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Abstract

Empirical evidence on the evolution of innovation networks within high-tech industries is still scant. We investigate network formation processes by analyzing the timing of firms to enter R&D cooperations, using data on laser source manufacturers in Germany, 1990-2010. Network measures are constructed from a unique industry database that allows us to track both the formation and the termination of ties. Regression results reveal that a firm's knowledge endowment (and cooperation experience) shortens the duration to first (and consecutive) cooperation events. The previous occupation of strategic network positions is closely related to the establishment of further R&D cooperations at a swift pace. Geographic co-location produces mixed results in our analysis.

Keywords: laser industry, innovation network, R&D cooperation, event history

JEL Classification: O32, C41, D85

Netzwerkbildung: Kooperationsneigung und zeitliche Taktung von FuE-Kooperationen in der deutschen Laserindustrie

Zusammenfassung

Empirische Untersuchungen zur Evolution von Innovationsnetzwerken sind nach wie vor spärlich gesät. Der Schwerpunkt der vorliegenden Studie liegt auf der Untersuchung von Netzwerkentstehungsprozessen. Dabei konzentrieren wir uns in erster Linie auf die Analyse der zeitlichen Taktung von FuE-Kooperationsereignissen am Beispiel der deutschen Laserindustrie zwischen 1990 und 2010. Die Netzwerkindikatoren stammen aus einem in dieser Form einzigartigen Längsschnittdatensatz, der eine zeitpunktgenaue Erfassung von Kooperationsbildungs- und Kooperationsauflösungsereignissen erlaubt. Unsere Ergebnisse deuten darauf hin, dass die Wissensausstattung (und Kooperationserfahrung) der Firmen die Zeitspanne bis zum ersten (und konsekutiven) Kooperationsereignis verkürzt. Zudem zeigt sich, dass die Besetzung exponierter Netzwerkpositionen die Zeitspanne bis zur Bildung weiterer FuE-Kooperationen signifikant verkürzt. Die Untersuchung des Zusammenhangs zwischen geographischer Lage der Firmen und deren Kooperationsverhalten liefert einige unerwartete, jedoch hochinteressante Befunde.

Schlagwörter: Laserindustrie, Innovationsnetzwerk, FuE-Kooperation, Verweildauer-analyse

JEL-Klassifikation: O32, C41, D85

1 Introduction

The generation of new ideas and innovations is often a collective phenomenon, and technological progress is fundamental to firm performance and economic prosperity (Graf 2006). Starting in the early 1990s, a rich body of literature has emerged on the motives and economic rationales for cooperation in research and development (R&D) among firms of high-tech industries (Hagedoorn 1993). On average, R&D cooperations generate a value-added in this regard for the firms involved (Faulkner 2006). Today, research on innovation networks is a vibrant and interdisciplinary field, with significant contributions from economics, management science, and sociology.

Proponents of the knowledge-based view have argued that alliances allow firms to gain access to external stocks of knowledge, to recombine existing knowledge, and to learn from cooperation partners in order to gain a competitive advantage (Kogut and Zander 1992; Spender and Grant 1996; Grant 1996; Grant and Baden-Fuller 2004; Hamel 1991; Kale et al. 2000; Dierickx and Cool 1989; Coff 2003). In a similar vein, the Neo-Schumpeterian approach to economics explicitly acknowledges the collective nature of innovation process: innovation is regarded as the outcome of interactions between heterogeneous economic actors (Hanusch and Pyka 2007; Pyka 2002; Pyka 2007). The common denominator of these two approaches is that knowledge becomes the cornerstone of the analysis. Both approaches acknowledge the role of interorganizational innovation networks for knowledge exchange and learning processes and address the dynamics of these networks.

Yet, as far as the evolution of large-scale networks is concerned, researchers still face more questions than answers. In particular, the timing of network entry has virtually remained unexplored. This omission is quite astonishing insofar as a firm's early access to an innovation network is likely to bring about first mover advantages, in a sense that these firms may outperform competitors at later points in time. It is against this backdrop that the present study seeks to contribute some first empirical evidence based on a unique dataset that covers an entire industry of a country: the laser source manufacturers (LSM) in Germany in the period 1990-2010. We address the question what factors determine the ability of firms to initiate their first R&D cooperation and thus gain access to a new pool of technological knowledge. We then extend the scope to consecutive cooperations. In order to account for the science-driven nature of the laser industry we explicitly consider firm linkages to laser-related public research organizations (PRO) throughout the entire period under consideration (Grupp 2000). Our analysis also involves a geographical dimension, which is frequently assumed to affect cooperation decisions.

The remainder of the paper is structured as follows: section 2 provides a brief overview on the relevant literature and section 3 introduces the German laser industry. Section 4 is devoted to developing our research hypotheses. The dataset and method are described in section 5, and section 6 presents results. These are then discussed in section 7, along with some remarks on possible limitations and fruitful avenues for future inquiry.

