS project database¹¹ encompassing a complete collection of R&D projects for all German companies which have been funded by the European Commission between 1990 and 2010. Data on EU Framework programs has also been applied by other researchers to construct R&D networks (Cassi et al. 2008; Protogerou et al. 2010). Our extraction of the CORDIS project database encompasses all seven EU-Framework Programs and covers a time span from 1983 until 2010.¹² In sum, this database extract encompasses a project data-set with over 31,000 project-files and an organization data-set with over 57,100 German organizations and about 194000 international project partners. Based on this raw data, we identify for the full sample of German laser source manufacturers 154 R&D projects with up to 53 project partners. Finally, both cooperation data sources were used to construct interorganizational innovation networks on a yearly basis.

We employ both data sources on publicly funded projects because the German national funding paradigm differs in several ways from the supranationally oriented funding paradigm of the European Union. For instance, the comparison of *Foerderkatalog* and CORDIS data shows a much higher heterogeneity of projects in terms of partner nationality, number of project partners and received funding (Kudic et al., 2011c). In addition, other researchers have pointed out that supranational projects show a much higher involvement of public research organizations (Scherngell & Barber, 2011; Broeckel & Graf, 2011, p. 5)

¹⁰ These are the following ministries according to the database description (URL: www.foerderkatalog.de). Federal Ministry of Education and Research (BMBF), Federal Ministry for the Environment, Nature Conservation and Nuclear Safety (BMU), Federal Ministry of Economics and Technology (BMW), Federal Ministry of Food, Agriculture and Consumer Protection (BMELV), Federal Ministry of Transport, Building and Urban Development (BMVBS). For further information on the use of “Foerderkatalog” data in field of innovation research see Fornahl et al. (2011) and Broeckel & Graf (2011). They analyze drivers of patent performance in the German biotech industry by using the same raw database like applied in this study.

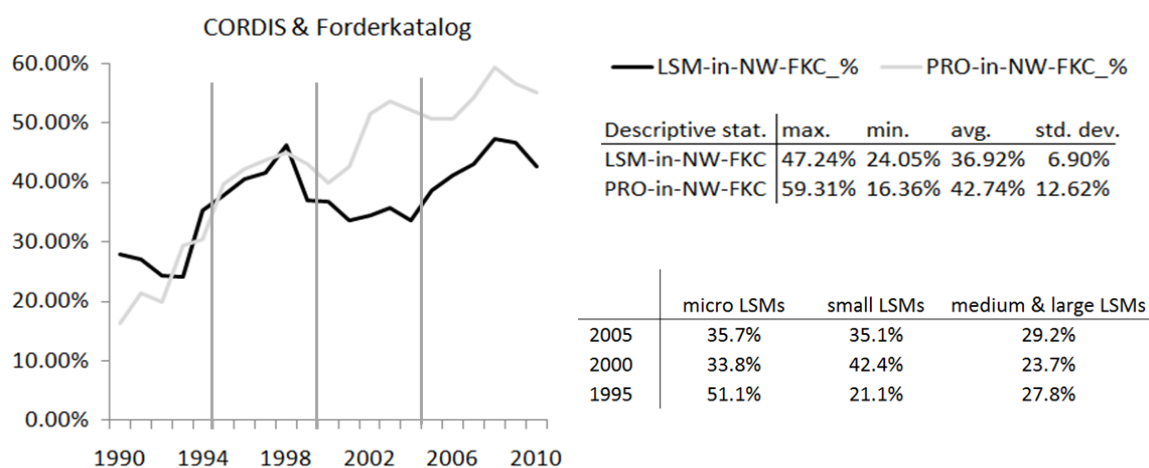
¹¹ CORDIS (Community Research and Development Information Service) provides a broad range of information and resource with regard to European R&D funding activities. We thank the CORDIS Support Team, and especially Mrs. Evi Guinou, for the friendly support and for providing an extraction of the CORDIS project database.

¹² Additional programs are included such as “Education & Training”, “Energy & Environment”, “Health & Safty”, “Information Society”, “International Cooperation”, “EURATOM Framework Program” as well as some regional programs.

Using information about publicly funded research projects to construct R&D networks raises potentially grave selectivity concerns. It is conceivable – and indeed desirable from a societal perspective – that funding decisions reflect the heterogeneous quality of applicants. In this case, empirical findings of higher innovativeness being related to larger networks might simply be caused by the inherent superiority of those actors that have won more grants. In our empirical setting, this concern seems to be of limited salience for two reasons. First, we employ panel estimation techniques to allow for firm-specific effects. Second, prior work on German technology policy vis-à-vis the laser industry has shown that beginning in the mid-1980s, German policy makers identified lasers as a crucial technology for the future competitiveness of various German industries (Fabian, 2011). As a consequence, substantial efforts were undertaken to support the industry, and funding of collaborative R&D projects was selected as a key policy instrument to this purpose. In other words, funding decisions were primarily motivated by the objective to improve the competitiveness of German actors relative to their international competition, while spurring domestic competition by highly selective merit-based funding decisions appears to have been of secondary importance. For the European funding decisions, it may likewise be argued that in addition to applicant quality, several other criteria have a strong influence on funding decisions. These considerations are consistent with our data showing that not only medium and large sized firm but also a significantly high proportion of micro and small firms have received public funding for R&D cooperation (cf. Figure 3). The diagram below gives an overview of received funding, either from “Foerderkatalog” or “CORDIS” programs, differentiated by partner type firm size.

Figure 3:

Received cooperation funding - differentiated by partner type and firm size



Source: authors own illustration.

Another potential concern is that public funded R&D projects primarily affect innovation outcomes through its resource effects. We control for the resource effect by including received funding as a control variable in our empirical analysis.

4.2 Methods

The empirical analysis is based on the full population of German laser source manufacturers between 1990 and 2010; an unbalanced panel of 233 firms with a total of 2645 firm years. Over the whole period under observation we have in average 11.08 observations per firm. Annual counts of patent grants and applications are used as the measure of innovation output, with a two year lag structure accounting for the time required to arrive at patentable innovations.

To construct the R&D network we had to identify in a first step all laser-related public research organizations (PROs). Two complementary methods were applied to get a complete list of all involved PROs: We started with the “expanding selection method” according to Doreian and Woodard (1992). Beginning with the initial list of 233 laser source manufacturers we added all non-profit research organizations and universities active in the field of laser research to our sample as long as these organizations established several links to at least one firm on our starting list. In contrast to the “snowball sampling method” (Frank, 2005) we did not include organizations with just one link directly in our sample. Instead, we check for all these cases whether the cooperation has a laser-related content or not. In sum we identified 138 laser-related public research organizations. This procedure, however, neglects all laser-related PROs which have not cooperated with LSMs in the period under observation. Thus, we apply a second method to complement our sample. Based on a bibliometric analysis we identifying all organizations which have published on laser topics in conference proceedings and academic journals over the past two decades. Raw data for this analysis stem from the LASSSIE project (Albrecht et al., 2011) was supplemented by searches for laser related publications listed in the ISI-Web of Science database. In this way, a complete list of all PROs which have published at least once in the field of laser research was generated. By comparing and consolidating the results of these two data gathering methods we end up with a final list of 145 laser active PROs for the time span from 1990 and 2010. Finally, entry and exit dates and address data were retrieved for all indentified PROs in the dataset.

In a second step we decomposed 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 was determined by the number of active laser source manufacturing firms in a given year. The decomposition of multi-partner R&D cooperation projects into dyadic network linkages is based on the assumption that all involved partners have linkages to each other. 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 to calculate ego-network measures (Borgatti et al. 2002).

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 an applicant and either applicant or inventor had a German address. We also traced changes in corporate names and legal status, as well as organizational changes and the establishment of spin-offs for the allocation of yearly patent counts to each company.

4.3 Variable Specification

Following other network studies analyzing innovative performance of firms and industries (Ahuja, 2000; Stuart, 1999; Stuart, 2000), we use patent counts per year as a proxy for firm-level innovation output. Both patent applications and grants are employed as innovation proxies (Powell et al. 1996; Ahuja, 2000; Jaffe et al. 1993). For the purpose of this study we choose a more restrictive innovation indicator and decide in favor of grants (Jaffe et al. 1993). Nonetheless we use application count for consistency check. A two year time-lag structure is utilized in line with other research in this area.

