Chapter 9
Causes and Consequences of Network Evolution

> *Scholars are slowly shifting from positing simple systems to using more complex frameworks, theories, and models to understand the diversity of puzzles and problems facing humans interacting in contemporary societies*
>
> (Source: Ostrom 2009)

Abstract In this chapter we analyze a firm's propensity and timing to cooperate and enter the industry's innovation network. The conceptual framework considers three groups of determinants – organizational, relational and contextual. Selected factors within these groups are assumed to cause network change processes at the micro-level – tie formations and tie terminations – and shape the structural network configuration at the overall network level. The elements of the framework are substantiated by drawing upon evolutionary ideas and concepts from organization science, sociology and evolutionary economics. The following chapter is organized as follows: We start with a brief introduction in Sect. 9.1. Section 9.2 provides a literature review and introduces the theoretical cornerstones needed for an in-depth discussion on evolutionary network change. Based on these ideas we derive our conceptual framework in Sect. 9.3 and formulate a set of testable hypothesis in Sect. 9.4. Section 9.5 addresses some methodological issues and provides an overview of data and variables used. In Sect. 9.6 we introduce our empirical approach and present estimation results from our non-parametric event history model. Section 9.7 concludes with a summary and discussion on the implications of our key findings.

9.1 On the Evolutionary Nature of Innovation Networks

In this investigation we seek to understand the relationship between network change determinants, network change processes at the micro-level and structural consequences at the overall network level.[1] We employ an event history dataset on

[1] This chapter draws upon a joint research project conducted by Andreas Pyka, Chair for the Economics of Innovation, University of Hohenheim, and Jutta Guenther and Muhamed Kudic

M. Kudic, *Innovation Networks in the German Laser Industry*,
Economic Complexity and Evolution, DOI 10.1007/978-3-319-07935-6_9

publicly-funded R&D cooperation projects in the German laser industry to analyze one specific facet of the entire network evolution process, i.e. a firm's propensity and timing to cooperate and enter the industry's innovation network.[2]

Innovation networks have been the subject of a broad range of theoretical and empirical studies over the past decades.[3] Both organizational scholars and economists agree that the evolutionary change of complex networks still represents a widely unexplored area of research (Parkhe et al. 2006, p. 562; Brenner et al. 2011, p. 5). Quite recently scholars from various scientific disciplines such as physics (Albert and Barabasi 2000; Jeong et al. 2003), biology (Nowak et al. 2010), sociology (Doreian and Stokman 2005; Snijders 2004; Powell et al. 2005), organization and management science (Walker et al. 1997; Gulati and Gargiulo 1999; Koka et al. 2006; Zaheer and Soda 2009), economic geography (Glueckler 2007) and economics (Jackson and Watts 2002; Cowan et al. 2006; Jun and Sethi 2009) have started to intensify their research efforts in this area in order to understand the determinants and mechanisms affecting the structural evolution of networks. Despite this progress, we still face more questions than answers and empirical evidence remains scarce.

There are many reasons for this. Firstly, network evolution is a complex phenomenon encompassing causes and consequences of network change among multiple levels of analysis. In the most basic sense, all types of networks consist of nodes and connections among these nodes (Wasserman and Faust 1994). The concept of network evolution "[...] captures the idea of understanding change via some *understood* process [...]" whereas these underlying processes can be defined as a "[...] *series of events that create, sustain and dissolve* [...]" the network structure over time (Doreian and Stokman 2005, pp. 3–5). Thus, network change processes at the micro-level – i.e. tie formations or tie terminations – as well as changes with regard to network nodes – i.e. node entries or node exits – affect the structural configuration of overall networks over time. These processes of creative destruction are clearly Schumpeterian in nature and provide the basis for explaining the evolution of networks (Boschma and Frenken 2010, p. 129).

However, due to both the conceptual ambiguities caused by the complex nature of networks and the extensive data requirements needed to analyze the evolution of these entities, research in this field is still in its inception. Secondly, micro-level network change processes are determined by several factors which can be grouped

from the Department for Structural Economics at the Halle Institute for Economic Research. An early draft was presented at the 14th ISS Conference in Brisbane, Australia (Kudic et al. 2012). We are grateful to Wilfried Ehrenfeld for his helpful suggestions. This chapter has greatly benefited from the comments made by audience members at the Buchenbach Workshop on evolutionary economics in 2009 and is strongly influenced by the ideas and concepts discussed at the summer-school on organizational ecology in 2007 taught by Terry Amburgey, Rotman School of Management, Toronto, Canada. I take full responsibility for any errors in this chapter.

[2] We used STATA 10.1 (Stata 2007), a standard software package for statistical data analysis.

[3] For a comprehensive overview of the research conducted in this field see Pittaway et al. (2004) or Ozman (2009).

into three categories: organizational, relational and contextual. Previous research has predominantly concentrated on network formation processes affected by individual factors within one of these three groups. Surprisingly little research has been conducted on network formation processes affected by both endogenous and exogenous factors. Finally, even though tie terminations are as important as tie formations in understanding network evolution, there is a strong bias in the literature towards the presence of relationships versus their absence (Kenis and Oerlmans 2008, p. 299). This arises, on the one hand, from data availability issues as the majority of empirical studies in this field are based on alliance network databases in which tie terminations are systematically underrepresented.[4] On the other hand we can observe a construct validity problem in most studies as often no distinction is made conceptually between tie failures and intended tie terminations (Kenis and Oerlmans 2008, p. 299).

Against the backdrop of these issues, the aim of this analysis can be summarized as follows. On the one hand, an in-depth analysis of network change determinants requires a comprehensive understanding of network evolution in general. Thus, we propose a conceptual framework that consists of three building blocks: determinants, micro-level network change processes and structural consequences. Starting from an evolutionary economic perspective (Hanusch and Pyka 2007b) we consider innovation networks as an integral part of an innovation system that can be both spatially and sectorally delimited (Cooke 2001; Malerba 2002). We apply an interdisciplinary approach to substantiate the building blocks of our framework by drawing upon concepts from evolutionary economics, sociology and organizational science. On the other hand, we derive and test a set of hypotheses that addresses some selected facets of evolutionary network change processes.

The analytical part is inspired by two empirically observable large-scale network properties of the German laser industry's innovation network. Firstly, the German laser industry innovation network shows a fat-tailed degree distribution indicating that some nodes attract ties at a higher rate than others once they have entered the network (cf. Sect. 8.3.1). The same properties have been observed in other real-world networks such as in the US biotech innovation industry (Powell et al. 2005). Secondly, a substantial number of potential network entrants do not cooperate at all (cf. Sect. 8.2.1).[5]

In this analysis we are especially interested in analyzing network entry processes. More precisely, we ask the following research question: what are the endogenous or exogenous determinants affecting a firm's propensity and timing

[4] For an overview of the most frequently used alliance databases and their limitations, see Schilling (2009).

[5] The descriptive analysis reveals a minimum network participation rate of 20.1 % in 1990 and a maximum network participation rate of 52.92 % in 2008 for LSMs and PROs under observation.

to cooperate for the first time and enter the industry's innovation network? To answer this question we employ a single-episode event history dataset (cf. Sect. 6.2.1). This dataset allows for an exact time tracking of all node entries and exits as well as all tie formations and tie terminations.

9.2 State of the Art and Theoretical Background

This section starts with a brief review of the literature on the dynamics of alliances and networks. Then we turn our attention to some evolutionary concepts that provide the theoretical basis for our conceptual framework.

9.2.1 Literature on the Dynamics of Alliances and Networks

The literature on the dynamics of alliances and networks is quite heterogeneous. Several scholars have provided schemes to systematize the work that is been done in this field.[6] In this chapter we draw upon a general systematization scheme originally proposed by Van De Ven and Poole (1995) which has been applied and adapted to categorize dynamically oriented conceptualizations in the field of alliance research (De Rond and Bouchiki 2004) and network research (Parkhe et al. 2006) into three[7] groups: life-cycle model, teleological approaches and evolutionary approaches.

The use of life-cycle analogies is not new to economics and has been employed to capture product exploitation stages (Levitt 1965) as well as change patterns of industries (Klepper 1997) or clusters (Menzel and Fornahl 2009) over time. Life-cycle conceptualizations of alliance and network change are based on the notion of "[. . .] linear, irreversible and predictable progressions of events or states over time" (Parkhe et al. 2006, p. 562). The basic idea that underlies most of these models is that one can identify ideal development stages like initialization, growth, maturity and decline. Thus, some authors often refer to these models as phase models (Schwerk 2000; Sydow 2003). Change is imminent in life-cycle models which indicate that the developing entity has an underlying logic within itself that regu-

[6] For instance, Sydow (2003) has proposed a separation of dynamic network approaches in five model categories: life-cycle models, non-linear process models, intervention oriented process models, evolutionary models and co-evolutionary models. For other systematization schemes see for example Schwerk (2000) or Tiberius (2008).

[7] In contrast to De Rond and Bouchiki (2004) our review does not consider the dialectic approach. This is in line with the systematization applied by Parkhe et al. (2006). Hence, we end up with three instead of four categories.

lates the process of change (Van De Ven and Poole 1995, p. 515). The change process itself is regarded as a linear sequence of events where all development stages are traversed only once without disruptions or feedback loops along the way. These events are cumulative in nature which means that each development stage in both alliance and network life-cycle models can be seen as a precursor to successive stages (Van De Ven and Poole 1995, p. 515; De Rond and Bouchiki 2004, p. 57).