2 Previous research on the dynamics of innovation networks

We start with a brief review of theoretical and empirical contributions that focus on the dynamic nature of interorganizational networks. In the most basic sense, a network can be defined "[…] as a set of nodes and the set of ties representing some relationship, or lack of relationship, between the nodes" (Brass et al. 2004, p. 795). The specification of the network nodes and ties determines the very nature of a particular network. It is important to note that innovation networks are by no means static. Instead they can be characterized as rather complex structural entities that underlie continuous change processes due to entries and exits of nodes and ties.

In economics, a theoretical foundation for studying antecedents and consequences of innovation networks from a dynamic perspective is provided by the systemic approaches to networks. A notion of mutually interconnected economic actors is clearly reflected in the concept of national innovation systems (Freeman 1988; Lundvall 1988, 1992; Nelson 1992) and in the refinements of this approach, such as regional innovation systems (Cook 2001), sectoral innovation systems (Malerba 2002), and technological innovation systems (Carlsson et al. 2002). Common to all these conceptualizations is that they involve creation, diffusion and use of knowledge. Each of them can be fully described by a set of components, relationships among these components, and their attributes. Systems are characterized by built-in feed-back mechanisms, and time plays an important role as the configuration of components, attributes, and relationships is constantly changing in these systems (Carlsson et al. 2002).

The concept of network evolution focuses on processes that contribute to network formation, sustainment, and fragmentation, which are believed to be neither random nor fully deterministic. This means that mechanisms have to be considered that create cumulative causation and lead to path-dependence as well as those mechanisms that produce contingency in the sense that the strategies and actions of agents may deviate from existing development paths, resulting in path destruction (Glueckler 2007; Doreian and Stokman 2005).

Empirical research on the issue is scant. The seminal study of Powell et al. (2005) addresses different attachment logics to explain the network dynamics in the US Life Science industry. In a similar vein, Venkatrama and Lee (2004) study preferential attachment mechanism in the U.S. video game industry and explore how network structures (density overlap and embeddedness on the one hand, and technology characteristics of the underlying technological platform such as novelty and dominance on the other hand) shape interorganizational coordination of product launches over time. Some empirical studies focus explicitly on dyadic tie-formation processes. For instance, Colombo et al. (2006) explore the determinants of alliance formation processes of high-tech start-ups. Others have considered, at least implicitly, the importance of timing issues when exploring the determinants and mechanisms of evolutionary network change processes. For instance, Balland (2012) employs an agent-based model to simulate the relationship between various proximity dimensions and the evolution of collaboration in the global navigation satellite system (GNSS) industry. In a similar vein, Buchmann et al. (2013) study the how technological and geographical proximity affect the evolution of networks in matured vs. high-tech industries by using the same methodological approach.

A few studies address R&D cooperation activities and innovation networks in laser-related industries from a dynamic perspective. Ouiment et al. (2007) explore the relationship between a firm's position within the network and its innovativeness in Canadian optics and photonics clusters. Lerch (2009) investigates network dynamics in the optical cluster in the Berlin-Brandenburg region in Germany. Similarly, Sydow et al. (2010) study path dependencies in a network context in the Berlin-Brandenburg optics cluster. Interorganizational networks in the laser industry have attracted little attention in the empirical literature so far. Noyon et al. (1994) explore the science and technology linkages by addressing inventor-author relations in laser medicine research. Shimizu and Hirao (2009) analyze interorganizational networks in the semiconductor laser industry in North America, Europe and Asia between 1975 and 1994. The two latter studies build upon patent data and bibliometric data, respectively. The results of both studies are exploratory in nature. The timing of initial and repeated cooperation events– if addressed at all–is mentioned only en passant. Thus, to the best of our knowledge, the timing of the onset of R&D cooperations – a crucial element in network formation – has remained a widely neglected topic in the empirical literature.

3 The German laser industry

To begin with, we take a brief look at the German laser industry and its industry value chain (cf. Kudic 2013). Lasers are artificial light sources that emit a coherent light beam characterized by some distinctive physical properties that make lasers useful for a broad range of technological applications (Buenstorf 2007, p. 182). The term laser (an acronym for "Light Amplification by Stimulated Emission of Radiation") was originally coined by Gould R. Gordon (1959), who is considered by many experts to be the actual inventor of the laser (Hecht 2005, p. 46). Almost instantly after Theodore H. Maiman (1960) put the first stable laser device into operation, the commercial sector took notice of the new technology. Numerous laser source manufacturing firms entered the scene, not only in the U.S. but also in Germany. In the early 1960s, the Siemens Group, whose headquarters were located in Munich at that time, started to play a dominant role in the development and manufacturing of lasers in Germany. Shortly afterwards, an entire industry, characterized by a high number of micro and small-sized firms, started to emerge (Buenstorf 2007). Today, laser applications can be found in nearly every sphere of life, with output a great range of output power: from 1-5 mW lasers used in DVD-ROM drives or laser pointers, 1-5 kW lasers for industrial laser cutting to petawatt-class lasers (10^{15} Watt) used for experiments in plasma and atomic physics. In 2006, the revenue of German laser sources and optical component producers amounted to 8.0 billion €, and about 45,000 workers were employed in the industry (Giesekus 2007, p. 11).