The key explanatory variables are two types of cooperation counts and three basic ego-network measures. On the one hand, we measure firm specific cooperation propensity with two cooperation count measures based on the *Foerderkatalog* data [*coopcnt_fk*] and CORDIS data [*coopcnt_c*], respectively, as well as a combined cooperation count indicator [*coopcnt_fkc*] consisting of the sum of both. On the other hand we measure three structural ego-network measures. We use procedures implemented in UCINET 6 (Borgatti et al. 2002) to generate our ego-network variables. The implemented routines systematically construct the ego-networks and structural positions for every actor within the network. We repeated this procedure for each year under observation. The first 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, multiplied by a factor of 100.¹³ The third ego-network variable is a normalized ego-network brokerage indicator [*ego-nbroke*]. This measure captures the number of times a focal actor of an ego-network lies on the shortest path between two alters, normalized by number of brokerage opportunities, which is a function of ego-network size.

As firm-level control variables, we include firm age linearly [*firmage*] as well as a squared term [*firmage_sq*]. To account for overall network effects we include two types of network-level control variables. The first variable captures the size of the overall network [*nw_size*] defined as the proportion of firm which with at least on dyadic part-

¹³ 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.

nership in a given year. The second variable measures the connectedness of the overall network [*nw_densit*] calculated by using the standard network density procedure implemented in UCINET 6 (Borgatti et al. 2002). In addition, we include yearly time-dummies to control for inter-temporal effects. Finally, we include a cooperation funding [*coop_fund*] variable in our model.

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

Table 1:
Variable description and summary statistics

Variable definition		Summary Statistics			
		Mean	Sd.	Min	Max
ENDOGENOUS VARIABLE					
patcount_grt	patents grants of firm <i>i</i> in year <i>t</i>	0.3391304	1.635554	0	28
patcount_app	patents applications of firm <i>i</i> in year <i>t</i>	2.662004	17.43323	0	366
CONTROL VARIABLES					
firm age	Firm age in years	8.0559	6.8005	1	43
firm age2	Firm age squared	111.1274	177.8146	1	1849
NW size	Size of the overall network	0.3818	0.0621	0.24051	0.47239
NW density	Density of the overall network	0.088119	0.069955	0.0373	0.4405
dummy1997	=1 if firm is observed in 1997	0.04272	0.20227	0	1
dummy1998	=1 if firm is observed in 1998	0.04499	0.27322	0	1
dummy1999	=1 if firm is observed in 1999	0.05217	0.22241	0	1
dummy2000	=1 if firm is observed in 2000	0.05252	0.22318	0	1
dummy2001	=1 if firm is observed in 2001	0.05861	0.23492	0	1
dummy2002	=1 if firm is observed in 2002	0.06049	0.23844	0	1
dummy2003	=1 if firm is observed in 2003	0.06049	0.23844	0	1
dummy2004	=1 if firm is observed in 2004	0.06201	0.24131	0	1
dummy2005	=1 if firm is observed in 2005	0.06351	0.24393	0	1
dummy2006	=1 if firm is observed in 2006	0.06162	0.24052	0	1
dummy2007	=1 if firm is observed in 2007	0.06049	0.22384	0	1
dummy2008	=1 if firm is observed in 2008	0.06163	0.24051	0	1
EGO-NETWORK VARIABLES					
coop_cnt_c	Count of CORDIS Coop. of a firm <i>i</i> in year <i>t</i>	0.06578	0.322242	0	4
coop_cnt_fk	Count of FK Coop. of a firm <i>i</i> in year <i>t</i>	0.21921	0.632911	0	8
coop_cnt_fkc	Count of CORDIS & FK Coop. of firm <i>i</i> in year <i>t</i>	0.27599	0.774139	0	8
EGO NETWORK VARIABLES					
ego-size	Ego network size	2.46992	5.25304	0	41
ego-density	Ego network density	13.89213	25.73445	0	100
ego-nbroke	Normalized ego-network brokerage	24.8449	67.4958	0	65.09

Source: authors own illustration.

Table 2:
Correlation matrix

	patcount_ grants	patcount_ appl	NW- size	NW- density	firm age	firmage _sq	coop- fund	coop- count_	coop- count_fk	coop- count_fkc	ego_ size	ego_ density	ego_ nbroke
patcount_grt	1.0000												
patcount_app	0.6506	1.0000											
NW-size	0.0670	0.0448	1.0000										
NW-density	-0.0831	-0.0529	-0.6576	1.0000									
firmage	0.0106	-0.0566	0.2138	-0.2007	1.0000								
firmage_sq	-0.0046	-0.0455	0.1609	-0.1451	0.9275	1.0000							
coop_fund_tsd	0.3114	0.3922	0.0146	-0.0144	-0.0279	-0.0100	1.0000						
coopcount_c	0.2310	0.1754	0.0234	-0.0175	0.0193	0.0266	0.3144	1.0000					
coopcount_fk	0.2157	0.2208	0.0420	-0.0132	0.0027	0.0200	0.4651	0.2326	1.0000				
coopcount_fkc	0.2725	0.2535	0.0441	-0.0181	0.0102	0.0274	0.5112	0.6064	0.9144	1.0000			
ego_size	0.3170	0.2732	0.0313	-0.0071	0.1101	0.1306	0.3393	0.3217	0.6128	0.6349	1.0000		
ego_density	0.0542	0.0908	0.1265	-0.0724	0.0654	0.0754	0.0783	0.0661	0.2496	0.2316	0.4129	1.0000	
ego_n-broke	0.2733	0.2352	0.0959	-0.1032	0.1149	0.1244	0.2875	0.2442	0.4740	0.4892	0.6607	0.2035	1.0000

Source: authors own calculation.

5 Empirical Analysis – Models Specification and Results

5.1 Estimation Approach

In this paper we use panel count data techniques to test our hypotheses. Following Ahuja (2000) and Stuart (2000) we estimated panel count models and adopted the following estimation strategy to test our hypotheses. In a first step we estimated a poisson model to get a first intuition of the network effects on patenting activity. As our endogenous variables exhibits strong overdispersion, we then turned to a negative binomial model specification with random effects. In the next step we estimated both, fixed-effects and random-effects models.¹⁴ The use of fixed-effects models provides some important advantages. The fixed-effects estimator is unbiased because it includes dummy variables for the different intercepts and more robust to selection bias problems compared to the random-effects estimator (Kennedy, 2003, p. 304). However, fixed effects models have also two considerable drawbacks. First, all time-invariant variables explanatory variables are thrown out because the estimation procedure fails to estimate a slope coefficient for variables that do not vary within an individual unit (Kennedy, 2003, p. 304). Second, using only within-variation leads to less efficient estimates and the model loses explanatory power (Cameron & Trivedi, 2009, p. 259). The random ef-

¹⁴ The main difference between the estimation techniques is that fixed-effects models allows for correlation between the unobserved individual effect and the included explanatory variables whereas random effects models requires the unobserved individual effect and the explanatory variables to be uncorrelated (Green, 2003, p. 293).

fects model compensates for some of these disadvantages. On the one hand random effects estimators make a better use of the information values of patent data and generate efficient estimates with higher explanatory power. In addition, random-effects estimator can generate coefficient estimates of both time variant as well as time-invariant explanatory variables (Kennedy, 2003, p. 307). The major drawback of the random-effects model is that correlations between the error term and explanatory variables generate biased estimates (Kennedy, 2003, p. 306). In other words, the random effects estimator generates potentially inconsistent results when the model assumptions are violated. We use the Standard Hausman Test (1978) to decide which results to interpret.¹⁵ Finally, we ran several consistency checks to ensure robustness of reported results. We use several time lags for the dependent variable in our estimations. Additionally, we employ in some cases patent applications as an additional innovation measure to substantiate our findings.