Literature often contains examples of life-cycle or phase models that address alliance and network change. For instance, Dwyer and his colleagues (1987) have proposed a model of buyer-seller linkages in which relationships evolve in general phases: awareness, exploration, expansion, commitment and dissolution. Murray and Mahon (1993) have proposed a somewhat similar phase model for strategic alliances that contains five distinct stages: courtship, negotiation, start-up, maintenance, and ending. Other authors have proposed phase models that encompass four stages. For instance, Forrest and Martin (1992) suggest an alliance process model based on their findings from an interview-based survey of senior executives in 70 North American biotech firms. Their model consists of four distinct stages: matching, negotiation, agreement and implementation. The last category comprises three-stage life-cycle models that are predominantly growth-oriented. For instance, Larson (1992) has proposed an entrepreneurial dyad formation model whose stages consist of: preconditions to exchange, conditions to build, integration and control. In contrast to this dyadic conceptualization Lorenzoni and Ornati (1988) introduce one of the first growth-oriented network formation models by arguing that firms that are expanding pass through three cooperation stages: unilateral relationships, reciprocal relationships and network constellations. Critics of life-cycle models have argued that the phase specification and the length of stages in these models may vary arbitrarily (Sydow 2003, p. 332). In addition, the notion of a linear change process that does not consider disruptions or feedback loops is – to put it mildly – questionable at least.

According to the teleological school of thought, change in organizational entities is explained by relying on a philosophical doctrine according to which the purpose or goal is the ultimate cause of change (Van De Ven and Poole 1995, p. 515). From this point of view development is regarded as a "[. . .] repetitive sequence of goal formulation, implementation, evaluation and modification of goals [. . .]" whereas all of these sequences are affected by the experiences and intentions of an adaptive entity (Van De Ven and Poole 1995, p. 516). This means that organizational entities are able to learn at each stage of the repetitive sequences and reformulate their goals. In response to the limitations of the previously discussed lifecycle conceptualizations, scholars have applied this teleological perspective in order to gain more open-ended and iterative process models of alliance and network change in which the final goal guides the underlying change process (De Rond and Bouchiki 2004, p. 57). Teleological alliance and network change models do not explicitly refer to life cycle analogies. In summary, this view emphasizes "[. . .] purposeful cooperation by entities toward desired end states" (Parkhe et al. 2006, p. 562). As these models allow for learning and adaptation processes in all development stages, some authors refer to these models as non-linear process models (Schwerk 2000; Sydow 2003).

Non-linear process models operating on a dyadic level are the most prominent applications of teleological ideas in an alliance and network context (Ring and Van De Ven 1994; Doz 1996; Kumar and Nti 1998; Arino and De La Torre 1998). The advantages of these models over life-cycle models are obvious. Non-linear process models provide a basis for analyzing dynamics but also the instability of dyadic alliances by considering endogenous factors like social embeddedness, trust, learning and knowledge transfer processes. In addition these models integrate the idea of feedback loops which affect the alliance development process. They take formation and catalyst processes of alliances into consideration and place a greater importance on unplanned terminations (Schwerk 2000, p. 230). This means there is no fixed assumption with regard to phase transition patterns (ibid). One prominent example of a non-linear process model was proposed by Ring and Van De Ven (1994). This model seeks to explain how and why interorganizational relationships emerge, evolve and dissolve over time. It considers three basic processes (negotiation, commitment and realization) and refers to the idea that formal and informal aspects need to be balanced in every process. Another influential non-linear process model is the conceptualization by Doz (1996). This model includes several internal and external dimensions – environment, task, process skills and goals – which are assumed to affect the processes of alliance change over time. The change process itself is characterized by sequences of interactive learning processes, reevaluation and readjustment. It explains both the successful development of alliances over time as well as the alliance failure as a result of little or divergent learning or frustrated expectations among partners (De Rond and Bouchiki 2004, p. 57).

Next, research delved further into network process models (Sydow 2003, p. 336). This approach has been strongly influenced by the contributions of the IMP research group (Hakansson and Johanson 1988; Hakansson and Snehota 1995; Halinen et al. 1999) and focuses predominantly on business relation networks. In these models, network change is driven by market access and internationalization goals. For instance, Halinen and colleagues (1999) have proposed a dynamic network model that includes radical and incremental change processes at the dyadic and network level. The framework integrates the ideas of mechanisms, nature and forces of change and contains two interdependent circles of radical and incremental change which are affected by external drivers of change and stability. In summary, the strength of teleological alliance and network change models lies in the rejection of simplistic, uniform and predictable sequences of change towards more realistic non-linear process models which recognize that unplanned events, unexpected results, as well as conflicting interpretations and interests can and do affect the change process over time (De Rond and Bouchiki 2004, p. 58).

Evolutionary conceptualizations of alliance and network change draw our attention to "[...] change and development in terms of recurrent, cumulative, and problematic sequences of variation, selection and retention." (Parkhe et al. 2006, p. 562). Evolutionary approaches seek to understand the forces that cause network change over time (Doreian and Stokman 2005, p. 5) which means that focus is placed on the underlying determinants and mechanisms of network change processes. In other words, understanding "[. . .] the 'rules' governing the sequence of change through time [. . .]" (Doreian and Stokman 2005, p. 5) provides an in-depth understanding of the network change process itself. These conceptualizations encompass the determinants that trigger the change processes at the micro-level, the mechanisms that generate change, and the structural consequences over multiple aggregation levels. Evolutionary conceptualizations of network change can be grouped into three partially overlapping categories: network emergence, network evolution and co-evolutionary approaches.

The first category – so-called network emergence or network growth approaches – focuses predominantly on determinants and mechanisms affecting alliance formations and associated network change patterns at the overall network level (Walker et al. 1997; Gulati 1995; Gulati and Gargiulo 1999; Hagedoorn 2006; Kenis and Knoke 2002). These growth oriented models consider both endogenous as well as exogenous factors of alliance and network change and recognize the importance of previous network structures in current cooperation decisions (Gulati and Gargiulo 1999). However, these studies clearly place little emphasis on tie termination processes and the associated structural consequences for the overall network configuration.

In response to these limitations, network evolution explicitly encompasses both network formation processes as well as network fragmentation processes by simultaneously considering the determinants and mechanisms behind these processes (Venkatraman and Lee 2004; Powell et al. 2005; Amburgey and Al-Laham 2005; Doreian and Stokman 2005; Glueckler 2007). The main point of network evolution models is to understand why and how networks emerge, solidify and dissolve over time. For instance, Powell and his colleagues (2005) have analyzed the underlying mechanisms such as "cumulative advantage", "homophily", "following the trend" and "multiconnectivity" in order to explain the structural evolution of complex networks in the US biotech industry. Organizational scholars have analyzed the impact of tie formations and tie terminations on the component structure and connectivity of networks (Amburgey and Al-Laham 2005). Economic geographers have argued that evolutionary processes of retention and variation in network structure are affected by a spatial dimension (Glueckler 2007). Co-evolutionary approaches concentrate on simultaneous change processes between networks and other subjects of change such as industries (Ter Wal and Boschma 2011), technologies (Rosenkopf and Tushman 1998) or even other types of networks between the same actors (Amburgey et al. 2008). The analytical focus is on understanding the interdependencies between simultaneously evolving network change patterns.

9.2.2 An Evolutionary View on Interorganizational Change

Despite the differences among evolutionary schools of thought, one can identify some cornerstones that create the common ground for evolutionary thinking in economics and related disciplines (Witt 2008b; Aldrich and Ruef 2006; Amburgey and Singh 2005; Dopfer 2005; Stokman and Doreian 2005).

Firstly, the preceding discussion reveals that evolutionary theories generally focus on dynamic change over time rather than on analyzing static or comparatively static snap-shots of economic activity. Closely related to the first point is the fact that evolutionary theories agree on the notion of path dependencies and irreversibilities, in other words, that past and present events affect the current decisions and behavior of economic actors (Arthur 1989; David 1985). Thirdly, the idea that change occurs simultaneously across multiple levels of analysis is common to most evolutionary approaches. For instance, organizational ecology scholars have analyzed intraorganizational evolution, organizational evolution, population evolution and institutional evolution (Amburgey and Rao 1996). Economists have proposed a differentiation between three levels of analysis: "micro", "meso" and "macro" (Dopfer et al. 2004). Thus, the majority of evolutionary theories are in line with the notion that change occurs simultaneously and interdependently across multiple levels (Amburgey and Singh 2005, p. 327). Finally, evolutionary theories explicitly include the underling mechanisms – the drivers or rules – that guide the change process. Most evolutionary scholars would agree that evolution includes an understanding of the forces that initiate or drive change (Doreian and Stokman 2005) and the mechanisms of modification or replacement of existing entities (Amburgey and Singh 2005). For instance, Glueckler (2007) proposes applying general evolutionary principles such as selection, retention and variation on relationships in networks. Below we concentrate on the neo-Schumpeterian school of thought (cf. Sect. 2.3).

Neo-Schumpeterian economics has its intellectual roots in evolutionary economics, industry life-cycle theory, complexity theory and systems theory and incorporates the ideas of path dependencies, irreversibilities, bounded rationality and collective innovation processes among heterogeneous actors (Hanusch and Pyka 2007a).

Research in this field is centered on the role of knowledge and innovation for the development and economic prosperity of firms and societies. Witt (2008a, p. 555) identifies the following topics as being at the core of the neo-Schumpeterian research agenda: innovation, R&D, firm routines, industrial dynamics, competition, growth and the institutional basis for innovation. Hanusch and Pyka (2007a, pp. 276–277) argue that the focus on novelty and uncertainty is what primarily sets neo-Schumpeterian economics apart. They highlight the following constitutive normative principles of neo-Schumpeterian economics: qualitative change affects all levels of economy; an idea of punctuated equilibria encompassing smooth as well as radical change; and change processes characterized by non-linearities and feedback effects responsible for pattern formation and spontaneous structuring.