The German laser industry provides an ideal setting for studying R&D cooperation activities and firm innovativeness in science-driven industries. Firstly, laser technology requires knowledge from various academic disciplines, such as physics, optics and electrical engineering (Fritsch and Medrano 2010). It can clearly be characterized as a science-driven industry in which a firm's ability to innovate is a key factor in its performance and success (Grupp 2000). The interdisciplinary and science-based character of the industry is reflected in the high level of collaboration activities between German LSMs among themselves and with laser-related PROs (Kudic 2013). Secondly, the economic potential of the industry is meanwhile well recognized by national and supra-national political authorities. The laser industry is a small but interesting part of the German optical technology industry, which is regarded as one of the key technologies for the innovativeness and prosperity of the German economy as a whole (BMBF 2010). Over the past few decades, Germany has developed into a world market leader in many fields of laser technology (Mayer 2004). Thirdly, our data reveal a pronounced tendency towards geographical clustering of LSMs and PROs. Hence, the industry provides an ideal setting to analyze as to what extent geographic factors affect the cooperation activities of firms. Our focus is on LSMs, which are at the heart of the of the value chain in the laser industry since they develop and produce the laser beam unit, the key component of every laser-based machine or system. In addition, we explicitly consider R&D linkages to all PROs actively operating in the field of laser research.

4 The proximity hypotheses

Now we turn our attention to the proximity concept that constitutes the theoretical foundation for deriving our hypotheses. Scholars from various disciplines have contributed to our understanding of how proximity–in all its facets–can improve a firm's ability to tap new sources of knowledge, to learn recombining existing stocks of knowledge to improve or create new products, processes, and services (Amin and Wilkinson 1999; Boschma 2005; Oerlemans et al. 2001; Knoben and Oerlemans 2006; Visser 2009; Whittington et al. 2009). The proximity concept acknowledges that firms usually operate within a multi-dimensional environment and thus face a variety of different proximity dimensions, such as institutional, organizational, cultural, technological, network and geographic proximity (Boschma 2005; Knoben and Oerlemans 2006). We follow the proximity concept proposed by Boschma (2005) for several reasons. Firstly, the theoretical framework allows for a clear analytical separation of distinct proximity dimensions. It provides a solid theoretical foundation for analyzing both distinct and combined proximity effects. Secondly, the framework applies a dynamic perspective. This, in turn, helps explaining the emergence of both positive and negative proximity effects over time. Finally, the conceptual openness of the concept warrants an exploration of the determinants of tie formation and tie termination processes. In a recent study, Boschma and Frenken (2010) apply this theoretical concept to explain as to what extent selected proximity dimensions affect the spatial evolution of innovation networks. From this theoretical foundation, we seek to identify factors that should affect a firm's ability to cooperate and the timing of initial and consecutive cooperation events.

Let us first consider organizational factors. Especially in science-driven industries, access to external stocks of knowledge and the ability to acquire new knowledge is of vital importance (Al-Laham and Kudic 2008). Agency theory suggests that a larger stock of knowledge allows a firm to offer better cooperation opportunities to other organizations (Spence 1976, 2002). It is thus plausible to assume that firms with an extensive stock of knowledge are likely to attract new cooperative partnership at a higher rate and enter the network earlier compared to firms with low levels of knowledge endowment.

The next argument is closely related to the previous one. Once a firm has identified a promising cooperation partner, it passes through a learning process of how to successfully initiate, establish and manage a R&D partnership. It learns how to implement cooperation routines in order to reduce costs and gains knowledge of how to increase managerial efficiency over time (Zollo et al. 2002; Goerzen 2005). In other words, firms benefit from each cooperation event by building up what is frequently referred to as cooperation (or alliance) capabilities (Kale et al. 2000; Schilke and Goerzen 2010). Hence, we argue that the transition time for consecutive cooperation events is significantly shorter compared to time that elapses until a firm experiences its initial cooperation event.

Another factor determinant of cooperation timing could be the firm's geographic surroundings. In line with Boschma's (2005) proximity concept we argue that a firm's geographic location, in particular its geographical co-location to other LSMs and PROs, affects its cooperation timing decisions in multiple ways. On the one hand, it has been argued that the regional environment generates positive externalities in terms of knowledge spillovers (Audretsch and Feldman 1996; Feldman 1999). Information provided via these channels may enable firms to become aware of new cooperation opportunities earlier than others. Thus, it is plausible to assume that regional environments can speed up a firm's search for potential partners and shorten the time required to enter the network. On the other hand, geographic proximity can also be accompanied by negative effects. Boschma (2005) argues that highly specialized regions can become inward looking due to spatial lock-in effects and a lack of openness to the outside world. This could bring about a situation in which firms favor old and well-established knowledge channels and do not see the necessity of initializing new formal partnerships with other firms or organizations. As a consequence, a high level of geographic proximity may also hamper a firm's willingness to initialize new partnerships.

