Understanding the Complex Nature of Innovation Network Evolution

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Abstract In this article, we suggest a theoretical framework to explain how and why innovation networks emerge, change and eventually dissolve over time. We argue that network evolution is a multi-faceted phenomenon that needs to be studied at multiple levels. Our framework is based on the notion that network change is a result of exogenous and endogenous determinants. At the heart of our framework, we focus on four elementary network change processes at the micro level: the entry and exit of actors, and the formation and termination of the links between them. We integrate the actors' knowledge endowments and strategic orientations to emphasize the role of actor-specific decision making processes in explaining the emergence of characteristic network patterns over time. In doing so, we add still missing pieces of the puzzle to the contemporary network evolution literature.

1 Introduction

Previous empirical research shows that the structural configuration of innovation networks is characterized by typical properties. For instance, Barabasi and Albert (1999, p. 510) demonstrate that "[. . .] large networks self-organize into a scale-free state". Similarly, previous empirical studies confirm the emergence of small-world patterns (Kudic 2015; Tomasello et al. 2016). We also know that, over time, innovation networks tend to build up a densely connected core and a loosely connected periphery (Kudic et al. 2015a). This is usually referred to as a core-periphery structure (Borgatti and Everett 1999).

The configuration and positioning of actors within these structurally complex entities affects innovative outcomes in various ways. Powell et al. (1996) provide evidence that an actor's network positioning is closely related to its innovation performance. This insight was confirmed and extended by a number of subsequent studies (Stuart 2000; Baum et al. 2000). Several other studies have demonstrated that large-scale network characteristics, in particular small-world properties, are

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likely to affect the exchange of information, ideas and knowledge and thus enhance the creativity and innovativeness of embedded actors (Uzzi and Spiro 2005; Fleming et al. 2007; Schilling and Phelps 2007). Others have studied the relationship between core-periphery structures at the overall network level and the creative performance of the actors involved (Cattani and Ferriani 2008). Their results show that individuals who occupy an intermediate position between the core and the periphery of their social system are in a favorable position to achieve creative results (ibid.). At the same time, it is important to note that innovation networks are anything but stable. Structural network properties, as well as the actors' network positions, continuously change over time.

The considerations mentioned above point to that fact that an in-depth understanding of how and why innovation networks emerge, change and eventually dissolve over time is crucial, especially when studying the relationship between network structure, the actors' network embeddedness, and their subsequent innovation performance. Over the past year, remarkable progress has been made in this research domain (Pittaway et al. 2004; Bergenholz and Waldstrom 2011). Nevertheless, evolutionary change of networks still constitutes a widely unexplored area of research (Brenner et al. 2011, p. 5). We still face more questions than answers, especially when it comes to holistic theoretical explanations of causes and consequences of structural network change processes.

Accordingly, the aim of this study is to contribute to an in-depth understanding of the multi-faceted nature of innovation network evolution.[1] We propose a framework that considers both exogenous and endogenous determinants of structural network change. It incorporates four network change processes at the micro level, i.e. the entry and exit of actors, and the formation and termination of the links between them. These processes explain the emergence and structural evolution of characteristic innovation network patterns at higher aggregation levels.[2] Our framework explicitly acknowledges the role of the actors' knowledge endowments and strategic orientations. In doing so, we add a highly relevant but still missing piece of the puzzle to the discussion on the structural evolution of innovation networks.

The remainder is structured as follows. Section 2 provides a literature review. In Sect. 3 we present the main building blocks of our conceptual framework and we introduce the theoretical arguments that allow us to substantiate the four micro-level networks change processes at the heart of our framework. In Sect. 4 we discuss the structural implications of these processes at the micro level against the backdrop of actors' knowledge endowments and strategic orientations. Section 5 concludes with some implications, critical reflections, and suggestions for future research.

[1]The general idea of this study is based on Kudic (2015).

[2]In a most basic sense, any kind of network consists of two basic elements: nodes and the ties between these nodes (Wasserman and Faust 1994). This justifies our focus on the four micro-level processes.

2 State of the Art

In this section we start with a brief discussion on the most influential empirical contributions to real-world network topologies. Next, we provide an overview of network change conceptualization, refer to recent empirical findings, and provide a critical discussion on the typically assumed network change mechanisms in these papers. Finally, we briefly look at the most recent directions research has taken in the broad and highly interdisciplinary field of network evolution research.

2.1 What Do We Know About Real-World Network Topologies?

One of the very first formal network conceptualizations is the random-graph model, originally proposed by Solomonoff and Rapoport (1951) and applied in the field of mathematical biophysics. Only a few years later a seminal paper on the evolution of random graphs was published by Erdős and Rényi (1960). These types of models assume that links are placed on a purely random basis which means that the resulting system is characterized by nodes that have approximately the same number of links (Barabasi and Bonabeau 2003, p. 52). Random-graph models have dominated the debate in network research since the mid-twentieth century, even though the large-scale network topologies produced by these models are far from network structures observable in real-world.

Empirical explorations show—for nearly all kinds of real-world networks, ranging from technical to socio-economic networks—that links are not homogenously distributed across nodes. More precisely, real-world networks are typically characterized by a strongly skewed degree distribution. This implies that some actors obviously attract ties at a higher rate than others. This recognition led to the development of a new generation of network models which were able to reproduce real-world network topologies in a more realistic way. In a seminal paper on large-scale network properties Barabasi and Albert (1999) suggest a "preferential attachment" based network model that self-organizes into a scale-free state. The underlying logic of the applied preferential attachment mechanism is straightforward: highly connected nodes are more likely to connect to new nodes than sparsely connected nodes (Albert and Barabasi 2002) which is mirrored in the emergence of a typical power law degree distribution at higher aggregation levels.