5.2 Estimation Results – Summary of Findings and Discussion

Table 3 and 4 report the estimation results for patent grants based on panel negative binomial model with both fixed effects and random effects estimation techniques. Results are interpreted based on “Hausman-Test” results. In sum, ten models are reported for both patent grants with a lag of $t=1$ and for patent grants with a lag of $t=2$. We start with Table 3 which illustrates the estimation results for patent grants with time lag of two year.

The baseline model (Model 1, Tab. 3a) consist of a set of time-dummies, two firm age variables, two network control variables and a funding variable. The time dummies show positive and significant effects for the time period from 1998 to 2007. Models 2-4 (Tab. 3a) address direct cooperation effects. In a first step two types of cooperation variables are added. The fixed effects model shows no significant effects for CORDIS [*coopcnt_c*] or Foerderkatalog [*coopcnt_c*]. In Model 4 (Tab. 3a) we add a combined cooperation count measure [*coopcnt_fk*]. In a second step we focus on ego-network effects and specify three additional models [Model 5-7, Tab. 3a] by including ego-network size [*ego-size*], ego-network density [*ego-density*] and ego-network brokerage [*ego-nbroke*] measures. The ego-size variable as well as the ego-brokerage variable shows highly positive and significant coefficients at the 0.01 level for the fixed effects model. Surprisingly we have no significant effect for network-density measure (Model 6, Tab. 3a).

¹⁵ The basic idea of the Standard Hausman specification test is to test the null hypothesis that the unobserved effect is uncorrelated with the explanatory variables (Green, 2003, p. 301). In case the null hypothesis cannot be rejected both fixed-effects estimates as well as random-effects estimates are consistent and the model of choice is the random effects model due to its higher explanatory power. Under the alternative random-effects and fixed effects estimators diverge and it is argued that the latter model is the appropriate choice (Cameron & Trivedi, 2009, p. 260).

Table 3:

Estimation results – patent grants; time-lag (t+2); fixed and random effects models

Figure 3a: Estimation technique: fixed effects

Variable	Estimation results									
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
yr97	.28301	.27135	.33329	.33802	.23259	.25012	.25916	.24418	.28694	.30460
yr98	.63349	.63239	.69986	.70923	.56354	.65429	.55159	.56265	.69367	.62659
yr99	.82587 **	.88062 ***	.86092 ***	.90019 ***	.87293 ***	.82060 **	.75845 **	.90562 ***	.88918 ***	.85160 **
yr00	.95343 ***	.99923 ***	.98787 ***	1.02167 ***	1.03123 ***	.96581 ***	.90642 ***	1.05553 ***	1.02322 ***	.99004 ***
yr01	.92004 **	.98327 ***	.93150 **	.97398 ***	1.04913 ***	.92588 **	.82002 **	1.08250 ***	.98420 ***	.90723 **
yr02	.84997 **	.93087 **	.85295 **	.90519 **	1.03292 **	.84340 **	.85077 **	1.07814 ***	.91180 **	.94297 **
yr03	.97198 **	1.07525 ***	.98363 **	1.05167 ***	1.16526 ***	.97674 **	.90963 **	1.21989 ***	1.06866 ***	1.02099 **
yr04	1.08759 **	1.18641 **	1.07329 **	1.13483 **	1.29896 **	1.09024 **	1.00017 **	1.35237 ***	1.15849 **	1.09585 **
yr05	1.34788 ***	1.41771 ***	1.32162 ***	1.36245 ***	1.52105 ***	1.36237 ***	1.14194 **	1.55690 ***	1.38864 ***	1.21251 ***
yr06	1.12204 **	1.20555 ***	1.16512 **	1.22483 ***	1.32464 ***	1.13304 **	.93178 *	1.36713 ***	1.22506 ***	1.06515 **
yr07	.95981 *	1.08628 **	.99181 **	1.07776 **	1.13709 **	.95285 *	.76052	1.21156 **	1.07472 **	.93667 *
yr08	.67159	.77197	.70824	.77596	.83053	.68624	.50678	.88365	.78164	.64574
nw_size	.90264	.98554	.32529	.30543	1.04586	.62073	1.08114	1.09603	.33799	.66380
nw_density	-3.00125	-2.73575	-3.32123	-3.17230	-2.57979	-3.15022	-2.72188	-2.42853	-3.09625	-2.75881
firmage	.01605	.01039	.02263	.02011	.00762	.01785	.03357	.00449	.01887	.03181
firmage_sq	-.00152	-.00143	-.00165	-.00161	-.00092	-.00149	-.00170	-.00090	-.00152	-.00171
coopfund_fkc	5.63E-6	-1.18E-5	-1.42E-5	-1.98E-5	-1.15E-5	-1.10E-6	-1.69E-5	-1.49E-5	-1.43E-5	-3.01E-5
coopcnt_c		.14257						.07255	.13064	.11666
coopcnt_fk			.08656					-.00420	.06515	.06455
coopcnt_fkc				.09531 *						
ego_size					.03505 ***			.03404 ***		
ego_density						.00431			.00377	
ego_nbroke							.01321 ***			.01234 ***
_cons	-.01708	-.10816	.10311	.05881	-.44522	-.02884	-.27229	-.48102	-.03998	-.22027
chi ²	52.5	55.4	54.2	56.3	66.1	54.5	61.1	67.5	58.4	64.0
ll	-642.8	-641.8	-641.9	-641.2	-635.9	-641.7	-639.0	-635.6	-640.2	-637.7
aic	1322	1322	1322	1320.3	1309.7	1321.3	1316.0	1313.2	1322.5	1317.5
bic	1409	1414	1414	1412.7	1402.1	1413.7	1408.4	1415.3	1424.9	1419.6
N	956	956	956	956	956	956	956	956	956	956

Legend: *p<.1; **p<.05; ***p<.0

Figure 3b: Estimation technique: random effects

Variable	Estimation results									
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
yr97	.28958	.26156	.40949	.40042	.22462	.24614	.27303	.26438	.35063	.37382
yr98	.72303	.71322	.89549 *	.88202 *	.65198	.74708	.63789	.71807	.86407 *	.81087
yr99	.82908 ***	.88984 ***	.92799 ***	.96839 ***	.91596 ***	.82507 ***	.78335 **	.97467 ***	.94276 ***	.93589 ***
yr00	.95077 ***	.99707 ***	1.04826 ***	1.07753 ***	1.09750 ***	.97551 ***	.94378 ***	1.14092 ***	1.07742 ***	1.07933 ***
yr01	.83181 **	.89915 ***	.88611 ***	.93678 ***	1.03476 ***	.85001 **	.76243 **	1.07104 ***	.93901 ***	.89333 ***
yr02	.72282 **	.81511 **	.77725 **	.84520 **	1.00353 ***	.72687 **	.78667 **	1.05310 ***	.83582 **	.92122 ***
yr03	.89799 **	1.00978 ***	.97196 ***	1.05395 ***	1.18635 ***	.91525 **	.87846 **	1.24318 ***	1.05248 ***	1.03582 ***
yr04	.95081 **	1.05499 **	.97755 **	1.05522 **	1.26894 ***	.97051 **	.91899 **	1.30646 ***	1.06230 **	1.04215 **
yr05	1.24097 ***	1.29695 ***	1.24798 ***	1.28075 ***	1.50892 ***	1.26966 ***	1.06003 ***	1.52159 ***	1.29073 ***	1.14843 ***
yr06	1.03999 ***	1.11605 ***	1.18983 ***	1.24222 ***	1.34466 ***	1.06411 ***	.87002 **	1.40183 ***	1.22674 ***	1.08937 ***
yr07	.89269 **	1.02242 **	1.02644 **	1.12033 **	1.17082 ***	.89242 **	.72137 *	1.26767 ***	1.08632 **	.99479 **
yr08	.62559	.71950	.77728	.83710	.88455 *	.64516	.51333	.95571 *	.81283	.73223
nw_size	-.12371	-.01477	-1.32052	-1.17740	.09393	-.41115	.24701	-.22673	-1.17430	-.73962
nw_density	-3.18618	-2.81611	-3.70087	-3.34689	-2.74536	-3.35266	-2.93686	-2.70268	-3.40652	-3.07730
firmage	.01972	.01582	.02833	.025867	.00514	.02207	.03293	.00686	.02720	.03414
firmage_sq	-.00094	-.00085	-.00115	-.00108	-.00023	-.00098	-.00122	-.00031	-.00109	-.00125
coopfund_fkc	1.03E-5	2.85E-6	-5.78E-6	-1.27E-5	1.25E-6	1.54E-5	-5.25E-6	-6.41E-6	-6.53E-6	-.00003
coopcnt_c		.20296 **						.08821	.17173 *	.14649
coopcnt_fk			.17516 ***					.03175	.14508 **	.12989 **
coopcnt_fkc				.16548 ***						
ego_size					.04775 ***			.04410 ***		
ego_density						.00597 **			.00491 *	
ego_nbroke							.01818 ***			.01599 ***
_cons	.20850	.07201	.43884	.31596	-.36428	.17140	-.14703	-.29658	.22780	.02877
ln_r_cons	.79958 ***	.82965 ***	.82943 ***	.84929 ***	.91175 ***	.80721 ***	.83048 ***	.92260 ***	.85349 ***	.87567 ***
ln_s_cons	-1.48479 ***	-1.46487 ***	-1.41464 ***	-1.40396 ***	-1.32712 ***	-1.45832 ***	-1.39722 ***	-1.32141 ***	-1.38950 ***	-1.35266 ***
chi ²	54.4	60.4	61.9	67.3	84.7	59.3	72.7	86.9	70.9	81.1
ll	-1037.6	-1035.6	-1033.8	-1032.4	-1023.0	-1035.1	-1030.1	-1022.5	-1030.7	-1026.5
aic	2115.3	2113.1	2109.7	2106.7	2088.0	2112.2	2102.2	2090.9	2107.4	2099.0
bic	2228.9	2232.5	2229.1	2226.1	2207.4	2231.6	2221.6	2221.7	2238.1	2229.8
N	2179	2179	2179	2179	2177	2177	2177	2177	2177	2177