A firm's cooperation experience and its strategic network positioning are likely to affect its future cooperation activities. Based on Boschma (2005) we argue that the network proximity dimension not only affects the formation of repeated ties but also the timing of these events. A firm's cooperation history and its strategic network positioning provide important signals to other participants in the market. It has been argued that the status of a market participant affects the expectation of others through two channels: his past signals of quality and the status of his exchange partners (Podolny 1993; Podolny 1994; Benjamin and Podolny 1999, p. 563). Similarly, reputation is an important signaling device that allows others to judge an organization's reliability; firms spend time and considerable effort in building up reputation (Weigel and Camerer, 1988; Fombrun and Shanley, 1990). Small (or new) firms often had a hard time gaining acceptance in the market, so that building up status and reputation through cooperation activities can be an important catalyst for the initialization and formation of further R&D linkages. In a nutshell, we argue that firms occupying prominent network positions have a comparably high visibility due to a high number of direct partners or due to brokerage activities. Hence, the duration until well-positioned firms experience their subsequent cooperation event should be shorter.

Finally, Boschma's (2005) proximity concept provides good reason to assume that geographic proximity and network integration do not affect the timing of consecutive cooperation events in isolation. To the contrary, there are solid arguments that support the idea of mutually interdependent proximity effects. We argue that a disadvantageous position in the geographic proximity dimension can–at least to some extent–be compensated by a prominent position in the network dimension (and vice versa). Cooperation-intensive firms become aware of new cooperation opportunities through existing network linkages, whereas geographically well-positioned firms may receive similar information through very different information channels, such as regional knowledge spillovers. Firms that benefit from both dimensions simultaneously are likely to identify potentially suitable R&D cooperation partners even earlier. As a consequence, we assume that the aforementioned additional information advantage of socially and geographically well-embedded firms is likely to speed up the search for new partners and shorten the time needed to enter consecutive cooperation events.

5 Data and method

For the purpose of this study we employ a unique longitudinal database for the German laser industry that covers the entire population of laser source manufacturing firms in the years 1990-2010. Several data sources were employed to conduct this study: industry data, geographical data, patent data, and network data.

5.1 Data sources

Industry data: A roster of the entire population of German LSMs in the period 1969-2005 was generously provided by Guido Buenstorf (Buenstorf 2007). Based on this initial dataset we collected additional information on firm entries and exits after 2005. For the purpose of this study, we consider the business unit or firm level: corporate level entities were decomposed and broken down into the business functions or market segments they serve. Furthermore, we included predecessors of currently existing firms in our sample. Firm exits as a result of mergers, acquisitions, or insolvencies, as well as different modes of population entries, such as new company formations or spin-offs from existing firms or PROs, were treated separately.[1] We ended up with an industry dataset encompassing 233 LSMs over the full period under observation. Based on the number of employees we defined four firm size categories: micro (1-9 employees), small (10-49 employees), medium (50-249 employees), and large (250+ employees).

Moreover, we identified 145 PROs (including universities) with laser-related activities by using two complementary methods. We started with the "expanding selection method" due to Doreian & Woodard (1992). Taking the initial list of 233 LSMs we screened our collaboration database and marked all laser-related research entities as long as these organizations established a link to at least one firm of our initial list. For each of these cases we checked whether the identified research entity was active in the field of laser research or not. We created an extended membership list that contains the full set of all identified PROs. We marked all PROs that were observed only once over the entire observation period. Next we excluded all non laser-related PROs from the list. By the end of this procedure 138 laser-related PROs remained in the sample. This method, however, is limited insofar as it completely ignores non-cooperating laser-related PROs. As a consequence, we applied a second methodological approach to solve this problem. Based on a bibliometric analysis we identified all German PROs which published laser papers, conference proceedings or articles in

[1] Three additional data sources were used: 1) updated German laser industry data, again provided by Guido Buenstorf; 2) annual laser industry business directories ("Europäischer Laser Markt") provided by the B-Quadrat Publishing Company; 3) data from the official German trade register and Creditreform.

academic journals over the past two decades. These data–provided by the LASSSIE project consortium (Albrecht et al. 2011)–originate from the INSPEC database.[2] They were augmented by a search for laser-related publications in the ISI Web of Science database.[3] This allowed us to generate a comprehensive list of all PROs which have published at least one paper in the field of laser research. By comparing and consolidating the results of the expanding selection method and the bibliometric analysis we ended up with a final list of 145 laser-related PROs for the time span between 1990 and 2010. Then, entry and exit dates were retrieved for all PROs in the dataset.

Geographic data for all LSMs and PROs in the sample were reconstructed over the period under consideration, 1990-2010. Data from Germany's official company register (*Bundesanzeiger*) were used to reconstruct firms' current addresses and address changes for the entire observation period. We employed the ESRI ArcMap 10.0 Software package and a freely accessible geo-coding application[4] to gather GPS coordinates (latitude and longitude) on an annual basis for each firm in the sample. We then calculated the dyadic distances between all organizations in the sample.