Only a few years after the development of the Erdős-Rényi random-graph model, psychologist Stanley Milgram conducted his famous "letter-passing experiment" in which he showed that people in the United States are separated by more or less six degrees of separation (Milgram 1967). Surprisingly, it took about 30 years to apply Milgram's initial idea in the field of socio-economic network research. Watts and Strogatz (1998) were the first to show that the small-world phenomenon can be explained and quantified by applying a graph-theoretical approach and using relatively simple network measures. The authors argued that a compression of real-world networks and randomly generated networks should reveal some systematic differences with regard to network clustering and actor reachability. They proposed using two simple graph theoretical indicators—"cluster coefficient" and "average distance"—and calculating two ratios—"clustering coefficient ratio" (CC ratio) and "path length ratio" (PL ratio)—in order to check for the existence of small-world properties in real-world networks. Since then a number of excellent empirical studies have been conducted analyzing the relationship between small-world properties and the creation of novelty and innovation (Uzzi and Spiro 2005; Fleming et al. 2007; Schilling and Phelps 2007) and the emergence and evolution of small-world structures in an innovation network context (Baum et al. 2003; Corrado and Zollo 2006; Mueller et al. 2014).

Finally, we refer to a so-called core-periphery (CP) structure in innovation networks. The CP concept is based on the notion of "[...] a dense, cohesive core and a sparse, loosely connected periphery" (Borgatti and Everett 1999, p. 375). The core of the network occupies a dominant position in contrast to the subordinated network periphery (Muniz et al. 2010, p. 113). Cattani and Ferriani (2008, p. 826) point to the fact that the core is typically composed of "[...] key members of the community, including many who act as network coordinators and have developed dense connections between themselves." The existence of such a CP structure in an innovation network is accompanied by important implications. Accordingly, Rank et al. (2006) argue that a firm embedded in the core of an industry's innovation network has better access to critical information and knowledge. Hence, the occupation of a prominent position by a firm, e.g. in terms of its network core embeddedness, is typically assumed to be positively related to above-average innovation outcomes. However, actors who bridge the gap between a network's core and its periphery also seem to fulfil an important role. Cattani and Ferriani (2008) looked at the relationship between core-periphery structures in social networks and the creative performance of the actors involved by analyzing data from the Hollywood motion picture industry between 1992 and 2003. Their results show that individuals who occupy an intermediate position between the core and the periphery of their social system are in a favorable position to achieve creative results.

2.2 *What Do We Know About the Emergence and Evolution of Real-World Networks?*

The literature on network dynamics is quite heterogeneous[3]. Several scholars have provided schemes to systematize the work that has been done in this field. In accordance with Parkhe et al. (2006), we draw upon a general systematization scheme, originally proposed by Van De Ven and Poole (1995). This enables us to

[3]For an in-depth discussion, see Kudic (2015).

categorize the most influential contributions to network dynamics into three 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 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 such as 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 indicates that the developing entity has an underlying logic within itself that regulates 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 (ibid.). Literature often contains examples of life-cycle or phase models that address network change. For instance, Lorenzoni and Ornati (1988) introduce one of the first growth-oriented network formation models by arguing that expanding firms pass through three cooperation stages: unilateral relationships, reciprocal relationships and network constellations. However, these models have often been criticized. Sydow (2003, p. 332) puts forward the argument that the phase specification and the length of the stages in these models may vary arbitrarily. In addition, the notion of a linear change process that does not consider disruptions or feedback loops is—to formulate it in a cautious way—questionable in the 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 sequence 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).

Non-linear process models of network change are among the most prominent applications of teleological ideas in network research. This strand of research has been strongly influenced by the contributions of the IMP research group (Hakansson and Johanson 1988; Hakansson and Snehota 1995; Halinen et al. 1999). In these models, network change is driven by market access and internationalization goals. For instance, Halinen et al. (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. The strength of teleological conceptualizations lies in their 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 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 the focus is placed on the underlying determinants and mechanisms of network change processes. In other words, the understanding of "[. . .] the 'rules' governing the sequence of change through time [. . .]". Doreian and Stokman (2005, p. 5) provide 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; Hite and Hesterly 2001; Hagedoorn 2006; Kenis and Knoke 2002). These growth-oriented models consider both endogenous as well as exogenous factors of alliance and network change. They recognize the importance of previous network structures in current cooperation decisions (Gulati and Gargiulo 1999). However, these studies place little emphasis on tie termination processes and the associated structural consequences for the overall network configuration.

In response to these limitations, network evolution models explicitly account for 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 et al. 2008; Doreian and Stokman 2005; Glueckler 2007). The main point of network evolution models is to understand how and why 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. Others have analyzed the impact of tie formations and tie terminations on the component structure and connectivity of networks (Amburgey et al. 2008). Economic geographers have argued that evolutionary processes of retention and variation in network structure are affected by a spatial dimension (Glueckler 2007). The concept of co-evolution refers to the notion that two or more dimensions change simultaneously and affect each other while they evolve. Co-evolutionary network change models 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 lies on understanding the interdependencies between simultaneously evolving network change patterns. Theoretical contributions addressing the multi-faceted nature of innovation network evolution are still very rare (most notable exceptions: Glueckler 2007 and Hite 2008).

2.3 Recent Developments in Network Evolution Research

Two classes of network evolution models seem to have the potential to break new ground, i.e. stochastic and numerical agent-based simulation approaches.