The neo-Schumpeterian, or knowledge-based approach, regards innovation as a collective process of interacting heterogeneous economic actors (Pyka 2002). These actors can be characterized as bounded rational agents with incomplete knowledge bases and capabilities (Pyka 2002). The importance of formal as well as informal networks for the creation of novelty was recognized quite early on as "[. . .] networks were shown to be essential both in the acquisition and in the processing of information inputs" (Freeman 1991, p. 501). Networks allow firms to share knowledge, learn from each other and innovate (Pyka 2002; Hanusch and Pyka 2007a). In addition, networks are not static; they change over time. New relationships are established and existing relationships may be adjusted or even dissolved depending on the needs, capabilities and cooperation strategies of the actors involved. Due to the very nature of these underlying processes, networks are regarded as evolving organizational entities. Most recently we can observe the emergence of interesting intersections with related disciplines like economic geography (Boschma and Martin 2010) which provide a fertile ground for a greater consideration of the spatial dimension in evolutionary change processes.

In summary, the neo-Schumpeterian approach provides a powerful framework for analyzing knowledge transfer and interorganizational learning processes among heterogeneous economic actors in sectoral and spatial delimited systems in their efforts to innovate. It also takes into consideration the evolutionary change of complex collaborative systems driven by endogenous as well as exogenous determinants and mechanisms of micro-level change processes.

9.3 Linking Micro-Level Processes and Macro-Level Change

Drawing upon our previous considerations, in this section we introduce and discuss five general principles of network evolution models proposed by Stokman and Doreian (2005) in light of innovation networks, and incorporate the notion of network evolution according to Glueckler (2007) and Doreian and Stokman (2005). Based on these theoretical underpinnings we derive a conceptual framework that aims to provide an in-depth understanding of evolutionary change in innovation networks.

9.3.1 General Principles of Network Evolution Models

Stokman and Doreian (2005, pp. 244–251) recommend five general principles for constructing network evolution models which guide the following discussion.

Firstly, the instrumental character of networks provides the starting point for modeling network evolution. This means that the motives or goals of the actors involved have to be taken into consideration right from the very beginning. Innovation research has identified a broad range of reasons for why firms participate in innovation networks (Parkhe 1993; Pyka 2002) whereas the exchange of knowledge and initialization of mutual learning processes can be regarded as the most salient for successfully generating novelty.

Secondly, in order to gain an in-depth understanding of the actors' actions and the structural consequences of those actions it is appropriate to assume that a network actor possesses only partial or limited local information. This means that network actors possess global knowledge in the rarest cases. Instead, Stokman and Doreian (2005, p. 245) argue that network actors should be seen and modeled as adaptive entities that learn through experience and imitation. This principle is consistent with the neo-Schumpeterian notion of bounded rational agents with incomplete knowledge bases and capabilities (Pyka 2002).

The third principle highlights the importance of the relational dimension of cooperation. This means that the parallel tracking of goals by network actors affects the emergence of ties in a sense that both entities have to agree upon common goals and parallelize decisions. From an innovation network perspective, this principle highlights the importance of integrating concepts that operate primarily on the dyadic level, such as mutual trust or tensions between partners.

The fourth basic principle refers to the complexity of evolutionary processes in networks. Consequently, Stokman and Doreian (2005, p. 247) recommend designing network evolution models that are as simple as possible.

The fifth principle refers to the falsifiability of network evolution models. The authors suggest that network evolution models should have sufficient empirical reference and conclude that "statistical models are strongly preferred, as they enable the estimation of essential parameters and test the goodness of fit of the model" (Stokman and Doreian 2005, p. 249).

9.3.2 Building Blocks of the Network Evolution Framework

Network evolution is neither random nor determined (Glueckler 2007, p. 620). This means that mechanisms have to be considered that create cumulative causation and lead to path-dependency and mechanisms that produce contingency in the sense that the agent's strategies and actions may deviate from existing development paths that result in path destruction (ibid). In line with Doreian and Stokman (2005, p. 5) we regard the designations "network dynamics" or "network development" as more general terms to describe networks change over time. In contrast, network evolution "[. . .] has a stricter meaning that captures the idea of understanding change via some *understood* process [. . .]" whereas these underlying processes can be defined as a "[. . .] *series of events that create, sustain and dissolve* [. . .]" the network structure over time (Doreian and Stokman 2005, pp. 3–5). In addition, we have to note "[. . .] that the unit of analysis is always dyadic tie formation, whereas the object of knowledge is network structure" (Glueckler 2007, p. 622).

Based on the ideas outlined above, we specify three elementary building-blocks in our conceptual framework (cf. Fig. 9.1): (**I**) determinants of network change (**II**) micro-level network change processes and (**III**) structural consequences over multiple levels.

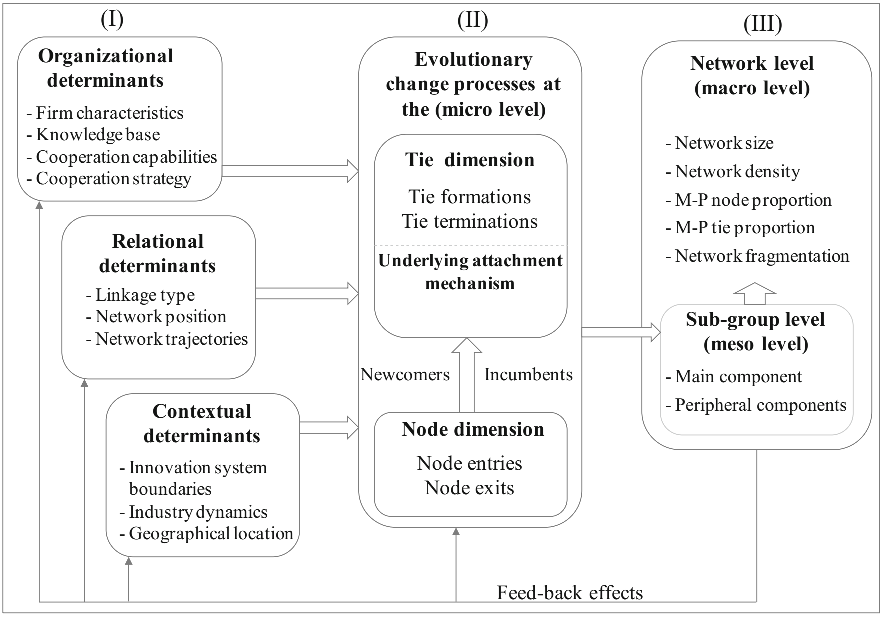

Fig. 9.1 Conceptual framework – causes and consequences of evolutionary network change processes (Source: Author's own illustration)

9.3.2.1 Determinants of Evolutionary Micro-level Network Change Processes

Due to their very nature, determinants that affect evolutionary micro-level network change processes can be categorized as organizational, relational and contextual.

To start with, we turn our attention to contextual determinants (cf. Fig. 9.1, left). Firms and organizations in interorganizational networks are considered to be an integral part of a spatial-sectoral innovation system (Cooke 2001; Malerba 2002). Innovation systems have several characterizing features.[8] Firstly, they consist of heterogeneous economic actors that are dispersed throughout geographical space within the system boundaries.[9] Secondly, populations of actors in the system can change over time which means that, for instance, firms or other types of organizations can, over time, enter the system (i.e. new company founding, spin-offs etc.)

[8] For the purpose of this study we focus on some selected features of innovation systems. Note that the innovation system approach is much richer than described here (cf. Sect. 2.3.3).

[9] Network actors are simultaneously embedded in multiple proximity dimensions (Boschma 2005) each of which is likely to affect a firm's cooperation behavior (Boschma and Frenken 2010). For the sake of simplicity, we include only the geographical dimension in the framework.

and exit the system (i.e. closures, failures, bankruptcies etc.). Thirdly, the system's elements do not exist in isolation; they are interconnected by various types of formal or informal linkages.

This leads to the relational determinants in our framework. Dyads consist of at least one directed or undirected tie connecting two nodes in a well-defined population and, at the same time, constitute the most basic building block of a network (Wasserman and Faust 1994). Triadic components are more complex network building blocks (ibid). Below, we refer to all components with more than two nodes as multi-node components. For the purpose of this analysis we specify innovation networks as formal, knowledge-related and publicly funded R&D partnerships among a well-defined population of firms and public research organizations.[10] The existence of a tie among two nodes in an innovation network implies a certain degree of partner fit, mutual trust, cooperation capabilities and commitment to common goals between both parties. The sum of these dyadic network ties spans the overall innovation network within the system boundaries. Firms and organizations occupy qualitatively different positions within the overall network structure. These network positions are the result of cooperation decisions taking place in the shadow of the past (Gulati and Gargiulo 1999). Soda and Zaheer (2004) argue that networks have a "memory" in the sense that past and present networks affect current actions. Doreian (2008) refers to this issue by introducing the concept of "network trajectories" in the context of the evolutionary change process of networks.

Finally, we move on to organizational determinants in our framework. As we will establish in more detail later, firm characteristics such as size, age, origin, knowledge stock and cooperation capabilities etc. are likely to affect knowledge-related cooperation behavior in innovation networks.

9.3.2.2 Micro-Level Network Change Processes at the Core of the Model

We continue the debate by moving on to micro-level network change processes at the core of the model (cf. Fig. 9.1, center). In a similar vein, Hite (2008) highlights in her model the importance of micro-level network change processes in the context of network evolution. Glueckler (2007, p. 623) argues that "[. . .] a complete theory of network evolution [. . .] has to theorize both the emergence and disappearance of ties *and* nodes".