Patent data were used to measure the knowledge endowment of the firms in our sample. Our data[5] on patents included patent applications as well as patents granted by the German Patent Office and by the European Patent Office (including Euro-PCT patents). The *DEPATISnet* and *ESPACEnet* databases were employed to cross check the

2 The INSPEC database contains over 11 million abstracts. The database includes journal articles, conference proceedings, technical reports and other literature in the fields of physics, electronics and computing. For further information see http://www.ovid.com/site/catalog/DataBase/107.jsp

3 The following ISI Web of Science archives were used: SCI 1995-2011, SSCI 1980-2011, AHCI 1995-2011. For detailed information on the database packages, their scope, and contents see http://www.wokinfo.com

4 http://www.netzwelt.de/software/google-maps.html (accessed: Nov. 2011)

5 In order to gather patent data we used the names of the companies in the sample and assigned a patent to a company if its name appeared as a patent applicant and if either the patent applicant or the inventor had an address in Germany. In an effort to overcome spelling issues when searching the database, we prepared a list containing the various ways of spelling each firm’s name. Additionally, in order to obtain yearly patent counts for each company we traced changes in corporate names, changes in the legal status of the firms, organizational changes and the establishment of spin-offs and considered these accordingly.

results.[6] Finally, we specified a cumulative patent application count variable to track the knowledge endowment at the firm level.

Network data used for this study came from two electronically available archival sources: the *Förderkatalog* database provided by the German Federal Ministry of Education and Research (BMBF) and the *CORDIS* database provided by the European Community Research and Development Information Service (CORDIS). Both sources provide detailed information on the starting date, duration, funding, and characteristic features of the project partners involved. We identified 416 R&D projects (with up to 33 project partners from various industry sectors, non-profit research organizations, and universities) funded by the BMBF and 154 R&D projects (with up to 53 project partners for the entire sample of German LSMs) funded by CORDIS. Based on this information we calculated the degree centrality and betweenness centrality for the LSMs and PROs at a quarterly basis.

Data on publicly funded R&D cooperation projects has been used before in the literature to construct knowledge-related innovation networks (Broekel and Graf 2011; Fornahl et al. 2011; Scherngell and Barber 2009; Scherngell and Barber 2011; Cassi et al. 2008). There are good arguments for the use of these archival data sources in analyses of the evolution of innovation networks. Organizations that participate in R&D cooperation projects subsidized by the German federal state have to agree upon a number of regulations that facilitate mutual knowledge exchange and provide incentives to innovate (Broeckel and Graf 2011). In a similar vein, the EU has funded thousands of collaborative R&D projects in order to support transnational cooperation activities, increase mobility, strengthen the scientific and technological bases of industries, and foster international competitiveness (Scherngell and Barber 2009). Both data sources provide exact information on the timing of the tie formation as well as the tie termination processes.

Based on the data described above we define two subsamples that cover LSMs at risk for a first cooperation as well as consecutive spells for second and further cooperation events and conduct the following duration analysis.

6 Online access: www.depatisnet.de & www.espacenet.com (accessedJune - August 2011).

5.2 Duration analysis

The timing of the transition to the first cooperation is analyzed with a duration model (Kiefer 1988). This allows us to consider both completed spells (for which the start of a cooperation is observed) and censored ones. The first spell starts once the firm enters the population. We exclude cases where the cooperation starts at the same time as the firm enters, i.e. R&D joint ventures are not considered; and we exclude firms that entered the population before 1990, as most of the earlier cooperation events are not covered by our data base.

The quantity of interest is the hazard rate h, the probability that the transition to a cooperation occurs, given that it has not occurred before. This rate may depend on time t and covariates $\boldsymbol{x}_{ij}$ of firm i and sub-period j. The sub-periods arise by introducing splits at the start of each new quarter in calendar time, which allows us to consider time-varying covariates. As the different observations belonging to one firm are not independent, standard errors are clustered at the firm level. We assume that covariates exert a proportional effect on the hazard rate, and we allow the baseline hazard to exhibit duration dependence. The latter may reflect reputation that may be built up over time–or lost if no cooperation takes place for an extended period of time. We choose a Weibull specification for the hazard rate:

$$h_{ij}(t) = h(t \,|\, \mathbf{x}_{ij}) = p \cdot \exp\{\boldsymbol{\beta}'\mathbf{x}_{ij}\} \cdot t^{p-1}$$

The shape parameter p reflects the amount of duration dependence: $p < 1$ ($p > 1$) indicates that the baseline hazard declines (increases) over time; the special case $p = 1$ means that it is constant over time, such that the model boils down to an exponential hazard model. Duration dependence may arise due to calendar time effects, if. e.g., the extent to which cooperations were supported by public policy varied over time. In order to disentangle these effects, we introduce calendar period dummy variables as regressors.

Transitions to consecutive cooperations are treated separately, as we believe that the very first cooperation could be governed by a different mechanism. Quite obviously, firms cannot be part of a cooperation network by our definition as long as the first transition has not been completed. All spells on further cooperations are pooled into one model with repeated events. In this case, analysis time starts once the prior spell has ended, and we introduce a final, right-censored spell that extends into the year 2010. While we assume in this model that the shape of the baseline hazard and the effect of covariates are equal across spells, we allow the level of the hazard rate to vary by (groups of) spells. The unit of analysis i is now spell rather than the firm. A problem with this approach could be that the composition of the risk pool changes with further transitions not only in terms of observed variables but also due to unobserved heterogeneity. We therefore consider a multiplicative frailty term α_k for each firm k, assumed to be drawn from a Gamma distribution with a mean of one. The hazard rate for spell i then becomes

$$h_{ijk}(t \mid \alpha_k) = \alpha_k \cdot p \cdot \exp\{\boldsymbol{\beta}'\mathbf{x}_{ij}\} \cdot t^{p-1}.$$

Again, only firms that entered the population after 1990 are considered, and spells with zero duration are disregarded in the analysis. Nonetheless, all cooperations are used in the construction of the time-varying network variables. To avoid reverse causality by design, they are defined for the last day of the preceding (calendar) quarter.