The first class of models is typically referred to as SIENA models. SIENA stands for Simulation Investigation for Empirical Network Analysis (Huisman and Snijders 2003; Snijders 2004; Snijders et al. 2010). These types of simulation models allow us to analyze the mechanisms that fuel the structural change of networks between two or more discrete points in time. Stochastic actor-based models possess several distinctive features, including flexibility and accessibility of procedures to estimate and test the parameters which support the description of mechanisms or tendencies of network change (Snijders et al. 2010, p. 2).

Others have used agent-based simulation models to investigate the origins of variation in the structures of interorganizational networks across industries (Tatarynowicz et al. 2015). This study provides important insights into the relatedness between technological dynamics in six industries from 1983 to 1999 and the firms' collaborative behavior. Another example of agent-based models are simulation models based on the SKIN (Simulating Knowledge Dynamics in Innovation Networks) approach (Gilbert et al. 2001; Gilbert et al. 2007; Pyka et al. 2007). The general idea behind these models is to include firms' knowledge bases, market processes, individual and interorganizational learning processes, and the transfer of knowledge in the analysis of complex networks. These types of agent-based models were recently applied to analyze how the actors' strategies at the micro-level shape macro-level network patterns (Mueller et al. 2014).

3 Towards a Conceptual Framework for Explaining How Networks Change

We start by introducing the general principles of network evolution models. Next, we continue with a discussion on exogenous and endogenous determinants of network change which finally results in the derivation of the superordinate structure of our conceptual framework. Subsequently, we turn our attention to the very core of our model by taking a closer look at four micro-level network change processes. Finally, we incorporate the actors' knowledge-related cooperation strategies in our framework.

3.1 Some General Considerations on Evolutionary Network Change

We start in this section with some general principles of network evolution models proposed by Stockman and Doreian (2005). First, 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 from the very beginning. Innovation research has identified a broad range of reasons for why firms participate in innovation networks (Pyka 2002). However, 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 only possess global knowledge in the rarest of cases. Instead, Stockman 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 (Lui 2009; Das and Teng 2000).

The fourth basic principle refers to the complexity of evolutionary processes in networks. Neo-Schumpeterian scholars have proposed a broad range of concepts about the complexity of agents, their decisions and their interaction patterns in complex adaptive systems.[4] Consequently, Stockman 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).

[4]For an overview of contemporary research in the field of complexity economics, see Antonelli (2011).

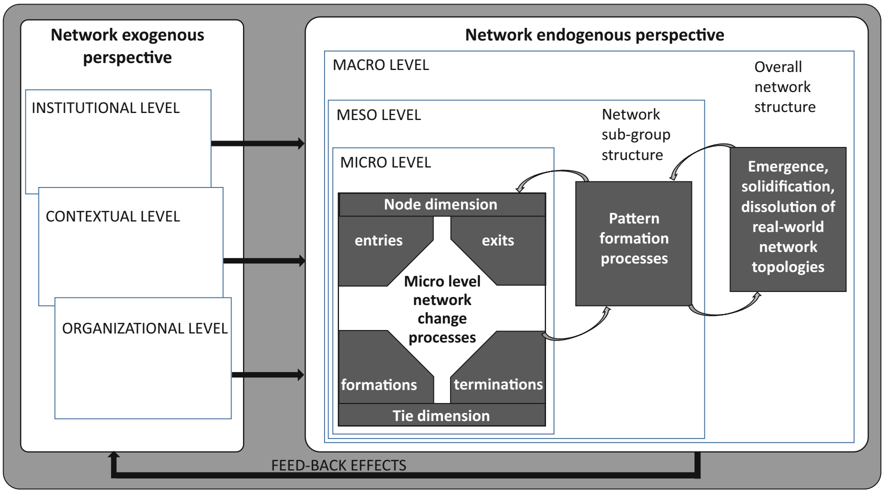

Fig. 1 Causes and consequences of evolutionary network change processes. Source: Authors' own illustration, based on Kudic (2015), modified

3.2 *Exogenous and Endogenous Determinants of Structural Network Change*

Based on the general considerations outlined above, we now introduce the overall structure of our conceptual framework (cf. Fig. 1), which will be specified in more detail in the course of this article. In the most general sense, the framework accounts for the following, closely related aspects of evolutionary network change processes (cf. Kudic 2015): (1) network exogenous determinants, (2) driving forces and mechanisms of network change at the micro level, (3) structural consequences along multiple levels of analysis, and (4) feedback effects, both within the network dimension and across network boundaries.

3.2.1 The Network Exogenous Perspective

Even though this article focuses on the network endogenous perspective (Fig. 1, right), we would like to take the opportunity to briefly outline and discuss the role of network exogenous factors. It is important to note that the institutional, contextual and organizational levels addressed here are not mutually exclusive.

To start with, we turn our attention to the role of institutions in explaining structural network change. It is common knowledge that institutions play a role in socio-economic processes.[5] Formal institutions (e.g. laws, rules, norms etc.) and

[5]For an in-depth discussion on the role of generic rules for economic evolution, see Dopfer and Potts (2008).

informal institutions (e.g. values or habits etc.) affect the extent and way in which organizations interact. In an innovation network context, institutions take on the role of enabling mechanisms that stabilize the environment in which knowledge transfer and interactive learning processes take place. On the other hand, institutions can also hinder or prevent organizations from cooperating with one another. Between these two extremes, there is a range of ways that cooperation among organizations can be orchestrated and can force cooperation into a desired direction through the setting of institutions. Funding initiatives, initialized by regional, national or supranational authorities aimed at promoting collective innovation though publicly funded cooperation, are only one example of how institutions affect the formation, structural configuration and stability as well as scientific productivity of R&D project consortia (Defazio et al. 2009). In summary, rules, norms, and institutions, are very likely to play an important role for explaining and understanding structuration processes in complex dynamic system. Yet they are barely considered in the network evolution literature. Over the past decades, institutional economists have developed a rich theoretical toolbox that has the potential to significantly contribute to an in-depth understanding of structural network change (Hodgson 2012; Elsner 2017).