We will start by turning our attention to the node dimension. In the most basic sense we can differentiate between system actors who participate and those who do not participate in a particular network. The first group includes all actively

[10] Informal partnerships and other structural collaborative forms such as short-term contracts, licensing and franchise agreements, consultancy contracts, consortia, non-funded long-term partnerships or joint ventures were deliberately excluded from the framework.

cooperating network actors, whereas the second group provides a pool of potentially available network actors. We follow the suggestion made by Guimera et al. (2005) and differentiate between two groups of potential network actors: "incumbents" and "newcomers". Both groups are subject to change due to dynamics at the industry level. Entries and exits affecting actors within the first group (i.e. active network actors) have direct consequences for the structural configuration of the network, whereas the same events affecting actors in the second group (i.e. potential network actors) have an indirect impact by enlarging or reducing the pool of cooperation partners that are potentially available. To control for this node-related dimension of change in the German laser industry innovation network, one needs to have an exact picture of all laser source manufacturers and laser-related public research organizations over time. In this analysis we choose yearly time period to capture the industry's configuration.

Now we will take a closer look at the tie dimension by considering two types of events – tie formations and tie terminations – to explain the structural change of the network. In line with Hite (2008) we refer to these events below as micro-level network change processes. Moreover, tie formation and tie termination processes can be coupled or uncoupled. A good example of coupled micro-level network change processes are joint R&D projects with a fixed timeframe. In contrast, strategic long-term partnerships have no predefined end date and provide a concrete example of uncoupled micro-level network change processes. For reasons of simplicity, we focus on coupled events. This approach has two considerable advantages. Firstly, we have an exact time tracking of all tie termination events which are, from a structural point of view, as important as tie formation events. Secondly, we considerably reduce complexity as tie termination processes do not follow their own underlying logic. We argue, in line with Nelson and Winter (2002) and with reference to Glueckler (2007), that micro-level network change processes can be explained by the general evolutionary mechanisms of variation, selection and retention.[11] At the same time, the formation and termination of partnerships are affected by the previously discussed determinants and follow the logic of underlying network change mechanisms. The preferential attachment concept provides one of the most frequently discussed tie formation mechanisms in network studies. The underlying logic is quite simple: highly connected nodes are more likely to connect to new nodes than sparsely connected nodes (Barabasi and Albert 1999; Albert and Barabasi 2002). The mechanism generates quite a unique structural pattern at the overall network level which is characterized by a power law degree distribution (cf. Sect. 8.3.1). Several other mechanisms and underlying logic of network formation processes have been discussed in the literature. These include "homophily" according to which actors with similarities are more likely to connect to one another (McPherson et al. 2001), "heterophily" according to which heterogeneous actors attract one another (Amburgey et al. 2009), "herding behavior" where actors follow the crowd

[11] For an in-depth discussion, see Glueckler (2007, pp. 623–630).

(Kirman 1993; Powell et al. 2005) and “transitive closure” where two nodes, which are both connected to a third partner, attract one another (Snijders et al. 2010).

9.3.2.3 Structural Consequences of Micro-Level Network Change Processes

Only a few previous studies have analyzed the structural consequences of micro-level network change processes (Elfring and Hulsink 2007; Baum et al. 2003; Amburgey and Al-Laham 2005). We draw upon evolutionary ideas and network change models proposed by Amburgey et al. (2008), Guimera et al. (2005) and Glueckler (2007) to substantiate this part of the puzzle in our framework.

We start by looking at the model proposed by Amburgey et al. (2008). The authors provide a conclusive theoretical explanation for structural consequences of tie formations and tie terminations by introducing four distinct structural processes: (a) the creation of a bridge between components, (b) the creation of a new component, (c) the creation of a pendant to an existing component and (d) the creation of an additional intra-component tie (Amburgey et al. 2008, pp. 184–186). The framework provides us with very valuable insights. Nonetheless, we argue that these considerations have to be extended and refined in several ways.

Firstly, we argue that tie formations and tie terminations, as well as subsequent structural consequences, depend on the actor’s strategic orientation. Strategies and actions of network actors can result in the destruction of existing network paths (Glueckler 2007, p. 620) and they determine, at the same time, the scope of future cooperation options and possibilities. Therefore, we propose and integrate three basic types of knowledge-related cooperation strategies into our framework: progressive, moderate and conservative. Progressive strategies are characterized by a firm’s objective to considerably improve its knowledge base by accessing multiple knowledge sources simultaneously or by establishing and controlling global knowledge streams that connect entire groups of actors in the networks. The underlying objective of moderate strategies is to gradually improve the knowledge base through linkages to a few selected individual partners or through the establishment and control of local knowledge streams. Conservative strategies aim to secure a firm’s knowledge base by protecting the existing knowledge stock or by securing and sustaining existing local or global knowledge channels.

Secondly, the framework of Amburgey et al. (2008, pp. 184–186) primarily focuses on the tie dimension and neglects the importance of different types of actors for the structural evolution of networks. As outlined above, not all innovation system actors are involved in a particular type of innovation network. Instead, a considerable number of system actors are not embedded at all, whereas others cooperate repeatedly with the same partners. To account for this fact we follow the suggestion of Guimera et al. (2005, p. 698) and split the population into “newcomers” and “incumbents”. This gives us four distinct partnership constellations: “newcomer-newcomer” (NN), “incumbent-newcomer” (IN), “incumbent-incumbent” (II) and “repeated incumbent-incumbent” (RI).

Partner types	Cooperation options		Knowledge-related cooperation strategies: Progressive	Moderate	Conservative	Structural consequences: Size	Density	Fragmentation	M-P node proportion	M-P tie proportion
N	NN	N1			*No cooperation*	/	/	/	/	/
		N2		*New dyadic component*		⇧	/	⇧	⇩	/
		N3	*New multi-node component*			⬆	/	⬆	⬇	/
	NI	N4			*No extension*	/	/	/	/	/
		N5		*P component extension*		⇧	/	/	⇩	/
		N6	*M component extension*			⇧	/	/	⇧	/
I	II	I1			*M-comp. fragmentation*	/	⇩	⇧	⇩	/
		I2		*P component consolidation*		/	⇧	/	/	⇩
		I3	*M component consolidation*			/	⇧	/	/	⇧
		I4			*P-P component merger (dyad)*	/	⇧	⇩	⇩	/
		I5		*P-P component merger*		/	⇧	⬇	⬇	/
		I6	*M-P component merger*			/	⇧	⬇	⬆	/
	RI	I7	*Network solidification*	*Network solidification*		/	⇧	/	/	/
		I8		*Network fragmentation*	*Network fragmentation*	/	⬆	/	/	/

Legend:

N = Newcomer
I = Incumbent

NN = Newcomer-Newcomer
NI = Newcomer-Incumbent
II = Incumbent-Incumbent
RI = Repeated Incumbent -Incumbent

M = Main component
P = Peripheral component

⬆⬇ Pronounced structural effect
⇩⇧ Moderate structural effect
/ No structural effect

Fig. 9.2 Partner constellations, cooperation strategies and structural consequences (Source: Author's own illustration)

Thirdly, under real-world conditions we can frequently observe the formation and termination of both dyadic ties connecting two actors but also of large-scale multi-partner projects that encompass a large number of actors. Consequently, we differentiate between dyadic and multi-node components in our framework.

Finally, in the majority of real world networks, the main component usually fills more than 90 % of the entire network (Newman 2010, p. 235).[12] This substantiates the assumption that essential elements of industry-specific technological knowledge are tied to the main component. In contrast, peripheral components are likely to entail only small, rather specific fragments of the industry's technological knowledge. Thus, we argue that there is a qualitative difference between whether network change processes affect the core or the periphery of the network.

Figure 9.2 (left) summarizes our previous considerations and illustrates the anticipated structural consequences at the overall network level (Fig. 9.2, right).[13] To address the structural consequences at the network level we now take a closer

[12] For the German laser industry network we found that the main component fills 94.51 % of the network on average (cf. Sect. 8.3.3).

[13] In line with Amburgey et al. (2008) we use three simple indicators to discuss structural network change: network size, network density and overall network fragmentation. To account for processes affecting the core-periphery structure of the network, we introduce two additional ratios to measure the proportion of nodes and ties in peripheral components in relation to the size and density of the main component (cf. Sect. 8.3.3).

look at newcomers who have basically two possible partner constellations (NN and NI) and six cooperation options (N1–N6). We start our discussion on structural consequences by focusing on the moderate knowledge-related cooperation strategy of newcomers.

Actors aiming to gradually improve their knowledge base through selected individual collaborations basically have two options: either they can cooperate with another potential newcomer, which would lead to the creation of a new dyadic component (N2), or they can connect with an incumbent who is embedded in a peripheral component (N5). The structural consequences are consistent with the structural processes (b) and (c) identified by Amburgey et al. (2008). However, we have to consider two additional knowledge-related cooperation strategies. Conservatively oriented actors who predominantly aim to protect their existing knowledge stock are likely to isolate themselves from other newcomers or incumbents. Thus, neither is a new component created (N1) nor an existing component extended (N4). In both cases, the structural configuration of the network is not affected. Even though these two cooperation strategies have no direct structural consequences they are important in understanding what prevents potential network entrants from cooperating for the first time. In contrast, progressively oriented actors seek to improve their knowledge stock considerably by accessing multiple diverse knowledge bases simultaneously. The initialization of multi-partner projects among newcomers (N3) leads, from a structural standpoint, to the creation of a multi-node component. In contrast, the establishment of a linkage to an incumbent in the main component of the network offers a broad variety of direct and indirect knowledge-accessing opportunities (N6) and is reflected in the extension of the main component.