6 Results

We define two subsamples that cover firms at risk for a first cooperation on the one hand and consecutive spells for second and further cooperations on the other hand (Table 1). Spells in the latter category originate when the previous transition occurs, i.e. they do not start when the firm enters the population. As we do not analyze durations of zero length, some cooperations, especially in the category for first cooperations, are ignored in terms of observations in the estimation samples, so that the number of first cooperations analyzed is smaller than the number of firms observed for second and further cooperations. A higher degree centrality indicates that a firm has more direct PRO or LSM partners in the network, whereas a high betweenness centrality means that the firm is important in bridging different regions of the network. Furthermore, we have constructed spatial proximity measures for the nearest PRO or LSM, respectively, defined as $(1+[\textit{distance in km}])^{-1}$, i.e. a larger value indicates a shorter distance.

Alternative distances, such as the one to the third-nearest entity or the mean distance did not yield superior *results* and are thus not discussed below.

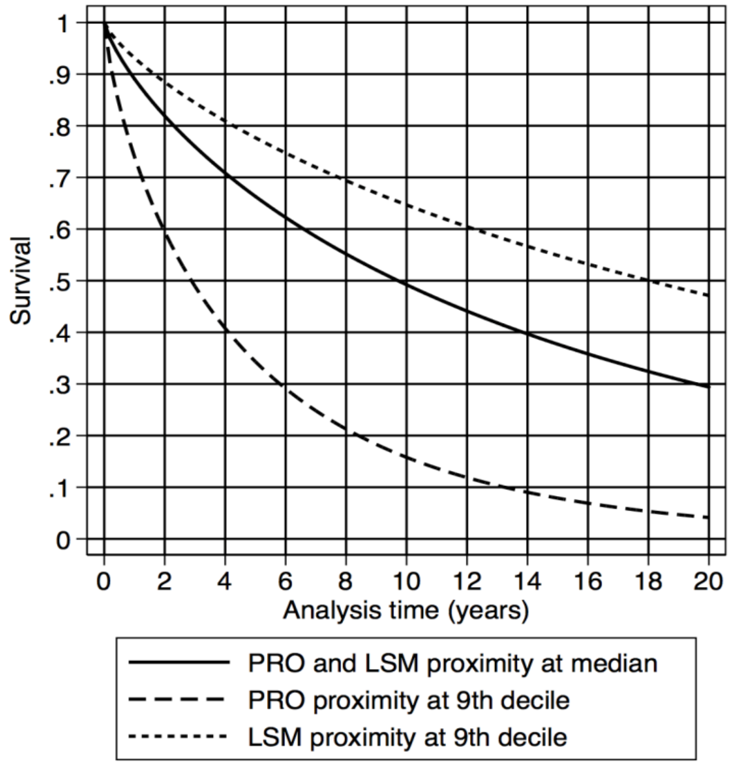
Table 2 provides the coefficients of the estimated Weibull regression models. Positive (negative) coefficients indicate that an increase in the regressor variable is associated with a higher (lower) transition probability. The first column addresses the transition to a firm's first cooperation. The coefficients of the spatial proximity variables suggest that a nearby PRO is associated with significantly higher transition rates–and thus with a lower survival without cooperation. Figure 1 illustrates the implied survival probabilities for hypothetical firms with all binary regressors set to their reference values (*Ref.*) and spatial proximity variables set to the respective sample median. The survival probability is 50% after about 9.7 years for such a firm, i.e. 9.7 years is the prediction of the median time spent in the state of no cooperation. With PRO proximity set to the 90th percentile, this median duration drops to 2.9 years. LSM proximity is not statistically significant in the model. The point estimate is not even negative but predicts an increase of the median duration to 18.0 years for the 90th percentile of LSM proximity.

Table 1: Characteristics of the estimation samples

	First cooperation		*Second and further cooperations*	
Firms		157		111
Spells		157		480
Time at risk (years)		1062.8		875.5
Transitions		74		369
Incidence rate		0.070		0.421
Median survival time (years)		10.3		1.0
	Median	90th percentile	Median	90th percentile
Proximity PRO	0.117	0.723	0.234	0.816
Proximity LSM	0.117	0.650	0.142	0.790
Degree centrality			0.020	0.115
Betweenness centrality			0.000	0.036

This kind of duration calculus may also be conducted for the other variables in the model. In particular, a higher stock of accumulated knowledge in terms of patent applications promotes the transition to a first cooperation. Compared to the 9.7 years of the baseline case, the median duration to cooperation declines to 4.3 or 3.7 years in the hypothetical cases that the firm already entered the market with 1-4 or at least 5 patent applications, respectively. A more realistic scenario is of course an increase in patent applications over time, which would predict smaller declines in the median duration. Smaller firms are less likely to experience a transition into cooperation: the hazard rate of a micro firm is only one third of the rate for a large firm ($e^{-1.1}$). This translates into an increase of the median duration to 39 years compared to the baseline case. We find no significant differences across regions or calendar period. However, the model implies significantly negative duration dependence with a shape parameter *p* of 0.79 ($e^{-0.239}$).