Next, we move on to the contextual level. Innovation networks can be seen as an integral part of their surrounding innovation systems. According to Lundvall (1992), national innovation systems consist of elements and relationships between them which enable interaction in the production, diffusion and use of new, and economically useful, knowledge. The structural characteristics of innovation systems—such as the actors, types of relationships, system boundaries and the broader environments in which the system is embedded—affect the interactions of actors and subsequent innovation outcomes (Carlsson et al. 2002). Closely related to this strand of literature is the industry life-cycle perspective (Utterback and Abernathy 1975). Early studies show that some industries may be seen as evolving through this cycle several times. Studies in this tradition have significantly enhanced our understanding of how industries change over time (Jovanovic and McDonald 1994; Klepper 1997). Some researchers in this area (Buenstorf and Klepper 2010) have emphasized the importance of submarket dynamics in industries. Their findings suggest that the development of a new submarket can open up opportunities for new firm entries and stimulate innovation at the same time. They show that this situation can reinforce the advantages of the leading established firms, accentuating the shakeout of producers. Industry dynamics have some important implications for the entry and exit processes in innovation networks. An increasing number of firm entries due to new company founding, spin-offs etc. enhance the number of potentially new cooperation partners which are not yet part of the innovation network. Firm exits due to closures, failures, bankruptcies etc. can decrease the number of potential cooperation partners or disrupt an existing network structure.

Finally, we move on to the organizational determinants in our framework. In this context, organizations are considered to be the nodes (or potential nodes) of the network we look at. 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 an innovation network context.

3.2.2 The Network Endogenous Perspective

The network endogenous perspective (Fig. 1, right) is conceptualized by differentiating between three analytical levels. The distinction between multiple analytical levels is not new in evolutionary economics (cf. Dopfer and Potts 2008). However, we apply this general idea in a network context.

Accordingly, we argue that the macro level refers to the overall network perspective. Empirical evidence on real-world innovation network topologies is now available for a range of technological fields and industries. The discussion in Sect. 2.1 shows that innovation networks are not randomly structured but rather characterized by typical patterns such as fat-tailed degree distributions, small-world properties, core-periphery patterns etc. It is important to note that these structural particularities of the innovation network do not exist from the very beginning but rather emerge and solidify throughout the network evolution process.

The meso level addresses sub-group structures which are an integral part of the overall network. These sub-groups are part of the surrounding innovation network; however, they follow a different logic than simple dyadic linkages. For instance, ego networks are centered around a focal actor.[6] The ego network constitutes a structural entity in itself which is, at the same time, an integral part of the overall network structure. These types of network sub-structures are strongly influenced by the strategy of a focal actor (Hite and Hesterly 2001) and each tie formation or tie terminations is evaluated against the backdrop of the existing portfolio structure. Complementarity and synergy considerations typically play a key role in this context (Hoffmann 2007). Other types of sub-structures within networks can be the result of, or at least strongly affected by, informal or formal institutions such as publicly funded R&D project consortia. Accordingly, the size, configuration, duration etc. of new components entering an industry's innovation network can be the result of formal rules set by the funding authority (Schwartz et al. 2012). The bottom line is that even though the formation or existence of each sub-structure in an innovation network can be traced back to basic micro-level network change processes (cf. next paragraph), the consideration of additional formation logics can be required to gain an in-depth understanding of structuration processes in these complex dynamic systems.

Now we turn our attention to the micro level in our framework. The evolution of networks is typically explained by referring to a number of frequently discussed network change mechanisms. These mechanisms are typically assumed to operate on the micro level. For instance, the preferential attachment concept provides one

[6] A firm's ego network consists of its set of direct, dyadic ties and the relationships between these ties (Hite and Hesterly 2001; Wasserman and Faust 1994).

of the most frequently discussed tie formation mechanisms in network studies. The underlying logic is quite simple: highly connected nodes are more likely to attract new nodes at a higher rate than sparsely connected nodes (Barabasi and Albert 1999; Albert and Barabasi 2002). The mechanism generates a relatively unique structural pattern at the overall network level which is characterized by a power law degree distribution. Several other mechanisms and the 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), "herding behavior" where actors follow the crowd (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). Even though these mechanistic concepts provide us with some valuable insights, we argue that we need to take a closer look at node entries and exits as well as tie formations and terminations to gain an in-depth understanding of the structural evolution of innovation networks.

3.3 Micro-Level Network Change Processes at the Core of the Model: Node Entries and Exits as Well as Tie Formations and Terminations

Accordingly, we continue the debate by moving on to micro level network change processes at the core of the model (cf. Fig. 1, center). Only a few previous studies have analyzed the structural consequences of micro-level network change processes (Elfring and Hulsink 2007; Baum et al. 2003; Guimera et al. 2005; Amburgey et al. 2008). We follow Glueckler (2007, p. 623) who argues that "[. . .] a complete theory of network evolution [. . .] has to theorize both the emergence and disappearance of ties and nodes". Accordingly, both dimensions will be considered in this section. In accordance with Hite (2008), we explicitly acknowledge the particular importance of micro-level network change processes in the context of network evolution. In doing so, we draw upon evolutionary ideas and network change models proposed by Guimera et al. (2005) and Amburgey et al. (2008) to substantiate this part of the puzzle in our framework (cf. Fig. 2).