The structural consequences at the network level for the cooperation options (N2) and (N3) are quite similar but less pronounced in the former. The creation of new ties affects the number and size distribution of components (Amburgey et al. 2008, p. 186). This leads to increasing network fragmentation and a decreasing proportion of nodes in the main component in relation to the number of nodes in peripheral components. A look at the cooperation options (N5) and (N6) reveals that the number of components remains constant but the network size is affected. This is in line with structural implications anticipated by Amburgey et al. (2008, p. 186). However a closer look at the proportion of nodes in the main and peripheral components reveals two opposing structural effects for the cooperation options (N5) and (N6). Moderate cooperation strategies produce a situation in which the main component shrinks in relation to the network's periphery. On the other hand progressive strategies lead to a relative growth in the main component versus the network periphery.

Now we turn our attention to incumbents who, like the newcomers, basically have two possible partner constellations (II and RI). In this context, Amburgey et al. (2008, p. 186) differentiate between two structural processes: the creation of a bridge between two components and the creation of intra-component ties. This distinction provides valuable insight into the structural consequences of cooperation events between previously unconnected or indirectly connected network actors (I1–I6).

However, in order to refine the picture we have to separate consolidation processes from solidification and fragmentation tendencies in the network. Thus, we explicitly consider the structural consequences of repeated ties between already connected incumbents (I7–I8). Moreover, we account for path dependencies in our framework. By referring to Glueckler (2007, p. 620) we argue that the initial cooperation strategy of a network entrant affects its later cooperation path. In other words, the initial cooperation event is hereditary in a sense that it does restrict cooperation opportunities, yet at the same time it opens up new cooperation options. Below, we refer to this very specific type of network path dependency as "cooperation imprinting".

Figure 9.2 illustrates six potentially achievable cooperation options (I1–I6) among previously unconnected incumbents (II). Newcomers who have pursued a moderate network entry strategy start the next cooperation round out of a dyadic component located in the periphery of the network. In contrast, the situation looks quite different for newcomers who have a progressive strategic orientation at the onset. These actors started their cooperation path by creating a new multi-node component and linking themselves to the main component. In both cases the initial conditions for the next cooperation round are considerably better than for network entrants with a moderate strategy.

The previous considerations imply that incumbents, who are located in the network periphery and are still pursuing a moderate cooperation strategy, are likely to look for cooperation opportunities in their direct neighborhood. This case addresses the creation of alternative knowledge channels in peripheral components (I2). In contrast, there are peripheral incumbents who change their strategic orientation towards a more progressively oriented cooperation behavior. These actors actively search for novel knowledge stocks and tend to establish or control knowledge streams to other groups of network actors. This case is reflected, from a structural standpoint, in the emergence of brokerage ties among peripheral incumbents (I5). In summary, we can observe the consolidation of a connected peripheral subgraph on the one hand, and the amalgamation of two previously unconnected, peripheral sub-graphs on the other. Both structural processes are in line with the model proposed by Amburgey et al. (2008). However, it is important to note that the cooperation options (I2) and (I5) in our framework exclusively address structural consequences that occur in the periphery of the network due to the network entrants' cooperation imprinting.

Now we look at incumbents who entered the network by pursuing a progressive cooperation strategy (using N3 or N6). Network entrants who linked themselves to the main component (using N6) face quite a comfortable situation in the next cooperation round. On the one hand, they can expand their position in the main component by establishing direct links to new partners in the main component (I3) or they can wait for new specific knowledge-accessing opportunities to pop up in the network periphery in order to establish bridging ties (I6). However, main component actors can also pursue a conservative strategy in order to protect and secure the existing knowledge stock. In other words, a main component actor can decide to withdraw from the main component by leaving the main component either alone or together with a handful of strategic partners. The structural consequences are far-reaching, especially in the latter case (I1). The overall network density decreases, the fragmentation of the network increases and the component shrinks in relation to the periphery.

Actors with a progressive cooperation imprinting who entered the network through the creation of a new multi-node network component (using N3) start the second cooperation round from a peripheral position. However, multi-partner projects provide a better starting point than dyadic components because they are much more visible and prestigious. Incumbents with a progressive strategy can establish a bridging tie to an actor in the main component (I6).[14] This strategy provides access to essential elements of an industry-specific technological knowledge pool tied to the main component and leads to an amalgamation of a peripheral component with the main component. Incumbents pursuing a moderate cooperation strategy will try to gain access to the much more specific knowledge pool by bridging the gap to another peripheral multi-node component (I5) or, in the case of a conservative cooperation strategy, to another dyadic component (I4).

A comparison of options I2 and I3 reveals some interesting structural implications. In both cases the network density is affected. This is in line with structural implications anticipated by Amburgey et al. (2008, p. 186). At the same time the ratio of main-component ties to peripheral-component ties reveals an opposing structural effect. The amalgamation of two previously unconnected network components affects the density and fragmentation of the network (Amburgey et al. 2008, p. 186). Furthermore, the differentiation between main and peripheral components (I5 and I6) once again shows an opposing structural effect.

Finally, we take a look at repeated incumbent-incumbent partnerships. Repeated partnerships can occur sequentially (at different points in time) or in parallel (at the same point in time). Not only the former but also the latter case is quite important but frequently neglected in network evolution studies. We refer to these ties as redundant network ties. These ties secure access to external knowledge sources on the one hand, while providing the opportunity to exchange qualitatively different stocks of knowledge among the same partners. In addition, redundant ties have far-reaching implications for the overall network structure. We argue that redundant ties can affect the stability of the network in several ways. Basically we can distinguish between two cases. The previously outlined ideas substantiate the argument that a network in which progressive and moderate cooperation strategies dominate is likely to show a solidification tendency over time (I7). In contrast, a

[14] Note that there is a qualitative difference when comparing the cooperation option (I6) of an incumbent who is embedded in the main component with an incumbent who is embedded in a peripheral component. The former case reflects a strategically important gate-keeping position. This position allows an actor to control who gets access to essential elements of the industry's technological knowledge pool tied to the main component.

network in which moderate and conservative cooperation strategies dominate is likely to show fragmentation tendencies over time (I8).

9.4 Hypotheses Development for Network Entry Processes

Based on our previously introduced framework we now derive a set of hypotheses that address only a few selected facets of the entire evolutionary network change process described above. In order to answer the research question raised initially, we exclusively concentrate on network entry processes. As a consequence, the analytical part is confined to a firm's initial cooperation event. Secondly, each group of determinants in our framework contains a broad variety of factors that are likely to affect a firm's cooperation behavior. The hypotheses outlined below are centered on only a small selection of factors that are assumed to play a key role in explaining network entry processes of German laser source manufacturers.

Initially we take a closer look at firm-specific determinants. The resource-based view (Wernerfelt 1984; Barney 1991; Peteraf 1993) suggests that a firm's ability to achieve and maintain a profitable market position and outperform competitors depends, to a large extent, on its ability to exploit both internal resources (Barney 1991) and external resources (Gulati 2007) and to generate a competitive advantage.[15] In this context, it has been argued that small firms face some substantial disadvantages compared to larger firms in the form of limited reputational, human capital and financial resources (Lu and Beamish 2006). Small firms can overcome their resource constraints and counteract their comparably high risk of failure – also known as "liability of smallness" (Barron et al. 1994) – by forming alliances with external partners (Baum et al. 2000). Proponents of the knowledge-based view have argued that alliances allow firms to gain access to external knowledge stocks (Grant and Baden-Fuller 2004) and learn from cooperation partners (Hamel 1991) in order to gain competitive advantages (Dierickx and Cool 1989; Coff 2003) and resist the increasing pressure of global competition. Both resource-based as well as knowledge-based arguments provide solid theoretical arguments to substantiate high cooperation propensities of small firms in science-based industries.

However, given the need and willingness of these firms to cooperate, there are several factors that are likely to hamper their ability to cooperate for the first time or which delay network entry. Firstly, in the pre-cooperation phase it can be quite difficult to assess a potential partner's intentions (Dacin et al. 1997, p. 7). This enhances the level of uncertainty, especially in international alliances (ibid). Secondly, potential network entrants have to make a considerable effort and spend both time and limited resources on identifying potential cooperation partners (Dacin et al. 1997, p. 4). From a New Institutional Economic standpoint we would argue that a firm faces considerable screening costs to overcome information

[15] For an in-depth discussion on the resource-based view, see Sect. 2.4.2.

asymmetries and lower the adverse selection risk (Ackerlof 1970; Spence 1976, 2002). These search costs, however, are likely to cause a disproportional burden on small firms due to their comparably low resource endowment in the pre-cooperation phase. Once potential partners are identified, other obstacles are likely to delay network entry. Small firms lack alliance management capabilities (Schilke and Goerzen 2010) and standardized cooperation interfaces (Goerzen 2005). Finally, Lu and Beamish (2006) point to the fact that SMEs are usually owned and managed by the founders and decision-making is much more centralized compared to larger firms. This, however, is likely to delay the responsiveness of decision makers at lower hierarchy levels and may hamper the firm's ability to react rapidly to newly emerging cooperation opportunities. The arguments outlined above substantiate our first hypothesis:

H1 Small firms take longer than large firms to enter an innovation network for the first time.