Figure 1: Predicted survival rates for transition to first cooperation



Source: Table 2, column 1, with all categorical variables set to their reference values.

The other models of Table 2 consider the onset of further cooperations and take into account the firm's integration into the network. In all these specifications, likelihood ratio tests (against the respective model without heterogeneity term) indicate that unobserved heterogeneity is statistically significant. Our discussion of durations is conditional on the assumption that the firm's α_k is 1.

In model 2, network integration is measured by degree centrality. A stronger integration into the network fosters further cooperations. Let us consider the case that a firm becomes at risk of having its fourth cooperation (i.e. a spell in the category "4+"), that other categorical variables are at their reference values and spatial proximity variables are at the sample median. The median duration to the next cooperation is now 1.8 years if network integration is at its sample median. This duration declines by 0.4 years if degree centrality is set to its 90th percentile in the sample. Spatial proximity to a PRO again promotes the formation of cooperations. The ninth decile of this variable predicts a median duration of 1.2 years, whereas proximity to another LSM is not statistically significant.

In contrast to model 2, the third specification allows for an interaction effect between network integration and spatial proximity. According to the Akaike Information Criterion (AIC), this richer specification should actually be preferred. While the main effect of network integration is still positive for the transition rate, it is not statistically significant anymore. Rather, its interaction with LSM proximity play a role. In our baseline scenario, the median duration is now 1.6 years. Setting LSM proximity to its 90th percentile increases this duration to 2.5 years. This difference is considerably smaller if network integration is set to the 90th percentile: in this case, the greater LSM proximity amounts to an increase in duration from 1.4 to 1.5 years only. Interactions with network integration are not important for PRO proximity.

Specifications 4 and 5 extend the model by betweenness centrality as an additional indicator of network integration. This measure is more sensitive to the position of the firm within the network. The two network measures have a correlation coefficient of 0.76 in the sample, which may impede the interpretation. Nonetheless, model 4 is favored by the AIC over specifications without betweenness centrality. In our baseline scenario with betweenness centrality set to its median value, the median duration amounts to 1.5 years. This duration is reduced to 1.3 years if betweenness centrality takes on its ninth decile in the sample, whereas a change in degree centrality has virtually no effect. Introducing interactions with spatial proximity (column 5) does not supersede the more parsimonious specifications, according to the AIC.

In all specifications for consecutive cooperations, the firm's stock of knowledge again fosters the formation of new cooperations. It is also worth noting that durations become shorter with the spell category. E.g., the 1.5 years median duration of model 4 in our baseline scenario compare to 2.5 years in the case of the second spell. Inasmuch as this difference arises on top of network integration, it may reflect learning curve effects. Quite interestingly, there is no evidence of duration dependence in the models for further cooperations. While it does not come as a surprise that larger firms spend shorter durations up to their next cooperation, the negative coefficient for East German firms is somewhat puzzling as we do control for firm size. Compared to our northern baseline case of model 4, eastern firms wait one year longer for the onset of their next cooperation.

Table 2: Weibull models for the transition to cooperations

	First cooperation	*Second and further cooperations*			
	(1)	(2)	(3)	(4)	(5)
Spell					
2		*Ref.*	*Ref.*	*Ref.*	*Ref.*
3		0.319	0.348	0.352	0.396^{*}
4+		0.447^{*}	0.491^{**}	0.508^{**}	0.577^{**}
Calendar year					
1990-94	*Ref.*	*Ref.*	*Ref.*	*Ref.*	*Ref.*
1995-99	0.136	0.214	0.111	-0.079	-0.141
2000-04	-0.078	-0.032	-0.056	-0.216	-0.234
2005-10	0.476	0.097	0.069	-0.212	-0.243
Firm size					
Micro	-1.100^{**}	-1.152^{***}	-1.159^{***}	-1.039^{***}	-1.010^{***}
Small	-0.737	-0.696^{***}	-0.726^{***}	-0.586^{**}	-0.587^{**}
Medium	-1.077^{*}	-0.567^{**}	-0.576^{**}	-0.457^{*}	-0.457^{*}
Large	*Ref.*	*Ref.*	*Ref.*	*Ref.*	*Ref.*
Cumulative patent applications					
0	*Ref.*	*Ref.*	*Ref.*	*Ref.*	*Ref.*
1-4	0.649^{**}	0.663^{**}	0.663^{**}	0.683^{**}	0.702^{***}
5+	0.766^{**}	0.713^{**}	0.719^{**}	0.745^{**}	0.761^{**}
Region					
South	-0.090	0.028	0.033	0.037	0.036
East	0.426	-0.447^{*}	-0.439^{*}	-0.503^{**}	-0.490^{**}
North	*Ref.*	*Ref.*	*Ref.*	*Ref.*	*Ref.*
Proximity PRO	1.577^{***}	0.772^{**}	1.010^{***}	0.781^{**}	1.000^{***}
Proximity LSM	-0.913	-0.222	-0.773^{*}	-0.168	-0.638
Degree centrality		2.596^{***}	0.989	0.200	-2.265
Degree centrality × Proximity PRO			-2.041		0.009
Degree centrality × Proximity LSM			6.043^{**}		6.863^{*}
Betweenness centrality				5.250^{***}	8.988^{**}
Betweenness centrality × Proximity PRO					-7.146
Betweenness centrality × Proximity LSM					-3.465
Constant	-2.235^{***}	-1.621^{***}	-1.518^{***}	-1.478^{***}	-1.440^{***}
Logarithm of shape parameter *p*	-0.239^{**}	0.031	0.028	0.042	0.033
Heterogeneity (p-value)		0.000	0.000	0.000	0.003
Akaike Information Criterion	382.5	1402.8	1402.5	1394.1	1398.6