Legend: *p<.1; **p<.05; ***p<.01

Source: authors own calculation.

Next, we turn attention on the fully specified models (Models 8-10, Tab. 3a). The results are consistent with the results reported in Model 2 – 4 (Tab. 3a). Same is true for ego-network effects. The effects for ego-network size and ego-network brokerage remain robust in Model 8 and 10 (Tab. 3a) where no effect can be identified for ego-network density in Model 9 (Tab. 3a) based on fixed effect estimation techniques. However, a look at the random effects model results (Tab. 3b) reveals a slightly different picture. Even though we have to interpret these results with caution coefficients for both cooperation measures as well as ego-network measures are positive and significant in nearly all model specifications.

In order to check the robustness and consistency of these initial finding we estimate all previously discussed models again with a time-lag of one year (Tab.4a & Tab. 4b). Table 4a reports results for fixed effects estimation techniques whereas Table 4b provides results based of random effects estimators. Same as before, Models 2-4 (Tab. 4a) address direct cooperation effects. Based on this specification we find now an additional direct cooperation for Foerderkatalog cooperation projects [*coopcnt_fk*] at the 0.1 significance level and confirm the previously reported combined cooperation count effect [*coopcnt_fk*] with an increased 0.05 significance-level. The results for the ego-network effects (Model 5-7, Tab. 4a) are fully consistent with our previous findings (Model 5-7, Tab. 3a). Again, ego-size (Model 5, Tab. 4a) as well as the ego-brokerage variable (Model 7, Tab 4a) show highly positive and significant coefficients at the 0.01 level and no network-density effects (Model 6, Tab. 4a). The fully specified models (Model 8-10, Tab. 4a) confirm again our precious ego-network results and reveal some interesting insights with regard to cooperation effects. The effects for ego-network size and ego-network brokerage remain robust (Model 8 & 10 Tab. 4a) and ego-network density has no significant effect (Model 9, Tab. 4a). Surprisingly, now the direct Foerderkatalog cooperation measure [*coopcnt_fk*] is a directly related to innovation output, but the estimates are only marginally significant at the 10% level (Model 8, Tab 4b.). A look at the fully specified random effects model (Model 8-10, Tab. 4b) confirms this finding. Model 8 (Tab. 4b) reports a highly significant coefficient for Foerderkatalog cooperation counts at the 0.01 significance-level and no effect for ego-network density.

To sum up, we argue our first two hypotheses (H-1a & H-1b) that CORDIS as well as Foerderkatalog collaborations are positively related to firm innovativeness. Based on our previous discusses finding we must reject hypothesis H-1a. However, Foerderkatalog cooperation projects seem to be positively related to innovation output in three out of four fully specified models (Model 8, in: Tab. 3b; Tab. 4a; 4b). Thus we found at least modest support for hypotheses H-1b. We argue in Hypothesis H-2a that number of directly connected partners exerts a positive effect on firm-level innovation output. Estimation results supports H-2a predicting that innovation output increases in the number of linkages to other laser source manufacturers and laser-active public research organizations.

Table 4:

Estimation results – patent grants; time-lag (t+1); fixed and random effects models

Figure 4a: Estimation technique: fixed effects

Variable	Estimation results									
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
yr97	.68786 *	.66294	.74171 *	.72638 *	.67548 *	.69254 *	.87114 **	.67945 *	.73800 *	.89218 **
yr98	1.12791 **	1.09025 **	1.23458 **	1.19707 **	1.15294 **	1.12585 **	1.2608 **	1.15855 **	1.20740 **	1.34118 ***
yr99	.61629 **	.63617 **	.62699 **	.64986 **	.61404 **	.61774 **	.65599 **	.62535 **	.64956 **	.69014 ***
yr00	.84742 ***	.85623 ***	.87222 ***	.87943 ***	.88633 ***	.84600 ***	.85838 ***	.89263 ***	.87781 ***	.89306 ***
yr01	.22683	.24862	.19233	.21743	.24204	.22795	.17980	.24470	.21247	.18004
yr02	-.22577	-.18664	-.28804	-.24488	-.14146	-.22494	-.15822	-.13763	-.25651	-.18553
yr03	-.40211	-.35732	-.46965	-.41904	-.33127	-.40148	-.35362	-.32631	-.43294	-.38143
yr04	-.69303	-.65073	-.82785	-.77721	-.68068	-.69169	-.69602	-.68327	-.79497	-.77553
yr05	-.17804	-.15740	-.29019	-.26237	-.11707	-.17915	-.24835	-.12339	-.27782	-.31296
yr06	.32909	.33850	.30519	.31727	.38580	.32540	.26036	.38327	.30632	.25760
yr07	.15369	.18051	.13103	.16074	.20540	.15516	.09988	.21097	.15683	.11545
yr08	.43233 *	.42534 *	.42750 *	.42036 *	.43745 *	.43104 *	.42595 *	.43239 *	.41925 *	.41762 *
nw_size	-10.8193 **	-10.5055 **	-12.2049 **	-11.8302 **	-12.0577 **	-10.7712 **	-11.5198 **	-12.1072 **	-11.9121 **	-12.4781 ***
nw_density	-17.4099 **	-17.0331 **	-18.7696 ***	-18.2446 ***	-16.7734 **	-17.3848 **	-15.7096 **	-16.7890 **	-18.4247 ***	-16.6116 **
firmage	.10819 ***	.10748 ***	.11637 ***	.11580 ***	.12233 ***	.10791 ***	.13293 ***	.12373 ***	.11580 ***	.13944 ***
firmage_sq	-.00238	-.00226	-.00235	-.00223	-.00111	-.00238	-.00211	-.00112	-.00226	-.00207
coopfund_fkc	-1.60E-5	-1.95E-5	-3.60E-5	-3.95E-5	-3.26E-5	-1.66E-5	-3.24E-5	-3.35E-5	-4.15E-5	-5.12E-5
coopcnt_c		.10274						.03040	.09065	.07094
coopcnt_fk			.12046 *					.00820	.12122 *	.08744
coopcnt_fkc				.11098 **						
ego_size					.04275 ***			.04191 ***		
ego_density						-.00069			-.00135	
ego_nbroke							.01687 ***			.01573 ***
_cons	5.51808 **	5.33137 **	6.05866 **	5.84127 **	5.52254 **	5.51604 **	5.34671 **	5.53138 **	5.92268 **	5.71841 **
chi ²	67.7	68.2	71.3	71.3	87.2	67.8	81.3	86.9	71.6	82.4
ll	-687.9	-687.5	-686.1	-685.8	-676.9	-687.9	-681.6	-676.8	-685.7	-680.4
aic	1411.8	1412.9	1410.3	1409.6	1391.7	1413.8	1401.1	1395.6	1413.4	1402.7
bic	1501.3	1507.4	1504.7	1504.0	1486.1	1508.2	1495.5	1499.9	1517.7	1507.1
N	1063	1063	1063	1063	1063	1063	1063	1063	1063	1063