With regard to relational determinants the question arises as to how the type of cooperation impacts the time it takes a firm to initialize its first cooperation event. During the past decades substantial efforts were undertaken by both the EU and by the German government to support key industries. The funding of R&D cooperation projects is regarded as a key policy instrument. The main difference between these two types of cooperation is that EU-framework projects explicitly aim to encourage scientific and technological cooperation between member states whereas national funding initiatives predominantly aim to address domestic applicants. There are some clear benefits associated with international R&D project environments. According to Gunasekaran (1997, p. 639) these include access to new and different technologies, enhanced scope of potentially accessible technological knowledge stocks, better access to qualified employees and a broad range of training opportunities for technical personnel. Nonetheless, there are also some difficulties that go hand in hand with international R&D projects. The pre-formation phase is characterized by higher search costs to identify potential partners. In the post-formation phase, international alliances require greater investment in communication and transportation to support interaction among the partners involved (Lavie and Miller 2008, p. 625). Project governance costs tend to be higher due to a higher level of uncertainty (ibid). It is also well recognized that cross-national cultural differences may affect interaction between firms and organizations in multiple ways (Hofstede 2001). Firms entering cross-national cooperation projects face the challenge of adjusting to both a foreign country and to an alien corporate culture (Barkema et al. 1996, p. 154; Lavie and Miller 2008, p. 626). Differences in national culture are reflected in differing managerial ideologies of decision makers and have the potential to significantly affect strategic decisions in both the pre and post alliance formation phase (Dacin et al. 1997, p. 6). As a consequence, it has been argued that cross-national cultural differences are likely to affect a firm's attitude towards cooperation and thus the predisposition to enter international R&D consortia (Nakamura et al. 1997, p. 155). These considerations underpin our second hypothesis:

H2 A firm will enter a national innovation network sooner than an international network (mode of entry).

Finally, we take a closer look at the contextual dimension. Based on a proximity framework originally proposed by Boschma (2005), Boschma and Frenken (2010) have argued that network change is likely to be affected by other dimensions of proximity such as cognitive, organizational, institutional or geographical proximity. Like other science-driven industries (Owen-Smith et al. 2002), the German laser industry shows a pronounced tendency to cluster geographically (Kudic et al. 2011). Consequently, we focus on the relationship between geographical proximity and a firm's cooperation timing. More precisely, we distinguish between inside-cluster and outside-cluster firms and analyze the extent to which cluster membership affects cooperation timing. Firstly, it is important to note that cluster membership does not require or imply network membership. Firms can be located in a densely crowded region (agglomeration) without having formal partnerships with other firms or organizations in their immediate geographical surroundings. Theoretically, there are three potential ways in which cluster membership can affect a firm's propensity to cooperate and its timing to do so. A firm's cluster membership may have an accelerating impact, a decelerating impact or no impact at all on its propensity to cooperate for the first time and its timing to do so.

We follow the traditional line of argument which assumes a positive relationship between a firm's location in a geographically crowded region and its initial cooperation activities. In this context, it has been argued that the local environment generates positive externalities in terms of knowledge spillovers (Feldman 1999; Audretsch and Feldman 1996). Social interactions between employees and decision makers within a regional agglomeration are an important source of information. As a result, firms located in densely crowded industrial regions become aware of local cooperation opportunities sooner than others. It is therefore plausible that regional environments can speed up a firm's successful search for potential partners and shorten the time needed to enter the network. However, geographical proximity may also be accompanied by negative effects. Boschma (2005, p. 70) argues that highly specialized regions can become too inward-looking and this sensitizes them to the problem of spatial lock-in effects because of their lack of openness to the outside world. While there is a great deal of empirical evidence for the importance of spatial proximity over functioning spillover channels, other dimensions of proximity such as cognitive proximity (Boschma and Frenken 2010), might outperform spatial proximity in certain cases. In line with Feldman (1999) and with Audretsch and Feldman (1996) we formulate our last hypothesis:

H3 The time it takes to first enter an innovation network is shorter for firms located in densely crowded regions (agglomeration areas) than for firms located in remote regions.

9.5 Data and Variable Specification

This analytical section employs the previously introduced event history dataset (cf. Sect. 6.1.1) which is based on three main data sources: industry data, organizational data and cooperation data.

Industry data came from a proprietary dataset containing detailed information on firm entries and exits for the entire population of German laser source manufacturers between 1969 and 2005 (Buenstorf 2007). This initial industry dataset has been modified in several ways to meet the requirements of this analysis (cf. Sect. 6.1.1). We ended up with an industry dataset encompassing 233 laser source manufacturers for the entire observation period from 1990 to 2010. To analyze the transition from the origin state ("no-cooperation") to the destination state ("first cooperation") we had to account for all firms with "incomplete" cooperation histories to avoid left truncation and left censoring problems (Blossfeld and Rohwer 2002, pp. 39–41). In cases where the number of censored observation units is small, it is acceptable to simply exclude them (Allison 1984, p. 11). Starting with a full population of 233 LSMs in our sample, we identified 39 firms which were founded before 1990 and excluded them from the dataset. Thus, a total of 194 firms were potentially at risk of conducting the first cooperation event. Out of this population we ended up with a total of 112 cooperating firms whose first cooperation event unambiguously fell between 1990 and 2010.

Organizational level data was basically taken from the same raw data sources that were used at the industry level (cf. Sect. 4.2.1). Moreover, we used annually compiled count data on different types of laser related organizations – laser source manufacturers (LSMs), laser-related public research organizations (PROs) and laser system providers (LSPs) – which was supplied by the LASSSIE project consortium (Albrecht et al. 2011). Data was available at the planning region level. This allowed us to identify planning regions with an above-average number of LSMs, PROs and LSPs and to group these planning regions into clusters.

Network data came from two electronically available archive data sources: the *Foerderkatalog* database provided by the German Federal Ministry of Education and Research and the *CORDIS* databases provided by the European Community Research and Development Information Service (cf. Sect. 4.2.3).

We are not the first to use these archive data sources to construct knowledge-related innovation networks (cf. Broekel and Graf 2011, p. 6; Fornahl et al. 2011; Scherngell and Barber 2009, 2011; Cassi et al. 2008). There are solid arguments that advocate for the use of these archive data sources for analyzing the evolution of innovation networks. Organizations that participate in R&D cooperation projects subsidized by the German federal government have to agree on a number of regulations that facilitate mutual knowledge exchange and provide incentives to innovate (Broekel and Graf 2011, p. 6). In a similar vein, the European Commission 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, p. 534). Moreover, both data sources provide exact information on the timing of tie formation as well as tie termination processes. They were used to construct a single-episode event history dataset for the German laser industry (cf. Sect. 6.1.1).

The variables in this dataset were grouped into the following three categories: organizational, relational and contextual. An organizational variable was created to account for differences in firm size *[firmsize_cat_ev]*. The following size categories were used: firmsize_cat_ev1 = "micro firm" = 1–9 employees; firmsize_cat_ev2 = "small firm" = 10–49 employees; firmsize_cat_ev3 = "medium firm" = 50–249 employees; firmsize_cat_ev4 = "large firm" = more than 250 employees. A simple relational variable was included in the dataset to account for the type of cooperation. Thus, nationally funded and supra-nationally funded R&D cooperation projects were coded separately *[coop_type_ev]*. The variable was coded coop_type = 1 in the case of a *CORDIS* project and coop_type = 2 in the case of a Foerderkatalog project. Cooperation dates and duration were recorded in century months. Finally, we included a set of cluster variables *[clu_ev]* in our dataset indicating whether a firm was located inside or outside of a densely crowded region. The four geographical clusters were identified and defined as follows: planning regions: 72, 73, 74, 76 and 77 = clu_ev_bw, located in Baden-Württemberg; planning regions: 86, 90 and 93 = clu_ev_bay, located in Bavaria; planning regions: 54 and 56 = clu_ev_thu, located in Thuringia; region 30 = clu_ev_b, located in Berlin.

9.6 Empirical Model and Estimation Results

Non-parametric event history methods were used to test our hypotheses (cf. Sect. 6.2.1). We applied the product-limit estimator (Kaplan and Meier 1958).

9.6.1 Empirical Estimation Approach

The Kaplan and Meier (1958) estimation method has several advantages. Most importantly, it is straightforward to use, requires only weak assumptions and allows non-repeated events in single-episode event history data to be analyzed (Cleves et al. 2008, p. 93). In general, the survival function represents the probability of surviving past time *t*, or in other words, the probability of failing after time *t* (ibid).

The event of interest is the first cooperation for all LSMs which are at risk in the time period from 1990 to 2010. The unit of analysis is the firm. The time axis is defined on the basis of century months. All firm foundation dates as well as all start and end dates of cooperation events are given in century months. The dataset allows us to analyze the transition from the origin state ("no-cooperation") to the destination state ("first cooperation"). Repeated events were not taken into account. Thus, the survival function has to be interpreted as follows: the survival function estimates the firm's probability of having the first cooperation event after time *t*.

Non-parametric estimation methods provide the possibility of comparing survivor functions (cf. Sect. 6.2.1). The overall population can be divided into two or more subgroups by using an indicator variable to analyze whether the probability of failing after time *t* significantly differs among these subgroups. The indicator variable defines membership in a particular subgroup (Blossfeld et al. 2007, p. 76). We applied this approach to analyze the extent to which organizational, relational and contextual determinants affect cooperation behavior over time.

For the purpose of this analysis we make use of four commonly applied test statistics: i.e. the Log-Rank test, Cox test, Wilcoxon-Breslow test and Tarone-Ware test. These tests are designed to compare globally defined overall survival functions (Cleves et al. 2008, p. 123). The tests are based on the null hypothesis that the survivor functions do not differ significantly from one another (Blossfeld et al. 2007, p. 81). A significant test result indicates that the null hypothesis must be rejected (ibid). Or to put it another way, rejecting of the null hypothesis based on a significant test result supports the alternative hypothesis that the compared functions differ significantly from one another.