We start our argumentation by focusing on the node dimension and the concept provided by Guimera et al. (2005). In the most basic sense we can differentiate between system actors who participate (i.e. incumbents) and those who do not participate (i.e. newcomer) in a particular network (Fig. 2, top). The first group includes all actively cooperating network actors, whereas the second group provides a pool of potentially available network actors. The link to the contextual level in our framework (Fig. 1, left) is obvious. The innovation system approach entails all firms within well-specified system boundaries, irrespective of whether these firms are actively involved in the respective innovation network or not. We follow the suggestion made by Guimera et al. (2005) and differentiate between two groups

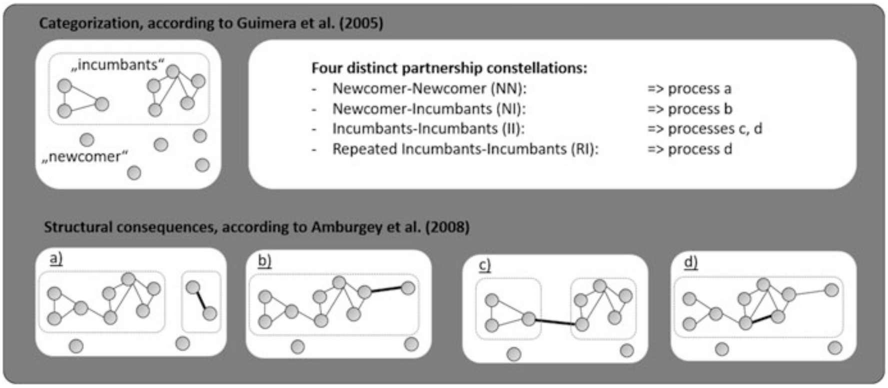

Fig. 2 Categorization and structural consequences of micro-level network change processes. Source: Authors' own illustration, based on Guimera et al. (2005) and Amburgey et al. (2008), modified

of potential network actors: "incumbents" and "newcomers" (Fig. 2, top). 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. The distinction between "incumbents" and "newcomers" gives us four distinct partnership constellations: "newcomer-newcomer" (NN), "incumbent-newcomer" (IN), "incumbent-incumbent" (II) and "repeated incumbent-incumbent" (RI). Finally, it is important to note that the distinction between newcomers and incumbents—and all possible combinations, i.e. NN, NI, II and RI—implicitly acknowledges cooperation histories of the actors involved and the network paths traversed by these actors.

These four partnership constellations can be translated into structural consequences. To establish this link, we refer to 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 (Amburgey et al. 2008, pp. 184–186): (a) the creation of a new component, (b) the creation of a pendant tie to an existing component, (c) the creation of a bridge between components, and (d) the creation of an additional intra-component tie (Fig. 2, bottom). Each of these processes shapes the size and/or the density of the network. Figure 2 also illustrates the relatedness of the two concepts. For instance, the constellation "newcomer-newcomer" (NN) is closely related to the creation of a new component in the network. Similarly, we can link the three remaining partnership constellations (IN, II, RI) to the structural processes (b, c, d).

Even though the consideration of this two concepts brings us closer to understanding the structural evolution of networks, a number of additional aspects needs to be account for. First, up to now the discussion on micro level network change processes has operated on a highly abstract level and the specific nature of innovation networks has yet to be considered adequately. Second, the knowledge endowment and the strategic orientation of the actors involved play no role in evolutionary network change processes. Finally, the structural implications that can be derived from the discussion so far are still too coarse-grained. For instance, the NN partnership constellation is very close to the notion of component-creating ties. However, no clear-cut differentiation can be made between the circumstances under which large or small components are established, enter the network and change their structural configuration (Fig. 2, process a). The NI partnership constellation and the formation of a pendent tie (Fig. 2, process b) contains no information about who the newcomer connects itself to—the most central network actor or a peripheral network actor. Similarly, the II partnership constellation, according to Guimera et al. (2005), can be related to both the establishment of a bridging tie (Fig. 2, process c) or to an intra-component tie (Fig. 2, process d) according to Amburgey et al. (2008).

All in all, it becomes obvious that a structural discussion is indispensable but reaches its limits sooner or later. We address this limitation by focusing on the actors' knowledge endowments and integrating a set of knowledge-related cooperation strategies into our framework. This shift from a purely structural discussion towards a content-driven elaboration allows us to gain a more differentiated picture and disentangle and refine our framework. In general, strategies and actions of network actors can result in the destruction of existing network paths (Glueckler 2007, p. 620) and determine, at the same time, the scope of future cooperation options and possibilities. Hence, we propose a classification of knowledge-related cooperation strategies along two dimensions (cf. Fig. 3) which allows us to integrate actors-specific R&D cooperation decisions in our framework. The first dimension is input-oriented and the second dimension is output-oriented.

To start with, we take a closer look at the input-oriented dimension. Organizations follow individual cooperation strategies that are guided by their individual goals and motives. Hagedoorn (1993, 2006) divides the broad variety of heterogonous and partially overlapping cooperation rationales into six groups: cost savings, risk reduction, time savings, access to national and international markets, status and reputation building, and knowledge-related motives. In R&D cooperation and innovation networks the latter category plays a particularly superordinate role. The reason for this is straightforward. Dosi (1988, p. 1126) argues that problem solving during the technological innovation processes involves the use of information drawn from previous experience, formal knowledge and various types of specific and uncodified capabilities. Knowledge and expertise which cannot be internally generated within the boundaries of a firm can be tapped via external channels (Malerba 1992).