Legend: *p<.1; **p<.05; ***p<.01

Figure 4b: Estimation technique: random effects

Variable	Estimation results									
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
yr97	.46325	.40007	.50604	.46998	.29400	.45051	.52573	.29577	.47138	.52550
yr98	.89284 *	.81495 *	1.00946 **	.94089 *	.74367	.89234 *	.87920 *	.72603	.94854 *	.94794 **
yr99	.61120 **	.64617 **	.63277 **	.66529 **	.62902 **	.60878 **	.64563 **	.64498 **	.66176 **	.69363 ***
yr00	.90012 ***	.91933 ***	.96037 ***	.97340 ***	1.02233 ***	.90548 ***	.93523 ***	1.03069 ***	.97565 ***	.99725 ***
yr01	.30509	.35439	.27663	.32587	.40339	.30744	.31199	.41252	.32292	.33409
yr02	-.21380	-.13330	-.26708	-.19457	-.04158	-.21184	-.08333	-.02591	-.20106	-.08751
yr03	-.35717	-.27471	-.42682	-.34933	-.23750	-.35554	-.27216	-.22154	-.35612	-.28790
yr04	-.61165	-.52957	-.77196	-.69117	-.52427	-.60949	-.54523	-.51478	-.69970	-.62492
yr05	-.13659	-.10159	-.27287	-.23641	-.02796	-.13150	-.16902	-.03261	-.23939	-.23870
yr06	.37005	.38796	.35984	.38037	.47572	.37912	.31453	.47093	.38170	.33173
yr07	.18871	.23819	.18055	.22661	.27930	.18764	.14667	.29181	.22209	.19573
yr08	.43895 *	.42518 *	.44610 *	.43231 *	.44699 *	.44038 *	.42527 *	.43339 *	.43375 *	.42198 *
nw_size	-9.60612 *	-8.91982 *	-11.2589 **	-10.5726 **	-9.6574 *	-9.6596 *	-9.25075 *	-9.54666 *	-10.6745 **	-10.2150 *
nw_density	-18.8794 **	-18.3737 **	-21.1498 ***	-20.5365 ***	-20.4581 ***	-18.9341 **	-17.8538 **	-20.4389 **	-20.6426 ***	-19.3785 ***
firmage	.07683 **	.07464 **	.08392 **	.08225 **	.06374 *	.07727 **	.08745 **	.06450	.08266 **	.09055 ***
firmage_sq	-.00216 *	-.00206	-.00225 *	-.00218 *	-.00112	-.00217 *	-.00224 *	-.00115	-.00219 *	-.00225 *
coopfund_fkc	2.43E-7	-6.56E-6	-2.41E-5	-3.03E-5	-2.09E-5	8.53E-7	-2.04E-5	-2.35E-5	-2.97E-5	-4.26E-5
coopcnt_c		.17768 *						.05607	.14824	.10678
coopcnt_fk			.17408 ***					.00337	.16471 ***	.11765 *
coopcnt_fkc				.16099 ***						
ego_size					.05133 ***			.05023 ***		
ego_density						0.00145			.00051	
ego_nbroke							.019559 ***			.01717 ***
_cons	5.22686 *	4.86567 *	5.89619 **	5.54272 **	4.97460 *	5.21511 *	4.72954 *	4.91953 *	5.57866 **	5.14083 *
ln_r_cons	.77644 ***	.79112 ***	.79492 ***	.80544 ***	.87562 ***	.77953 ***	.80295 ***	.87810 ***	.80648 ***	.82384 ***
ln_s_cons	-1.46619 ***	-1.44475 ***	-1.41633 ***	-1.40308 ***	-1.31099 ***	-1.45840 ***	-1.38551 ***	-1.30807 ***	-1.40020 ***	-1.35993 ***
chi ²	65.8	68.2	72.5	73.9	97.4	66.0	87.2	97.5	74.0	89.8
ll	-1097.0	-1095.6	-1093.1	-1092.1	-1079.1	-1096.8	-1087.6	-1078.9	-1092.1	-1085.2
aic	2234.0	2233.2	2228.2	2226.2	2200.3	2235.7	2217.3	2203.9	2230.1	2216.5
bic	2349.8	2354.8	2349.7	2347.8	2321.8	2357.2	2338.9	2337.1	2363.2	2349.6
N	2412	2412	2412	2412	2410	2410	2410	2410	2410	2410

Legend: *p<.1; **p<.05; ***p<.01

Source: authors own calculation.

Likewise our results provide strong support to Hypothesis H-2c suggesting that brokerage positions in ego-networks are positively related with subsequent firm level innovation outcomes. Results for ego-network size and brokerage are robust over all model specifications. Surprisingly, we found no support for hypothesis H-2b. In addition, funding shows no significant effects on firm innovativeness in our estimations indicating that not the reconceived funding but rather the cooperation activities itself matters. In sum it turned out that the estimation models show direct innovation effects of individual cooperation events as long as portfolio characteristics are neglected. These effects fade partially away when considering at the same time ego-network characteristics.

6 Conclusion, Limitations and Further Research

This study was motivated by the goal of deepening our understanding of the relationship between individual cooperation events, ego-network structures and firm-level innovation output in the German laser industry. Our efforts in this paper constitute a first step in this direction. We have started the analysis by taking a closer look at cooperation propensities of laser manufacturing firms. The results of our study imply 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. Surprisingly, this result holds only for nationally funded projects whereas the supranational funded cooperation projects turned out to show no significant effects. Furthermore, our findings relativize the argument according to which firms' innovative performance is rather affected by public funding than cooperation activities themselves as we include firm-level funding sums as a control variable in all models. 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, we found no support for ego-network density. In other words, the existence of ties among alter seems to be less important for firm level innovation outcome. Finally, it turns out that the ego-network brokerage has a significant and positive effect on patenting activity. In other words, the strategic positioning of focal actors seems to be important for the innovative performance of the focal actor.

As our research in this area is in a quite 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 extended. For example, we are currently including 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, in-depth research on the causes for evolutionary network change processes at the micro-level is required to understand the drivers of network change. These challenges build up the next steps on our research agenda.

References:

- Ahuja, G. (2000). Collaboration Networks, Structural Hole, and Innovation: A Longitudinal Study. *Administrative Science Quarterly* , 45 (3), pp. 425-455.
- Albert, R. & Barabasi, A-L. (2000). Topology of Evolving Networks: Local Events and Universality. In: *Physical Review Letters*, 85(24), pp. 5234-5237.
- Albrecht, H., Buenstorf, G. & Fritsch, M. (2011). System? What System? The (Co-) Evolution of Laser Research and Laser Innovation in Germany since 1960, Freiberg u. a. Mai 2011 (Working paper).
- Alic, J. A. (1990). Cooperation in R&D. *Technovation* , 10 (5), pp. 319-332.
- Al-Laham, A., & Kudic, M. (2008). Strategische Allianzen. In H. Corsten, & R. Goessinger, *Lexikon der Betriebswirtschaftslehre* (5 ed., pp. 39-41). München/Wien: Oldenburg Verlag.
- Amburgey, T. L., Dacin, T., & Singh, J. V. (1996). Learning Races, Patent Races, and Capital Races: Strategic Interaction and Embeddedness within Organizational Fields. In J. A. Baum, *Advances in Strategic Management* (pp. 303-322). New York: Elsevier.
- Anand, B. N., & Khanna, T. (2000). Do Firms Learn To Create Value ? The Case of Alliances. *Strategic Management Journal* , 21, pp. 295-315.
- Baum, J. A., Calabrese, T., & Silverman, B. S. (2000). Don't go it allone: Alliance Network Composition and Startups's Performance in Canadian Biotechnology. *Strategic Management Journal* , 21, pp. 267-294.
- Bergenholtz, C., & Waldstrom, C. (2011). Inter-Organizational Network Studies - A Literature Review. *Industry & Innovation* , 18 (6), pp. 539-562.
- Bertolotti, M. (2005). *The History of the Laser*. Bristol, UK: Institute of Physics Publishing.
- Bidault, F., & Cummings, T. (1994). Innovating through alliances: expectations and limitations. *R&D Management* , 24 (1), pp. 33-45.
- Bleeke, J.; Ernst, D. (1991): The Way to win in cross-border alliances. *Harvard Business Review*, 69 (6), pp. 127-135.
- Borgatti, S. P., Everett, M. G., & Freeman, L. C. (2002). *Ucinet for Windows: Software for Social Network Analysis*. Harvard, MA: Analytic Technologies.
- Borys, B., & Jemison, D. B. (1989). Hybrid Arrangements as Strategic Alliances: Theoretical Issues in Organizational Combinations. *Academy of Management Review* , 14 (2), pp. 234-249.
- Brenner, T., & Broekel, T. (2011). Methodological Issues in Measuring Innovation Performance of Spatial Units. *Industry & Innovation* , 18 (1).
- Broeckel, T., & Graf, H. (2011). Public research intensity and the structure of German R&D networks: A comparison of ten technologies. *Economics of Innovation and New Technology* , pp. 1-28.

- Buckley, P. J., Glaister, K. W., Klijn, E., & Tan, H. (2009). Knowledge Accession and Knowledge Acquisition in Strategic Alliances: The Impact of Supplementary and Complementary Dimensions. *British Journal of Management* , 20, pp. 598–609.
- Buenstorf, G. (2007). Evolution on the Shoulders of Giants: Entrepreneurship and Firm Survival in the German Laser Industry. *Review of Industrial Organization* , 30, pp. 179-202.
- Burt, R. S. (2005). *Brokerage & Closure - An Introduction to Social Capital* . Oxford: Oxford University Press.
- Burt, R. S. (1992). *Structural Holes: The Social Structure of Competition*. Cambridge: Harvard University Press.
- Cameron, C. A., & Trivedi, P. K. (2009). *Microeconometrics Using Stata*. Stata Press.
- Capaldo, A. (2007). Network Structure and Innovation: The Leveraging of a dual Network as a distinctive relational Capability. *Strategic Management Journal* , 28, pp. 585-608.
- Cassi, L., Corrocher, N., Malerba, F., & Vonortas, N. (2008). Research networks as infrastructure for knowledge diffusion in European regions. *Economics of Innovation and New Technology* , 17 (7), pp. 665-678.
- Ciesa, V., & Toletti, G. (2004). Network of Collaborations for Innovation: The Case of Biotechnology. *Technology Analysis & Strategic Management* , 16 (1), pp. 73-96.
- Coff, R. W. (2003). The Emergent Knowledge-Based Theory of Competitive Advantage: An Evolutionary Approach To Integrating Economics and Management. *Managerial and Decision Economics* , 24, pp. 245-251.
- Cohen, W. M., & Levinthal, D. A. (1990). Absorptive Capacity: A New Perspective on Learning and Innovation. *Administrative Science Quarterly* , 35 (3), pp. 128-152.
- Coleman, J. S. (1988). Social capital in the creation of human capital. *American Journal of Sociology* , 94, pp. 95-120.
- Cowan, R., Jonard, N., & Zimmermann, J.-B. (2006). Evolving Networks of Inventors. *Journal of Evolutionary Economics* , 16, pp. 155-174.
- Das, T. K., & Teng, B.-S. (2002). Alliance Constellations: A Social Exchange Perspective. *Academy of Management Journal* , 27 (3), pp. 445-456.
- Das, T. K., & Teng, B.-S. (2000). Instabilities of Strategic Alliances: An Internal Tensions Perspective. *Organization Science* , 11 (1), pp. 77-101.
- De Propriis, L. (2000). Innovation And Inter-Firm Co-Operation: The Case Of The West Midlands. *Economics of Innovation and New Technology* , 9 (5), pp. 421-446.
- Decarolis, D. M., & Deeds, D. L. (1999). The Impact of Stocks and Flows of Organizational Knowledge on Firm Performance: An Empirical Investigation of the Biotechnology Industry. *Strategic Management Journal* , 20, pp. 953-968.
- Dittrich, K., Duysters, G., & De Man, A.-P. (2007). Strategic repositioning by means of alliance networks: The case of IBM. *Research Policy* , 36, pp. 1496-1511.

- Doreian, P., & Stokman, F. N. (2005). The dynamics and evolution of social networks. In P. Doreian, & F. N. Stokman, *Evolution of Social Networks* (pp. 1-17). New York: Gordon and Breach.
- Doreian, P., & Woodward, K. L. (1992). Fixed list versus snowball selection of social networks. *Social networks* , 21, pp. 216-233.
- Doz, Y., & Hamel, G. (1997). The use of alliances in implementing technology strategies. In M. T. Tushman, & P. Anderson, *Managing strategic innovation and change* (pp. 556–580). New York: Oxford University Press.
- Dyer, J. H., & Nobeoka, K. (2000). Creating and Managing A High-Performance Knowledge-Sharing Network: The Toyota Case. *Strategic Management Journal* , 21, pp. 345-367.
- Dyer, J. H., & Singh, H. (1998). The Relational View: Cooperative Strategy and Sources of International Competitive Advantage. *Academy of Management Review* , 23 (4), pp. 660-680.
- Eraydin, A., & Aematli-Köroglu, B. (2005). Innovation, networking and the new industrial clusters: the characteristics of networks and local innovation capabilities in the Turkish industrial clusters. *Entrepreneurship & Regional Development* , 17, pp. 237-266.
- Fabian, C. (2011). *Technologieentwicklung im Spannungsfeld von Industrie, Wissenschaft und Staat: Zu den Anfängen des Innovationssystems der Materialbearbeitungslaser in der Bundesrepublik Deutschland 1960 bis 1997*, GNT-Verlag.
- Fornahl, D., Broeckel, T., & Boschma, R. (2011). What drives patent performance of German biotech firms? The impact of R&D subsidies, knowledge networks and their location. *Papers in Regional Science* , 90 (2), pp. 395-418.
- Frank, O. (2005). Network sampling and model fitting. In P. J. Carrington, J. Scott, & S. Wasserman, *Models and Methods in Social Network Analysis* (pp. 31-56). Cambridge: Cambridge University Press.
- Freel, M. S., & Harrison, R. T. (2006). Innovation and Cooperation in the Small Firm Sector: Evidence from 'Northern Britain'. *Regional Studies* , 40 (4), pp. 289-305.
- Fritsch, M. & Medrano, L. F. (2010). The Spatial Diffusion of a Knowledge Base – Laser Technology Research in West Germany, 1960 – 2005. *Jena Economic Research Papers 2010 – 048*.
- Fritsch, M., & Slavtshev, V. (2007). Universities and Innovation in Space. *Industry & Innovation* , 14 (2), pp. 201-218.
- Glueckler, J. (2007). Economic geography and the evolution of networks. *Journal of Economic Geography* , 7 (5), pp. 619-634.
- Goerzen, A. (2005). Managing Alliance Networks: Emerging Practices of Multinational Corporations. *Academy of Management Executive* , 19 (2), pp. 94-107.
- Gomes-Casseres, B. (2003). Competitive advantage in alliance constellations. *Strategic Organization* , 1 (3), pp. 327-335.