9.6.2 Estimation Results

A natural starting point for the presentation of our exploratory findings is to look at the overall survivor function. Figure 9.3 displays a plot of the survivor function.

The vertical axis contains values between zero and one whereas the horizontal axis represents time measured in century months. The interpretation is straightforward. The survivor function represents the firm's propensity and timing to move from the origin state ("no cooperation") to the destination state ("first cooperation"). To illustrate this, after 50 century months (i.e. 4 years and 2 months) about 66 % of all firms in our sample have entered the network, while about 34 % of all firms were still unable to initiate their first cooperation event. Only 50 century months later (i.e. 8 years and 4 months) about 84 % had achieved their first cooperation event and after 150 century months (i.e. 12 years and 6 months) 99.6 % of all firms had moved from the origin state to the destination state.

To test our hypotheses we have used several indicator variables to split the sample, compare survivor functions and analyze the extent to which the probability of entering the network is affected by organizational, relational or contextual factors.

We start the presentation and discussion of our findings by looking at firm size. A comparison of survivor functions for micro, small, medium and large firms reveals some unexpected but quite interesting findings (cf. Fig. 9.4). What we

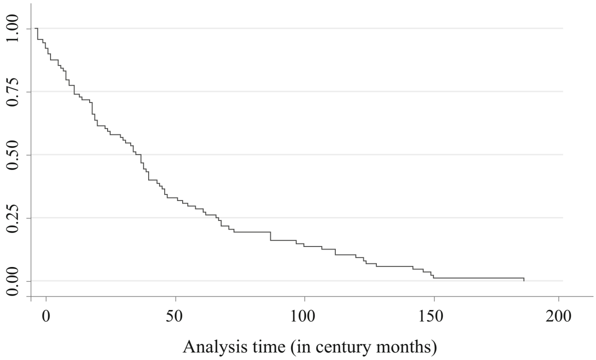

Fig. 9.3 Timing and propensity to cooperate and enter the network (Source: Author's own calculations and illustration)

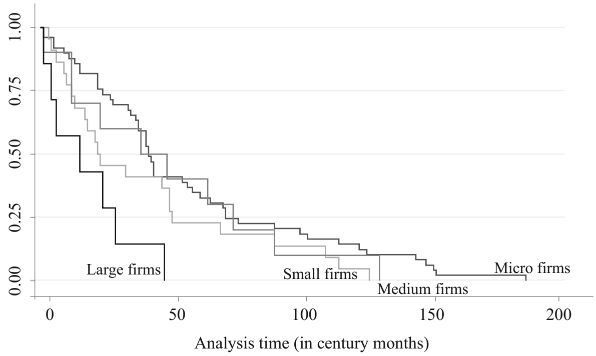

Fig. 9.4 The Kaplan-Meier approach – comparison of survivor functions based on firm size (Source: Author's own calculations and illustration)

observe is that micro firms enter the network significantly later than small and large firms. The sequence in which micro, small and large firms enter the network remains unchanged and stable throughout the entire observation period. The test statistics reported in Table 9.1 indicate that the null hypothesis must be rejected, in other words, the compared survivor functions differ significantly from one another.

These results seem to confirm, at least at first glance, Hypothesis H1 which states that smaller firms have higher resource constraints and cooperate later than larger firms. However, the group of medium-sized firms complicates the story. At some point in time (e.g. after 50 months) medium-sized firms enter the network significantly later than both large firms and micro and small-sized firms.

In a nutshell, we found only partial support for Hypothesis H1. The findings for micro, small and large firms are in line with our expectations. Moreover, the results clearly indicate that there must be another underlying process affecting a firm's timing in entering the network. An in-depth analysis of additional organizational level determinants is needed to understand what factors cause the delayed entry of medium-sized firms.

Next, we look at the relational dimension. Our initial assumption was that the type of cooperation used by a firm to enter the network is likely to affect how long it

Table 9.1 Test statistics – comparison of Kaplan Meier survivor functions based on firm size

Log-rank test for equality of survivor functions (by size)

	Events observed	Events expected
1	49	57.97
2	22	17.53
3	10	9.97
4	7	2.53
Total	88	88.00

chi2(3) = 11.05
Pr>chi2 = 0.0114

Wilcoxon (Breslow) test for equality of survivor functions (by size)

	Events observed	Events expected	Sum of ranks
1	49	57.97	-496
2	22	17.53	233
3	10	9.97	-26
4	7	2.53	289
Total	88	88.00	0

chi2(3) = 9.97
Pr>chi2 = 0.0188

Cox regression-based test for equality of survival curves (by size)

	Events observed	Events expected	Sum of ranks
1	49	57.97	0.8674
2	22	17.53	1.3254
3	10	9.97	1.0490
4	7	2.53	3.0565
Total	88	88.00	1.0000

chi2(3) = 8.26
Pr>chi2 = 0.0409

Tarone-Ware test for equality of survivor functions (by size)

	Events observed	Events expected	Sum of ranks
1	49	57.97	-62.730142
2	22	17.53	30.036592
3	10	9.97	-2.7858996
4	7	2.53	35.479449
Total	88	88.00	0

chi2(3) = 10.42
Pr>chi2 = 0.0153

(Source: Author's own calculations)

would take for the first cooperation event to occur. Figure 9.5 compares the survivor function based on cooperation type. Surprisingly, a comparison of nationally and supra-nationally funded R&D cooperation projects shows no significant differences (cf. Table 9.2). All four test statistics indicate that the null hypothesis must be confirmed, meaning that there is no significant difference between the compared survivor functions. In other words, it makes no difference whether a firm favors nationally funded (i.e. *Foerderkatalog*) or supra-nationally funded (i.e. CORDIS) R&D cooperation projects.

This result implies that the problem of "double layered acculturation" inherent to international cooperation projects (Barkema et al. 1996, p. 154) seems to play a subordinate role in this context. As a consequence we have to reject Hypothesis H2. One potential explanation for this result is that the previously existing interpersonal network between decision makers relativizes culturally contingent cooperation barriers.

Finally, we address here only one of several other contextual determinants by taking a closer look at the geographical proximity dimension. To analyze the extent to which cluster membership affects a firm's timing for entering the network we identified several planning regions with an above-average number of LSMs, PROs and LSPs and grouped them into four clusters: cluster_Th, cluster_Bay, cluster_B, cluster_Bw.

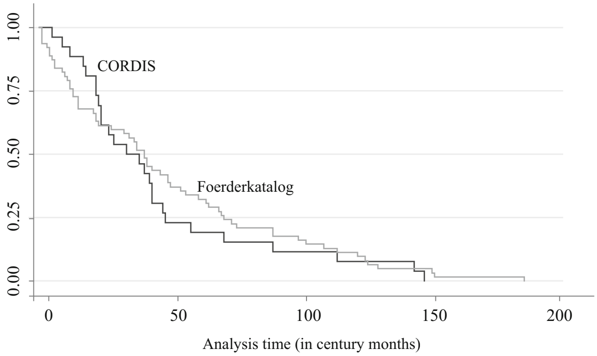

Fig. 9.5 Duration analysis based on cooperation type (Source: Author's own calculations and illustration)

Table 9.2 Test statistics – comparison of Kaplan Meier survivor functions based on cooperation type

Log-rank test for equality of survivor functions (by coop.-type)

	Events observed	Events expected
0	26	23.79
1	62	64.21
Total	88	88.00

chi2(1) = 0.29
Pr>chi2 = 0.5874

Wilcoxon (Breslow) test for equality of survivor functions

	Events observed	Events expected	Sum of ranks
0	26	23.79	-5
1	62	64.21	5
Total	88	88.00	0

chi2(1) = 0.00
Pr>chi2 = 0.9820

Cox regression-based test for equality of survival curves (by coop.-type)

	Events observed	Events expected	Sum of ranks
0	26	23.79	1.0971
1	62	64.21	0.9662
Total	88	88.00	1.0000

chi2(1) = 0.28
Pr>chi2 = 0.5948

Tarone-Ware test for equality of survivor functions (by coop.-type)

	Events observed	Events expected	Sum of ranks
0	26	23.79	7.4968264
1	62	64.21	-7.4968264
Total	88	88.00	0

chi2(1) = 0.07
Pr>chi2 = 0.7910

(Source: Author's own calculations)

Figure 9.6 illustrates our empirical results. Perhaps the most interesting finding is that cluster membership can have quite different effects on a firm's timing in entering the network. Our results show that firms located in the Thuringia Cluster (clu_Th) cooperate significantly earlier than firms that are located elsewhere. Exactly the opposite is true for firms located in the Bavarian Cluster (clu_Bay). In both cases test statistics (cf. Table 9.3) indicate that the compared survivor functions for inside-cluster and outside-cluster firms differ significantly.