When it comes to knowledge-related cooperation strategies, at least two qualitatively different types of exchange processes have to be distinguished (Grant and Baden-Fuller 2004; Buckley et al. 2009): the "knowledge accessing approach" and the "knowledge acquiring approach". At the very heart of the knowledge acquiring approach is the idea that firms cooperate to learn from one another and exchange non-codifiable (or "implicit") knowledge through multiple interactions. According

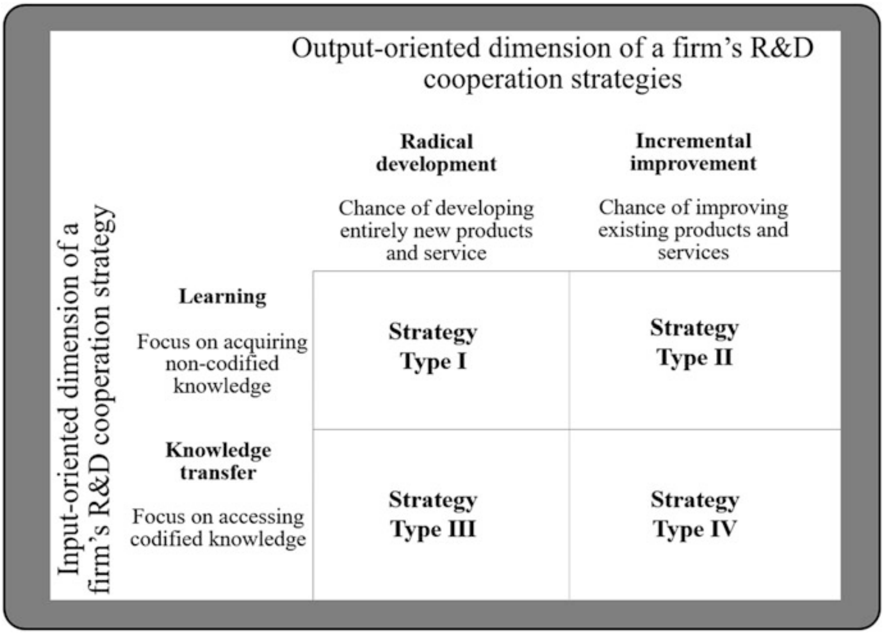

Fig. 3 Knowledge-oriented dimensions of R&D cooperation strategies. Source: Authors' own illustration

to Grant and Baden-Fuller (2004, p. 78) a knowledge acquiring strategy implies a limit to the number of cooperative partnerships a firm can pursue simultaneously due its constrained absorptive capacity. In addition, small teams of actors, interconnected by strong ties, provide the ideal basis for the generation of trust, a necessary prerequisite for the exchange of non-codifiable knowledge and the initialization of mutual learning processes. Prior research indicates that trust increases the amount of information that can be exchanged (Tsai and Ghoshal 1998) and decreases the cost of exchange (Zaheer et al. 1998). In contrast, proponents of the "knowledge accessing" perspective argue that R&D cooperation predominantly serves as a vehicle for accessing complementary stocks of codifiable (or "explicit") knowledge. The connectedness to as many partners as possible is important to get potential access to a broad variety on knowledge stocks. The knowledge accessing approach implies that a firm can engage in multiple alliances simultaneously without sharply declining marginal benefits (Grant and Baden-Fuller 2004, p. 78). Hence, large teams, interconnected by weak ties, provide the ideal basis for transferring tacit knowledge.

Our second dimension focuses on the output dimension of collective innovation processes. The main rational for firms to join forces, collaborate, exchange knowledge, and learn from each other is to generate novelty in terms of innovative products and services. We differentiate between incremental and radical innovations, even though this distinction is no always clear (Henderson and Clark 1990). On the one hand, technological change processes can be incremental in nature and innovation occurs rather gradually as a stepwise improvement process (cf. Levinthal 1998, p. 217). Thus, incremental innovations typically introduce minor changes to existing products and services, exploits existing potentials, and reinforces the dominance of established market actors (Henderson and Clark 1990, p. 9). On the other hand, innovations can also appear as spontaneous and rather discontinuous events (Levinthal 1998, p. 217). Radical innovation typically establishes a new dominant design and opens up entirely new market and new fields of application (Henderson and Clark 1990, pp. 9–11). We adopt and integrate this fundamental distinction between incremental and radical innovation in our framework by arguing that every kind of collective R&D process falls within one of these two output-oriented categories.

The combination of the input-oriented and output-oriented dimension leads to four distinct types of strategic R&D cooperation strategy. On the one extreme, we find actors who follow a Type I R&D cooperation strategy. In this case we assume that actors focus on acquiring new knowledge through the initialization of interorganizational learning processes (Hamel 1991; Lane and Lubatkin 1998; Kale et al. 2000) in order to have a realistic chance of developing entirely new products and services. On the other extreme, the Type IV R&D cooperation strategy constitutes cooperation efforts in which actors focus on knowledge transfer (Grant and Baden-Fuller 2004; Rothaermel 2001; Buckley et al. 2009) with the aim of achieving incremental improvements in existing goods and services. According to Grant and Baden-Fuller (2004) we assume that an organization acquires and accesses knowledge from a partner to extend its own knowledge base. However, the generation of novelty is a highly uncertain and risky endeavor (Henderson and Clark 1990) and interorganizational learning processes can be affected and hindered due to various reasons (Doz 1996). Hence, the Type II R&D cooperation strategy accounts for the fact that the desired outcome of the Type I R&D cooperation strategy cannot always be realized. As already outlined above, innovations can also occur as spontaneous events. The Type III R&D strategy reflects the case in which knowledge transfer processes lead to radical innovation. The important point in this context is that each of the four strategic options is accompanied by individual partner choices. As we will discuss later in more detail, not all strategic options are available to all actors over time. The respective consequences for the structural configuration of the industry's innovation network will be the subject of the discussion in Sect. 4.