- Graf, H., & Krueger, J. J. (2011). The Performance of Gatekeepers in Innovator Networks. *Industry & Innovation* , 18 (1), pp. 69-88.
- Grant, R. M. (1996). Towards a Knowledge Base Theory of the Firm. *Strategic Management Journal* , 17 (2), pp. 109-122.
- Grant, R. M., & Baden-Fuller, C. (2004). A Knowledge Accessing Theory of Strategic Alliances. *Journal of Management Studies* , 41 (1), pp. 61-84.
- Green, W. H. (2003). *Econometric Analysis* . Prentice Hall.
- Grunwald, R., & Kieser, A. (2007). Learning to Reduce Interorganizational Learning: An Analysis of Architectural Product Innovation in Strategic Alliances. *Journal of Product Innovation Management* , 24, pp. 369-391.
- Grupp, H. (2000). Learning in a Science Driven Market: The Case of Lasers. *Industrial and Corporate Change* , 9 (1), pp. 143-172.
- Gulati, R. (1998). Alliances and Networks. *Strategic Management Journal* , 19 (4), pp. 293-317.
- Gulati, R., & Gargiulo, M. (1999). Where Do Interorganizational Networks Come Form? *American Journal of Sociology* , 104 (5), pp. 1439-1493.
- Gulati, R., Nohria, N., & Zaheer, A. (2000). Strategic Networks. *Strategic Management Journal* , 21, pp. 203-215.
- Hagedoorn, J. (2002). Inter-Firm R&D partnership: An overview of major trends and patterns since 1960. *Research Policy* , 31, pp. 477-492.
- Hagedoorn, J. (1993). Understanding the Rational of Strategic Technology Partnering-Organizational Modes of Cooperation and Sectoral Differences. *Strategic Management Journal* , 14 (5), pp. 371-385.
- Hakansson, H., & Johanson, J. (1988). Formal and Informal Cooperation. Strategies in International Industrial Networks. In F. J. Contractor, & P. Lorange, *Cooperative Strategies in International Business* (pp. 369-379). Mass.: Lexington Books.
- Hamel, G. (1991). Competition for Competence and Inter-Partner Learning Within International Strategic Alliances, in: *Strategic Management Journal*. 12, pp. 83-103.
- Hamel, G., Doz, Y. L., & Prahalad, C. K. (1989). Collaborate With Your Competitors- And Win. *Harvard Business Review* , 67, pp. 133-139.
- Harabi, N. (2002). The Impact of Vertical R&D Cooperation on Firm Innovation: An Empirical Investigation. *Economics of Innovation and New Technology* , 11 (2), pp. 93-108.
- Harrigan, K. R. (1988). Joint Ventures and Competitive Strategy. *Strategic Management Journal* , 9 (2), pp. 141-158.
- Hausman, J. A. (1978). Specification Tests in Econometrics. *Econometrica* , 46, pp. 1251-1271.
- Hecht, J. (2005). *Beam - The Race to Make the Laser*. Oxford: Oxford University Press.

- Hecht, J. (2010). The First Half-Century of Laser Development - How a solution that once was looking for a problem has become part of everyday life. *Laser Technik Journal* , 7 (4), pp. 20-25.
- Hite, J. M., & Hesterly, W. S. (2001). The evolution of firm networks: from emergence to early growth of the firm. *Strategic Management Journal* , 22, pp. 275-286.
- Hoffmann, W. H. (2005). How to Manage a Portfolio of Alliances. *Long Range Planning* , 38 (2), pp. 121-143.
- Hoffmann, W. H. (2007). Strategies for Managing Alliance Portfolios. *Strategic Management Journal* , 28, pp. 827-856.
- Inkpen, A. C., & Beamish, P. W. (1997). Knowledge, Bargaining Power, And The Instability of International Joint Ventures. *Academy of Management Review* , 22 (1), pp. 177-202.
- Jackson, M. O., & Watts, A. (2002). The Evolution of Social and Economic Networks. *Journal of Economic Theory* , 106, pp. 265-295.
- Jaffe, A. B., Trajtenberg, M., & Henderson, R. (1993). Geographic localization of knowledge spillovers as evidenced by patent citations. *Quarterly Journal of Economics* , 108 (3), pp. 577-598.
- Jarillo, C. J. (1988). On Strategic Networks. *Strategic Management Journal* , 9, pp. 31-41.
- Jarvenpaa, S. L., & Majchrzak, A. (2008). Knowledge Collaboration Among Professionals Protecting National Security: Role of Transactive Memories in Ego-Centered Knowledge Networks. *Organization Science* , 19 (2), pp. 260-276.
- Jeong, H., Neda, Z., & Barabasi, A.-L. (2003). Measuring preferential attachment in evolving networks. *Europhysics Letters* , 61 (4), pp. 567-572.
- Johanson, J., & Mattson, L.-G. (1988). Internationalization in Industrial Systems - A Network Approach. In N. Hood, & J.-E. Vahlen, *Strategies in Global Competition* (pp. 287-331). New York: Croom Helm.
- Jun, T., & Sethi, R. (2009). Reciprocity in evolving social networks. *Journal of Evolutionary Economics* , 19, pp. 379-396.
- Kale, P., Singh, H., & Perlmutter, H. (2000). Learning and Protection of Proprietary Assets in Strategic Alliances: Building Relational Capital. *Strategic Management Journal* , 21, pp. 217-237.
- Kennedy, P. (2003). *A Guide to Econometrics*. Oxford: Blackwell Publishing.
- Khanna, T., Gulati, R., & Nohria, N. (1998). The Dynamics of Learning Alliances: Competition, Cooperation, and Relative Scope. *Strategic Management Journal* , 19, pp. 193-210.
- Kim, T.-Y., Oh, H., & Swaminathan, A. (2006). Framing Interorganizational Network Change: A Network Inertia Perspective. *Academy of Management Review* , 31 (3), pp. 704-720.

- Kogut, B. (1991). Joint Ventures and the option to expand and acquire. *Management Science* , 37, pp. 19-33.
- Kogut, B., & Zander, U. (1992). Knowledge of the Firm, Combinative Capabilities, and the Replication of Technology. *Organization Science* , 3 (3), pp. 383-397.
- Koka, B. R., Madhavan, R., & Prescott, J. E. (2006). The Evolution of Interfirm Networks: Environmental Effects on Patterns of Network Change. *Academy of Management Review* , 31 (3), pp. 721-737.
- Kudic, M., Buenstorf, G., Guhr, K. (2011a): The impact of evolving ego-network structures on innovation output – Empirical evidence from the German laser industry”. Conference paper, 7th EMAEE Conference, 14-16 Feb., Pisa, Italy.
- Kudic, M., Buenstorf, G., Guhr, K. (2011b): Disentangling the impact of single cooperation events and ego-network effects on firm innovativeness - Empirical Evidence from the German laser industry. Conference paper, 5th EMNET Conference, 1-3 Dec., Limassol, Cyprus.
- Kudic, M., Guhr, K., Bullmer, I., & Guenther, J. (2011c). Kooperationsintensität und Kooperationsförderung in der deutschen Laserindustrie. *Wirtschaft im Wandel*, 17 (3), pp. 121-129.
- Kudic, M. (2013): Innovation Networks in the German Laser Industry – Evolutionary Change, Strategic Positioning and Firm Innovativeness, Ph.D. Thesis, forthcoming.
- Lane, P. J., & Lubatkin, M. H. (1998). Relative Absorptive Capacity and Interorganizational Learning. *Strategic Management Journal* , 19 (5), pp. 461-477.
- Lane, P. J., Salk, J. E., & Lyles, M. A. (2001). Absorptive Capacity, Learning, and Performance in International Joint Ventures. 22, pp. 1139-1161.
- Lavie, D. (2007). Alliance Portfolios and Firm Performance: A Study of Value Creation and Appropriation in the U.S. Software Industry. *Strategic Management Journal* , 28 (12), pp. 1187-1212.
- Lavie, D., & Miller, S. R. (2008). Alliance Portfolio Internationalization and Firm Performance. *Organization Science* , 19 (4), pp. 623-646.
- Lee, J. J. (2010). Heterogeneity, Brokerage, and Innovative Performance: Endogenous Formation of Collaborative Inventor Networks. *Organization Science* , 21 (4), pp. 804-822.
- Lui, S. S. (2009). Interorganizational Learning The Roles of Competence Trust, Formal Contract, and Time Horizon in Interorganizational Learning. 30, pp. 333-353.
- Maiman, T. H. (1960). Stimulated optical radiation in ruby. *Nature* , 187, pp. 493-494.
- Markowitz, H. (1952). Portfolio selection. *Journal of Finance* , 7 (1), pp. 77-91.
- Mayer, A. (2004). Laser in der Materialbearbeitung - Eine Marktübersicht. *Laser Technik Journal* , 1 (1), pp. 9-12.
- Mowery, D. C., Oxley, J. E., & Silverman, B. S. (1996). Strategic Alliances and Interfirm Knowledge Transfer. *Strategic Management Journal* , 17 (2), pp. 77-92.

