Chapter 14
Further Research and Conclusions

Believing in progress does not mean believing that any progress has yet been made.

(Franz Kafka)

Abstract The paradox underlying each scientific research project is that once it comes to an end we face more questions than at the beginning of the process. Of course, not all of the interesting new questions can be addressed here in detail. Nonetheless, we believe that a comprehensive understanding of network dynamics is essential for nearly all other fields of cooperation and network research. The complexity of network change processes calls for the application of unconventional methods. In my point of view this opens up a most promising field of research and constitutes, at the same time, the core of the outlook that follows in Sect. 14.1. Finally, we conclude with some final remarks in Sect. 14.2.

14.1 Fruitful Avenues for Further Research

The preceding discussion shows that our database has to be extended in several ways. Even though data and methods used in this study provide a good starting point for the analysis of network change processes, they are limited in several ways and the German laser industry still has many interesting secrets to divulge. Widely unexplored archival raw data sources contain valuable information on firm characteristics and cooperation activities that are waiting to be explored. We have recently started to extend the database in all four of the following areas: industry data, firm data, network data and innovation data. Our efforts encompass not only data gathering but also the construction of more sophisticated indicators. For instance, a promising way to gather additional information on R&D cooperation activities between LSMs and PROs is the exploration and utilization of bibliometric data.

M. Kudic, *Innovation Networks in the German Laser Industry*,
Economic Complexity and Evolution, DOI 10.1007/978-3-319-07935-6_14

Bibliographical sources can also be employed to gather more comprehensive information on innovation activities at the firm level. Information on product placement and advertisement can be used to gather and construct market-based innovation indicators. Quite recently we started systematically exploring data on new product launches based on several archival raw data sources in order to gain a more appropriate picture of innovation processes at the firm level. One of our next steps will be to focus on the inclusion of international linkages in our database to lay the groundwork for studying networks in an international context.

Secondly, more sophisticated empirical estimation methods are needed to address some of the empirical limitations. Both parametric and semi-parametric estimation approaches (Blossfeld et al. 2007) provide a broad range of empirical models that can be used for an in-depth analysis of tie formation and tie termination processes at the firm level. Moreover, we used standard panel data count models for our estimation in Chaps. 10, 11, and 12. These methods are limited in at least two ways. Firstly, the conditional fixed effects estimation approach, which is usually implemented in standard software packages, has been criticized (Allison and Waterman 2002). Secondly, more sophisticated methods have recently been proposed in the literature to handle selection biases in panel data (Imbens and Wooldridge 2009). These empirical challenges need to be addressed in future.

In addition to the issues addressed above, other powerful methods are now available such as agent-based simulation approaches. We are convinced that the use of different methodological approaches adds value in understanding a specific phenomenon. Two classes of agent-based models seem to have the potential to break new ground in the field of interorganizational network research.

The first class of models, so-called stochastic agent-based models (Snijders 2004; Snijders et al. 2010; Huisman and Snijders 2003; Huisman and Steglich 2008), can be applied to explore the mechanism that fuels the structural change of networks between two or more discrete points in time. The main focus of stochastic actor-based simulation models is the analysis of network evolution processes and co-evolutionary processes between social networks and changeable actor attributes (Snijders 2004). At their core, stochastic agent-based models combine a random utility model, continuous-time Markov process, and Monte Carlo simulation (Buchmann et al. 2014, p. 27). One processing avenue is to apply these models to gain a more profound understanding of how and why interorganizational innovation networks change over time.[1]

Stochastic actor-based models possess several distinctive features, including flexibility and accessibility of procedures to estimate as well as to test parameters which support the description of mechanisms or tendencies (Snijders et al. 2010, p. 2). Therefore, they reflect “network dynamics as being driven by many different tendencies” (Snijders et al. 2010, p. 1). These tendencies may be, for example, reciprocity, transitivity or homophily (ibid). Stochastic actor-based models are

[1] The following discussion is guided by Snijders et al. (2010). See also, Huisman and Snijders (2003).

based on some basic assumptions (cf. Snijders et al. 2010 pp. 1–3). Firstly, the time parameter t is continuous. This postulation enables the representation of dependencies between ties which are the consequence of processes where one tie occurs due to the existence of others. Secondly, the modifications of the network are the result of a Markov process, i.e. that "for any point in time, the current state of the network determines probabilistically its further evolution, and there are no additional effects of the earlier past" (Snijders et al. 2010, p. 2). The third assumption is that the actors are in control of their outgoing ties. Therefore, the changes of ties occur as a result of the actions of the actors instigating the tie which is influenced by their and other actors' attributes, their location in the network as well as their awareness of the rest of the network. Fourthly, at a certain point in time one probabilistically chosen actor ('ego') may have the occasion to change one outgoing tie. This postulation ends by decomposing the process of change into its minimum of possible components and consequently in the implication that alterations are not implemented coordinately, but merely depends on each other sequentially (Snijders et al. 2010, p. 3).