4 Structural Consequences of Micro-Level Network Change Processes: An Exemplifying Discussion

In this section we bring together the preceding considerations by proposing a scheme that integrates partnership constellations, actors' strategic orientations, and structural network consequences. Based on our consideration in Sect. 3.3

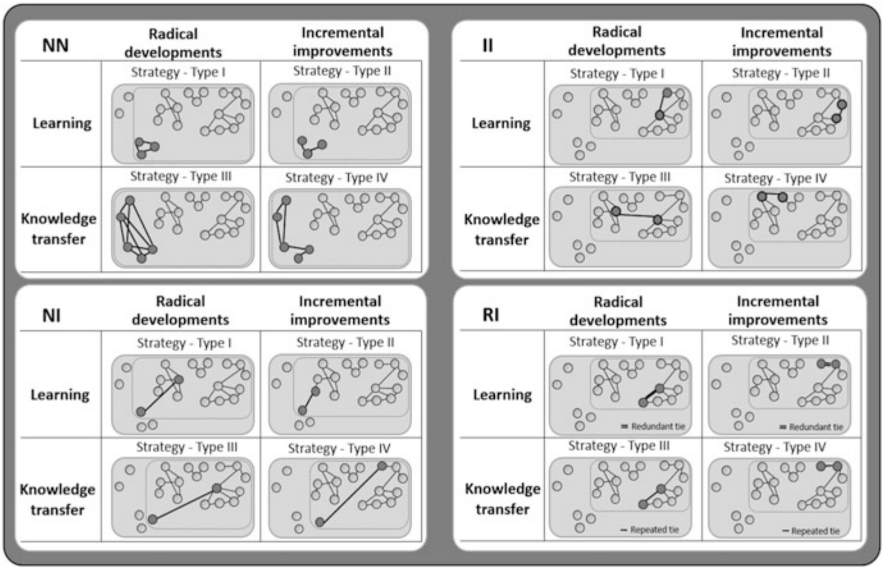

Fig. 4 Interrelatedness between partnership constellations, actors' strategic orientations and structural consequences. Source: Authors' own illustration

we have integrated the general distinction between newcomers (N) and incumbents (I) in the subsequent discussion. Figure 4 illustrates theoretically possible structural consequences resulting from actor-specific strategic orientations (i.e. Type I–Type IV) for each of the previously introduced partnership constellations (NN, NI, II, RI).

Figure 4 (top, left) points to the structural effects of cooperation events between newcomers (NN). These partnership constellations are typically reflected in the formation and entry of new network components into the system. Accordingly, the size of the network increases while changes to the network's density depend on the degree of connectedness within the new component. We argue that the formation of small components is closely related to an actors' strategic orientation towards learning. The rationale behind this assumption is straightforward. Small components can be interpreted as structural vehicles—or learning arenas—that provide the basis for intense interactions, initialization of trust building and interorganizational learning processes. In contrast, the formation of larger components is assumed to be accompanied by the knowledge exchange goals of the actors involved. Actors entering the network via the formation of large components rather aim at getting fast access to a broadly dispersed and easy absorbable knowledge stocks. A glance at the output-oriented dimension provides another important distinction. We argue that actors in densely connected components have a higher chance of realizing more radical innovations while the actors in sparsely connected components tend to generate relatively incremental innovations.

The partnership constellation reflecting cooperation activities between newcomers and incumbents (NI) is displayed in Fig. 4 (bottom, left). Each of the four actor-specific strategic orientations (i.e. Type I–Type IV) results in the attachment of a previously unconnected actor to the existing innovation network. As before, the size of the network increases due to NI cooperation events while the density of the system is not affected. The illustration shows that potential network entrants (newcomers) with a learning-oriented R&D cooperation strategy prefer to attach themselves to small components within the system. Actors oriented towards knowledge transfer aim to establish a link to larger components. The theoretical arguments behind these two attachment logics are the same as outlined above. Irrespective of a network component's size, we are able to identify more or less central actors. For instance, actors with an above average number of direct partners occupy a dominant role in their nearer cooperation environment. They are typically assumed to have qualitatively superior knowledge endowment compared to less integrated actors. Accordingly, we argue that the chances for developing entirely new products and services are higher for those newcomers who succeed in establishing a link to the most central actors in the respective component. In contrast, links between newcomers and peripheral incumbents are expected to be accompanied by rather incremental improvements.

Now we turn our attention to partner constellations displayed in Fig. 4 (top, right), a constellation in which incumbents establish links to other incumbents (II). First of all, it is important to note that an incumbent's cooperation environment strongly depends on its previous cooperation decisions. It also determines all future cooperation opportunities. In other words, an incumbent's network position is the result of previous cooperation events and reflects the path on which the respective actor has traversed through the network. As before, we distinguish between cooperation strategies that are oriented towards learning and those oriented towards knowledge transfer. In the first case, incumbents are expected to increase the density of their nearby cooperation environment through the establishment of intra-component ties. In the second case, incumbents seek to enlarge their nearby cooperation environment by acting as brokers and connecting otherwise unconnected (or loosely connected) components of the network.