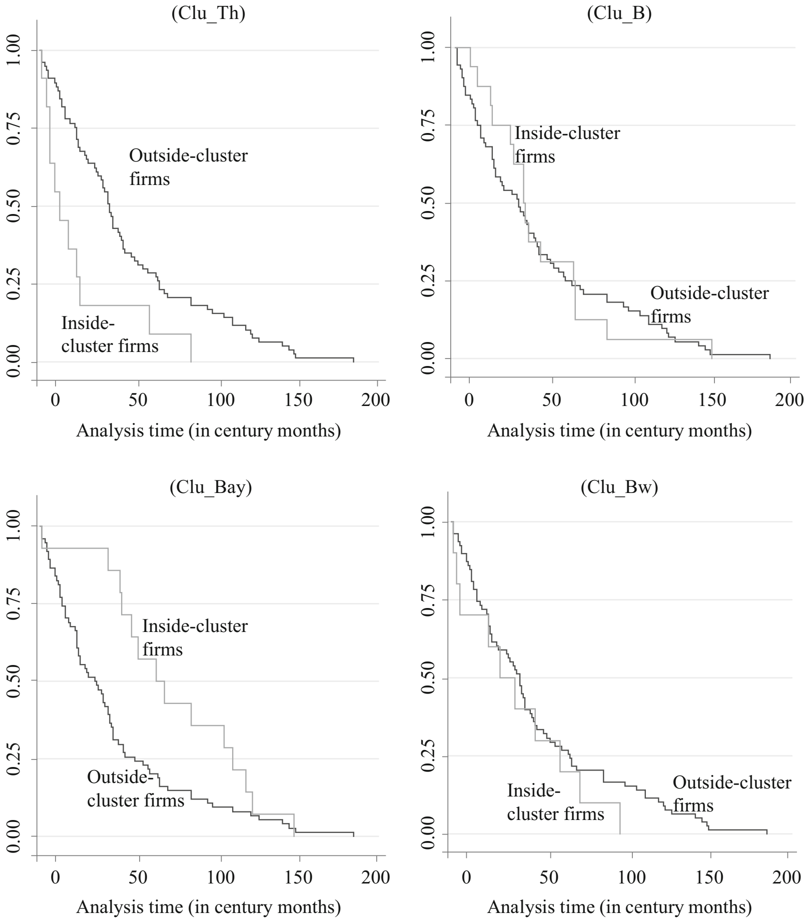

Fig. 9.6 Duration analysis based on cluster membership (Source: Author's own calculations and illustrations)

However, this is only half of the story. Our results for the Berlin Cluster (clu_B) and the Bavarian Cluster (clu_Bw) reveal quite a different picture (cf. Fig. 9.6, bottom). In both clusters we found no empirical evidence for significantly different survivor functions when comparing inside-cluster and outside-cluster firms (cf. Table 9.3). In summary, clusters can, but do not necessarily, affect a firm's timing in cooperating and entering the network. Thus, we found empirical support for each of the three cases proposed by Hypothesis H3. Our findings show that cluster membership is not generally associated with a higher propensity to cooperate. Instead, we need to take a closer look at the clusters themselves in order to disentangle the effects of cluster membership on the timing and propensity to cooperate.

Table 9.3 Test statistics – comparison of Kaplan Meier survivor functions based on cluster membership

Cluster Th

Log-rank test,
equality of survivor functions

	Events observed	Events expected
0	77	82.93
1	11	5.07
Total	88	88.00

chi2(1) = 7.6746
Pr>chi2 = 0.0056

Wilcoxon (Breslow) test,
equality of survivor functions

	Events observed	Events expected	Sum of ranks
0	77	82.93	412
1	11	5.07	-412
Total	88	88.00	0

chi2(1) = 9.85
Pr>chi2 = 0.0017

Cox regression-based test,
equality of survival functions

	Events observed	Events expected	Sum of ranks
0	77	82.93	0.9507
1	11	5.07	2.2829
Total	88	88.00	1.0000

chi2(1) = 5.77
Pr>chi2 = 0.0163

Tarone-Ware test,
equality of survivor functions

	Events observed	Events expected	Sum of ranks
0	77	82.93	-48.520825
1	11	5.07	-48.520825
Total	88	88.00	0

chi2(1) = 9.04
Pr>chi2 = 0.0026

Cluster B

Log-rank test,
equality of survivor functions

	Events observed	Events expected
0	72	71.18
1	16	16.82
Total	88	88.00

chi2(1) = 0.05
Pr>chi2 = 0.8205

Wilcoxon (Breslow) test,
equality of survivor functions

	Events observed	Events expected	Sum of ranks
0	72	71.18	136
1	16	16.82	-136
Total	88	88.00	0

chi2(1) = 0.50
Pr>chi2 = 0.4803

Cox regression-based test,
equality of survival functions

	Events observed	Events expected	Sum of ranks
0	72	71.18	1.0121
1	16	16.82	0.9505
Total	88	88.00	1.0000

chi2(1) = 0.05
Pr>chi2 = 0.8211

Tarone-Ware test,
equality of survivor functions

	Events observed	Events expected	Sum of ranks
0	72	71.18	11.394461
1	16	16.82	-11.394461
Total	88	88.00	0

chi2(1) = 0.21
Pr>chi2 = 0.6461

Cluster Bay

Log-rank test,
equality of survivor functions

	Events observed	Events expected
0	74	65.62
1	14	22.38
Total	88	88.00

chi2(1) = 4.46
Pr>chi2 = 0.0346

Wilcoxon (Breslow) test,
equality of survivor functions

	Events observed	Events expected	Sum of ranks
0	74	65.62	542
1	14	22.38	-542
Total	88	88.00	0

chi2(1) = 7.95
Pr>chi2 = 0.0048

(continued)

Table 9.3 (continued)

Cox regression-based test,
equality of survivor functions

	Events observed	Events expected	Sum of ranks
0	74	65.62	1.1670
1	14	22.38	0.6359
Total	88	88.00	1.0000

chi2(1) = 4.80
Pr>chi2 = 0.0284

Tarone-Ware test,
equality of survivor functions

	Events observed	Events expected	Sum of ranks
0	74	65.62	69.092798
1	14	22.38	-69.092798
Total	88	88.00	0

chi2(1) = 7.20
Pr>chi2 = 0.0073

Cluster BW

Log-rank test,
equality of survivor functions

	Events observed	Events expected
0	78	80.40
1	10	7.60
Total	88	88.00

chi2(1) = 0.86
Pr>chi2 = 0.3540

Wilcoxon (Breslow) test,
equality of survivor functions

	Events observed	Events expected	Sum of ranks
0	78	80.40	107
1	10	7.60	-107
Total	88	88.00	0

chi2(1) = 0.54
Pr>chi2 = 0.4622

Cox regression-based test,
equality of survivor functions

	Events observed	Events expected	Sum of ranks
0	78	80.40	0.9735
1	10	7.60	1.3283
Total	88	88.00	1.0000

chi2(1) = 0.77
Pr>chi2 = 0.3791

Tarone-Ware test,
equality of survivor functions

	Events observed	Events expected	Sum of ranks
0	78	80.40	-14.540845
1	10	7.60	14.540845
Total	88	88.00	0

chi2(1) = 0.61
Pr>chi2 = 0.4357

(Source: Author's own calculations)

9.7 Discussion and Implications

The first empirical part was motivated by a desire to deepen our understanding of how interorganizational innovation networks evolve. This quite demanding task was approached from two directions. On the one hand we proposed a conceptual framework that consists of three elementary building blocks – (**I**) "determinants", (**II**) "micro-level network change processes" and (**III**) "structural consequences" – to provide the theoretical basis for an in-depth analysis of evolutionary network change. On the other hand we conducted a non-parametric event history analysis to provide some empirical evidence on the propensity of LSMs to cooperate for the first time and enter the German laser industry innovation network.

The results of our analysis have interesting implications for both policy makers and practitioners. Firstly, our findings show that micro firms enter the network significantly later than small-sized and large firms but fail to explain the late entry of medium-sized firms. The underlying logic of this finding is straightforward. Even though SMEs depend more on access to external knowledge sources through interorganizational R&D linkages in order to keep pace with larger competitors, there are several factors hampering their ability to initiate R&D linkages for the first time. This finding supports the view of many European countries and regions that have instigated innovation policy programs for SMEs in order to strengthen R&D cooperation and innovation networks (e.g. Muldur et al. 2006; OECD 2008). This enables the joint research potential of SMEs to become effective more quickly. In further research it would be interesting to disentangle the extent to which factors such as search costs, a lack of alliance management capabilities or simply the absence of standardized cooperation interfaces explain the delayed entry of SMEs.

Our second result is surprising. The findings show that the choice of cooperation type (national or international) has no significant impact on a firm's timing in entering the network. Differences between nationally oriented and internationally oriented R&D cooperation projects seem to only play a subordinate role in the German laser industry. This can be taken as an indication of the high degree of internationalization of this technology; it is a cross-sectional technology with many applications in a truly interdisciplinary scientific field. Both factors clearly contribute to creating strongly internationalized networks. A second potential explanation is that previously existing interpersonal networks between decision makers relativize culturally contingent cooperation barriers.

The findings of the final empirical analysis indicate that cluster membership can have quite different effects on a firm's timing in entering the network. Traditionally, it has been argued that a geographically crowded region provides several benefits for firms. It appears that firms in some regions (e.g. Thuringia) tend to cooperate earlier and to have a significantly higher propensity to cooperate than those in other regions (e.g. Bavaria). A plausible explanation for this finding can be found in the spatial lock-in argument (cf. Boschma 2005; Boschma and Frenken 2010). In terms of policy making, this finding means that clustering processes are important but no remedy in and of themselves. Very specialized industries, like the laser industry, depend heavily on cooperation partners located anywhere in Germany and beyond. This corresponds to the findings on national versus international networks mentioned above.

This analysis provides us with interesting insights into firm-specific cooperation patterns and network entry processes. Nonetheless the analysis only reflects a very first step towards a better understanding of network change and a lot remains to be done.

Like any empirical study, this analysis also has some appreciable limitations (cf. Sect. 13.2) and we still face some theoretical and empirical challenges in obtaining a deeper understanding of causes and consequences of evolutionary network change processes. These challenges constitute the next steps in our research agenda (cf. Sect. 14.2).

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