In the application of stochastic actor-based models, the focal actor – the one who can make a change – has to be selected with equal probabilities or with probabilities that depend on features like network position or other attributes. His reaction possibilities include the opportunity to change one outgoing tie or to do nothing. Hence, the set of permissible actions includes n elements ($n-1$ changes and one non-change). "The probabilities for a choice depend on the so-called objective function" (Snijders et al. 2010, p. 3) which is the heart of this model. The objective function ultimately determines the probabilities of modification in the network. The occurring effects can be divided into two groups: (a) endogenous effects, such as basic effects, transitivity and other triadic effects and degree-related effects that solely depend on the network itself, (b) exogenous effects (covariates) and interactions that, in contrast, are external in nature.[2] Moreover, it needs to be emphasized that issues regarding statistical modeling may arise. This means, among other things, that certain data requirements have to be met e.g. number of actors, number of observation moments, and the total number of observations (Snijders et al. 2010, p. 6).

By now, there are some excellent studies using stochastic agent-based methods in an economic context (Van de Bunt and Groenewegen 2007; Balland et al. 2012; Ter Wal and Boschma 2011; Giuliani 2010). One of our current research projects also moves in this direction. The study conducted by Buchmann et al. (2014) explores evolutionary network change processes in the German laser and automotive industry by using a stochastic actor-based simulation approach. The results provide empirical evidence for the explanatory power of network-related determinants in both industries.

Another class of models, the so-called KENE approach (Gilbert et al. 2001, 2007; Pyka et al. 2007) allows a firm's knowledge base, learning processes and knowledge transfer in complex network structures to be modeled. These types of

[2] For further explanation, see Snijders et al. (2010, pp. 4–6).

agent-based models can be applied to simulate micro-level firm behavior which shapes the macro-level network patterns.

Work has already started in this research area. Mueller and colleagues (2014) draw upon the KENE approach to analyze the evolution of interfirm innovation networks. In this study we focus on the evolutionary change of innovation networks which are composed of and driven by individual strategies and goals of heterogeneous actors. These actors follow a number of well-defined cooperation partner selection strategies. The agent-based simulation model (ABSM) that was implemented allows the causal relationships between firm strategies and the emerging network structures to be analyzed.

Mueller and colleagues (2014) applied the model to test the following well-known mechanisms that are assumed to affect a firm's cooperation activities and affect the evolution of the overall network over time: homophily, reputation and cohesion mechanisms. An initial, simplified version of the model was extended by adding a market mechanism which linked the knowledge base of a firm with the rewards a firm receives and with its incentives to cooperate. The results of our study show that a transitive closure mechanism, combined with a tendency for preferential attachment, produces networks that exhibit both small-world characteristics and a power-law degree distribution. Moreover our simulation results suggest that diversity in the selection of cooperation partners is important when we consider an evolving network.

14.2 Some Concluding Considerations

An in-depth understanding of collective innovation processes and technological change patterns is a necessary prerequisite for creating appropriate conditions for economic growth and prosperity. Indeed, there are still a lot of open questions to be addressed in order to provide a more comprehensive understanding of the evolutionary nature of innovation networks.

This study demonstrates that the neo-Schumpeterian approach in economics provides an appropriate theoretical framework for studying firm innovativeness in evolving networks. We chose this theoretical framework and decided in favor of a longitudinal empirical setting because we were convinced that factors influencing the creation of novelty are best understood from a dynamic perspective. Similarly, methods used for the purpose of this study were selected on the basis of two criteria. One the one hand, they must allow for an exact measurement of industry, firm, network and innovation characteristics at multiple analytical levels. On the other hand, they must be able to account for change processes over time. In principle, all applied indicators and methods, i.e. basic descriptive indicators, social network analysis methods and empirical estimation techniques, meet these requirements.