Figure 4 (top, right) illustrates a learning-oriented R&D cooperation strategy between two incumbents which are located in the main component of the network. Again, the chances for realizing radical innovation are not equally distributed. We argue that learning-oriented incumbents who achieve an intra-component tie to the most central actor in the respective component have a higher chance of developing entirely new products or services. In contrast, incumbents following a learning-oriented strategy by establishing an intra-component tie to a peripheral incumbent in the same component are likely to generate incremental innovations. Now we turn attention to knowledge transfer oriented R&D cooperation strategy between two incumbents located in different network components. It is plausible to assume that two incumbents, which are not part of the same component, can maximize their potential information pool by acting as brokers. In this case, the chances of achieving a radical innovation are higher for those brokers who connect large components. In contrast, bridging the gap between two small components is accompanied by incremental improvements for the broker.

The last partnership constellation addresses repeated links between incumbents (RI). There are two qualitatively different types of repeated links which have to be differentiated. On the one hand, we can think of cooperation event sequences between two incumbents. In this case the termination of an existing link is directly followed by the establishment of a new, cooperative partnership between the same actors. Cooperation event sequences among the same partners ensure intertemporal structural stability of the system by simply reproducing existing network patterns. We argue that an incumbent's efforts to maintain its cooperation environment through sequential link formations is closely related to a knowledge-transfer oriented R&D cooperation strategy. On the other hand, there is the possibility that two incumbents establish more than one linkage. Technically speaking, in this case we have a redundant link structure. We argue that an incumbent's efforts to strengthen its nearer cooperation environment through redundant link formations is closely related to trust building and goes along with a learning-oriented R&D cooperation strategy. Similar like above, attachment processes among more or less central actors affect the chances of realizing radical innovations or rather increment improvements.

5 Conclusion, Limitations and Further Research

We intended to develop a theoretical framework that explains how micro-level activities of cooperation impact the overall structure of innovation networks. This is a subject with a clearly evolutionary nature. We refer to existing theoretical literature on network formation processes in order to differentiate between two types of actors (newcomers and incumbents) and derive a set of knowledge-related R&D cooperation strategies (differentiated by an input and output dimension) for these actors. At the very heart of this contribution we integrated elementary network change processes at the micro level and discussed the role of actors' knowledge endowments and strategic orientations for the emergence of characteristic network patterns. We ended up with a fine-grained systematization of structural network effects, each of which grounded in knowledge-related R&D cooperation decisions of actors at the micro level.

We do not claim that our theoretical concept is fully comprehensive or complete. Nonetheless, we strongly believe that a closer look at different types of knowledge-related R&D cooperation strategies significantly enhances our understanding of how and why structural large-scale networks patterns emerge and evolve over time. The distinction between newcomers and incumbents—and all possible combinations, i.e. NN, NI, II and RI—raises awareness for the importance of cooperation histories and network paths. We are convinced that the analysis of R&D cooperation cascades, against the backdrop of previous cooperation decisions and new cooperation options, is crucial for understanding structural network change. Our discussion revealed some highly interesting insights into the emergence of real-world network properties. First, our framework implies that the structuration processes at higher aggregation levels are not the result of individual actors' cooperation activities. Instead, the complex interplay of cooperation activities and structural consequences of multiple actors, operating at different stages of their individual cooperation paths, generate patterns that we typically refer to as real-world network properties. Second, we saw that structurally identical pattern formation processes at higher aggregation levels can be caused by completely different micro-level network change processes. Our framework raises awareness for this fact and provides a scheme that allows researchers to deepen and extend own knowledge on network evolution along these lines. Third, our theoretically motivated research raises awareness for the importance of policy interventions affecting the formation of sub-group structures at the meso level (cf. Fig. 1). Public support of collaborative innovation projects still ranks high in innovation policy agendas at different levels (local, regional, national and supranational). We should keep in mind that any public support means an intervention into otherwise "naturally" developing network structures. So far we know little about the interplay between different types of public support schemes and micro-level network change processes. This offers not only a great opportunity for further research but also for the intensification of the dialog between science and policy.

This study also has some limitations. For instance, we focus on economic actors, i.e. organizations as the smallest unit of analysis within the meaning of innovation system literature. R&D cooperation strategies, however, are always the result of decision processes at the individual or interpersonal level. Another issue is closely related to complex nature of networks. The exercise presented in Sects. 3 and 4 certainly provides some plausible explanations for pattern formation processes, but by far not all. We are well aware that the proposed and discussed interrelations between micro level network change processes, actors' knowledge endowments and strategic orientations, and structural network change processes provide at best one of several possible explanations.

In summary, the implications derived from our framework condense the complexity of possible structural consequences at the overall network level. They call for empirical tests and might be useful for conceptualizing data collection in further research projects. Some very initial steps in this direction have already been undertaken by using non-parametric (Kudic et al. 2015b) and parametric (Kudic et al. 2016) event history estimation techniques for analyzing network entry processes in the German laser industry. Beyond that, we believe there is high potential for applying agent-based simulation techniques in this context since these analytical tools allow the complex nature of network evolution and structuration processes to be dealt with—at least to some extent (cf. Mueller et al. 2014). Further refinements and empirical tests of the implications raised so far constitute the next steps in our research agenda.

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