- Narula, R., & Hagedoorn, J. (1999). Innovating through strategic alliances: moving towards international partnerships and contractual agreements. *Technovation* , 19, pp. 283-294.
- Nowak, M. A., Tarnita, C. E., & Antal, T. (2010). Evolutionary dynamics in structured populations. *Philosophical Transactions in the Royal Society B* , 365, pp. 19-30.
- Ohmae, K. (1989). The global logic of strategic alliances. *Harvard Business Review* , 67, pp. 143-154.
- Osborn, R. N., & Hagedoorn, J. (1997). The Institutionalization and Evolutionary Dynamics of Interorganizational Alliances and Networks. *Academy of Management Journal* , 40 (2), pp. 261-278.
- Owen-Smith, J., & Powell, W. W. (2004). Knowledge Networks as Channels and Conduits: The Effects of Spillovers in the Boston Biotechnology Community. *Organization Science* , 15 (1), pp. 5-21.
- Ozman, M. (2009). Inter-firm networks and innovation: a survey of literature. *Economics of Innovation and New Technology* , 18 (1), pp. 39-67.
- Parise, S., & Casher, A. (2003). Alliance Portfolios: Designing and Managing Your Network of Business-Partner Relationships. *Academy of Management Executive* , 17 (4), pp. 25-39.
- Park, S. H., & Russo, M. V. (1996). When Competition Eclipses Cooperation: An Event History Analysis of Joint Venture Failure. *Management Science* , 42 (6), pp. 875-890.
- Pittaway, L., Robertson, M., Munir, K., Denyer, D., & Neely, A. (2004). Networking and innovation: a systematic review of the evidence. *International Journal of Management Reviews* , 5 (6), pp. 137-168.
- Podolny, J. M. (2001). Networks as the Pipes and Prisms of the Market. *American Journal of Sociology* , 7 (1), pp. 33-60.
- Podolny, J. M., & Page, K. L. (1998). Network Forms of Organization. *Annual Review of Sociology* , 24, pp. 57-76.
- Powell, W. W. (1990). Neither Market nor Hierarchy: Networks Forms of Organization. *Research in Organizational Behavior* , 12, pp. 295-336.
- Powell, W. W., Koput, K. W., & Smith-Doerr, L. (1996). Interorganizational Collaboration and the Locus of Innovation - Networks of Learning in Biotechnology. *Administrative Science Quarterly* , 41 (1), pp. 116-145.
- Powell, W. W., White, D. R., Koput, K. W., & Owen-Smith, J. (2005). Network Dynamics and Field Evolution: The Growth of the Interorganizational Collaboration in the Life Sciences. *American Journal of Sociology* , 110 (4), pp. 1132-1205.
- Protogerou, A., Caloghirou, Y., & Siokas, E. (2010). Policy-driven collaborative research networks in Europe. *Economics of Innovation and New Technology* , 19 (4), pp. 349-372.

- Provan, K. G., Fish, A., & Sydow, J. (2007). Interorganizational Networks at the Network Level: A Review of the Empirical Literature on Whole Networks. *Journal of Management* , 33 (3), pp. 479-516.
- Rodan, S., & Galunic, C. (2004). More Than Network Structure: How Knowledge Heterogeneity Influences Managerial Performance and Innovativeness. *Strategic Management Journal* , 25, pp. 541-562.
- Rothaermel, F. T. (2001). Incumbent's Advantage through Exploiting Complementary Assets Via Interfirm Cooperation . *Strategic Management Journal* , 22 (6), pp. 687-699.
- Rothaermel, F. T., & Deeds, D. L. (2006). Alliance type, alliance experience and alliance management capability in high-technology ventures. *Journal of Business Venturing* , 22, pp. 429-460.
- Rowley, T. J., Behrens, D., & Krackhardt, D. (2000). Redundent Governance Structures: An Analysis of Structural and Relational Embeddedness in the Steel and Semiconductor Industries. *Strategic Management Journal* , 21, pp. 369-386.
- Scherngell, T., & Barber, M. J. (2011). Distinct spatial characteristics of industrial and public research collaborations: Evidence from the fifth EU framework programme. *Annals of Regional Science* , 46, pp. 247-266.
- Schilke, O., & Goerzen, A. (2010). Alliance Management Capability: An Investigation of the Construct and Its Measurement. *Journal of Management* , 36 (5), pp. 1192-1219.
- Schilling, M. A. (2009). Understanding the Alliance Data. *Strategic Management Journal* , 30, pp. 233-260.
- Schilling, M. A., & Phelps, C. C. (2007). Interfirm Collaboration Networks: The Impact of Large-Scale Network Structure on Firm Innovation. *Management Science* , 53 (7), pp. 1113-1126.
- Simonin, B. L. (1999). Ambiguity and the Process of Knowledge Transfer in Strategic Alliances. *Strategic Management Journal* , 20 (1), pp. 595-623.
- Sivadas, E., & Dwyer, R. F. (2000). An Examination of Organizational Factors Influencing New Product Success in Internal and Alliance-Based Processes. *Journal of Marketing* , 64, pp. 31-49.
- Snijders, T. A. (2004). Explained variation in dynamic network models. *Mathematical social sciences* , 42 (168), pp. 5-15.
- Spender, J. C., & Grant, R. M. (1996). Knowledge and the Firm: Overview. *Strategic Management Journal* , 17 (2), pp. 5-10.
- Stuart, T. E. (1999). A Structural Perspective on Organizational Performance. *Industrial and Corporate Change* , 8 (4), pp. 745-775.
- Stuart, T. E. (2000). Interorganizational Alliances and the Performance of Firms: A Study of Growth and Innovational Rates in a High-Technology Industry. *Strategic Management Journal* , 21 (8), pp. 791-811.

-
- Thorelli, H. B. (1986). Networks: Between Markets and Hierarchies. *Strategic Management Journal* , 7, pp. 37-51.
- Uzzi, B. (1997). Social Structure and Competition in Interfirm Networks: The Paradox of Embeddedness. *Administrative Science Quarterly* , 42 (1), pp. 35-67.
- Van Den Bosch, F. A., Volberda, H. W., & De Boer, M. (1999). Coevolution of Firm Absorptive Capacity and Knowledge Environment: Organizational Forms and Combinative Capabilities. *Organization Science* , 10 (5), pp. 551-568.
- Walker, G., Kogut, B., & Shan, W. (1997). Social Capital, Structural Holes and the Formation of an Industry Network. *Organization Science* , 8 (2), pp. 109-125.
- Wasserman, S., & Faust, K. (1994). *Social Network Analysis: Methods and Applications*. Cambridge: Cambridge University Press.
- Wassmer, U. (2010). Alliance Portfolios: A Review and Research Agenda. *Journal of Management* , 36 (1), pp. 141-171.
- White, S. (2005). Cooperation Costs, Governance Choice and Alliance Evolution. *Journal of Management Studies* , 42 (7), pp. 1383-1413.
- Williamson, O. E. (1991). Comparative Economic Organization: The Analysis of Discrete Structural Alternatives. *Administrative Science Quarterly* , 36 (2), pp. 269-296.
- Wuyts, S., Dutta, S., & Stremersch, S. (2004). Portfolios of Interfirm Agreements in Technology-Intensive Markets: Consequences for Innovation and Profitability. *Journal of Marketing* , 68, pp. 88-100.
- Zaheer, A., & Soda, G. (2009). Network Evolution: The Origins of Structural Holes. *Administrative Science Quarterly* , 54, pp. 1-31.
- Zahra, S. A., & George, G. (2002). Absorptive Capacity: A Review, Reconceptualization, and Extension. *Academy of Management Review* , 27 (2), pp. 185-203.