All in all our results show that R&D cooperation and innovation network involvement affects the innovativeness of science-driven firms in multiple ways. We believe that this book makes a valuable contribution to innovation network literature by exploring how and why firm-specific R&D cooperation activities and network positions, large-scale network patterns and evolutionary network change processes affect the innovative performance of laser source manufacturers in Germany. Nonetheless results should always be accessed and interpreted carefully in light of the limitations raised above. Current follow-up studies, using alternative methodological approaches, have already confirmed some of our findings and contributed towards a better understanding of network entry processes (Kudic et al. 2013; Kudic et. al. 2015) and network evolution processes (Mueller et al. 2014; Buchmann et al. 2014; Kudic and Guenther 2014). In a similar vein, recently started research projects on core-periphery patterns in Large-scale networks (Ehrenfeld et al. 2014) aim to complement and enhance our current picture of collective innovation processes in the German laser industry.

While this book is certainly a good starting point, there is yet much to be done to fully understand evolutionary network change, strategic positioning, and firm innovativeness in the German laser industry.

References

Allison PD, Waterman R (2002) Fixed-effects negative binomial regression models. Sociol Methodol 32(1):247–265

Balland PA, De Vaan M, Boschma R (2012) The dynamics of interfirm networks along the industry life cycle: the case of the global video game industry, 1987–2007. J Econ Geogr 13 (5):1–25

Blossfeld H-P, Golsch K, Rohwer G (2007) Event history analysis with Stata. Lawrence Erlbaum, London

Buchmann T, Hain D, Kudic M, Mueller M (2014) Exploring the evolution of innovation networks in science-driven and scale-intensive industries – new evidence from a stochastic actor-based approach. IWH discussion papers 01/2014, pp 1–42

Ehrenfeld W, Kudic M, Pusch T (2014) On the trail of core-periphery patterns – measurement and new empirical findings from the German laser industry. Conference proceedings, 17th Uddevalla symposium, Udevalla, pp 1–22

Gilbert N, Pyka A, Ahrweiler P (2001) Innovation networks – a simulation approach. J Artif Soc Soc Simul 4(3):1–13

Gilbert N, Ahrweiler P, Pyka A (2007) Learning in innovation networks: some simulation experiments. Phys A Stat Mech Appl 378(1):100–109

Giuliani E (2010) Network dynamics in regional clusters: the perspective of an emerging economy. Pap Evolut Econ Geogr (PEEG) (Online) 10(14)

Huisman M, Snijders TA (2003) Statistical analysis of longitudinal network data with changing composition. Sociol Methods Res 32:253–287

Huisman M, Steglich CE (2008) Treatment of non-response in longitudinal network data. Soc Networks 30:297–308

Imbens GW, Wooldridge JM (2009) Recent developments in the econometrics of program evaluation. J Econ Lit 47:5–86

Kudic M, Guenther J (2014) Towards an in-depth understanding of structural network change processes in innovation networks. In: International Schumpeter society conference proceedings, Jena, 27.30 July

Kudic M, Pyka A, Sunder M (2013) Network formation: R&D cooperation propensity and timing among German laser source manufacturers. IWH discussion papers, 01/2013, pp 1–25

Kudic M, Pyka A, Guenther J (2015) Taking the first step – what determines German laser source manufacturers' entry into innovation networks? Int J Innov Manag IJIM (forthcoming)

Mueller M, Buchmann T, Kudic M (2014) Micro strategies and macro patterns in the evolution of innovation networks: an agent-based simulation approach. In: Gilbert N, Ahrweiler P, Pyka A (eds) Simulating knowledge dynamics in innovation networks. Springer, Heidelberg/New York, pp. 73–95

Pyka A, Gilbert N, Ahrweiler P (2007) Simulating knowledge-generation and distribution processes in innovation collaborations and networks. Cybern Syst 38(7):667–693

Snijders TA (2004) Explained variation in dynamic network models. Math Soc Sci 42(168):5–15

Snijders TA, Van De Bunt GG, Steglich CE (2010) Introduction to actor-based models for network dynamics. Soc Networks 32(1):44–60

Ter Wal AL, Boschma R (2011) Co-evolution of firms, industries and networks in space. Reg Stud 45(7):919–933

Van de Bunt GG, Groenewegen P (2007) An actor-oriented dynamic network approach. Organ Res Methods 10(3):463–482