Remark: $^{*}/^{**}/^{***}$ indicates statistical significance at the 10, 5, and 1% level, respectively.

7 Discussion and conclusion

Understanding the evolution of innovation networks clearly requires a time dimension. However, the timing of tie formations has been a widely neglected issue in the empirical literature so far. The present study is a first attempt to fill this void by analyzing correlates of transition probabilities. To be sure, not all causal pathways can be identified; in particular, the intensities with which firms we seeking partners and the willingness of partner candidates to cooperate cannot be uncovered. Nonetheless, our findings on organizational, geographic, and structural factors provide clues about the mechanisms at work. The focus on the relatively narrow field of laser source manufacturing allows us to comprehensively reconstruct (formal) network affiliations. Science-based R&D plays an important role in this field, and the German laser industry is quite competitive in an international perspective. One would thus believe that the cooperations in this field are really meaningful in an economic sense, even though we do not analyze evidence on the outcomes of these cooperations, such as additional patents granted or growth in revenues.

As far as our results on cooperation timing are concerned, firm-level determinants do not deliver major surprises. A firm's knowledge endowment fosters the onset of new cooperations. This is compatible with our initial intuition that firms with an extensive stock of knowledge attract partners at a higher rate. This finding stirs up an interesting question for further research: are firms with quantitatively or qualitatively similar stocks of knowledge more likely to form cooperations? This would require a different set-up of the analysis with bilaterally defined regressors. In line with preceding studies (Kudic et al. 2012) our results show that size matters for a firm's ability to enter new R&D partnerships. That small firms enter the network significantly later (if at all) than larger firms supports the view that the formation of new R&D linkages requires a certain level of firm resources and cooperation experience. This is closely related to the finding that the time span between consecutive cooperation events is significantly shorter than the time that it takes a firm to enter the network. Thus, a "cooperation experience" effect seems to exist.

The geographic proximity dimension provides interesting insights. In preliminary models not shown here, we experimented with indicators for regional clusters, defined on the basis of the number of other LSMs, PROs and laser-related firms in the same statistical area. However, location in a regional cluster did not exert a significant impact on cooperation timing. This suggests that local cooperation opportunities seem to be of minor relevance for the formation of R&D linkages of German laser source manufacturers. Another intriguing result concerns the three geographic regions. The point estimates suggest that firms in the eastern part of the country join the network earlier but then have a longer waiting time to the next cooperation events. This may reflect peculiarities of the financial aid by the government to young, R&D oriented firms in East Germany. The distance-based co-location measures reveal mixed results that are nevertheless consistent across most model specifications. Our findings suggest that a nearby PRO is associated with significantly higher transition rates. One possible explanation for this result could be that PROs mainly serve as providers of basic technological knowledge that is rather tacit in nature. The geographic closeness to PROs facilitates face-to-face contacts and enables LSMs to absorb even non-codifyable stocks of technological knowledge. This, in turn, qualifies the benefiting firm as highly potential partner candidate in the next cooperation round. In line with this reasoning, the geographic closeness to competitors seems to be less important for the timing of cooperation events.

By its very nature, the cooperation history of a LSM and its network integration matters only for the timing of consecutive cooperation events. Degree centrality works well when used as the only network measure: the more existing ties a firm currently holds, the faster it can arrange additional ties. To be sure, this may also reflect heterogeneity with respect to preferences. More interestingly, the effect of degree centrality is dwarfed by betweenness centrality that reflects strategically oriented positions within the network. Brokerage positions allow firm bridge the gap between otherwise unconnected groups of network members. Our findings show that the main effect of betweenness centrality on cooperation timing remains stable, even when controling for potential interdependencies of betweenness centrality and LSM or PRO proximity. This is quite strong evidence for the relevance of network integration. Comparing the results of our different specifications, one could conclude that co-location to other LSMs plays a role for cooperation intensive firms with a high number of direct partners, whereas more strategically oriented LSMs are not dependent on their positioning in the geographic space.

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