UNIVERSITY OF HOHENHEIM

DOCTORAL THESIS

United we Stand, Divided we Fall - Essays on Knowledge and its Diffusion in Innovation Networks

A dissertation by:
Kristina Bogner, M.Sc.

Supervisor:
Prof. Dr. Andreas Pyka

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First advisor: Prof. Dr. Andreas Pyka
Second advisor: Prof. Dr. Bernd Ebersberger
Chair of the committee : Prof. Dr. Ulrich Schwalbe
Dean: Prof. Dr. Karsten Hadwich
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This doctoral thesis is dedicated to three people in particular.
It is dedicated to my ***precious sister*** *for always supporting and believing in me.*
It is dedicated to my ***beloved husband*** *for lighting up my life and being my best friend.*
It is dedicated to my ***dearest son*** *for proving me that I have forces I never knew I had.*

Chapter 1

Introduction

Chapter 1

Introduction

"Knowledge is the most valuable resource of the future" (Fraunhofer IMW 2018). Researchers and policy makers alike agree upon the fact that knowledge is a crucial economic resource both as an input and output of innovation processes (Lundvall and Johnson 1994; Foray and Lundvall 1998). However, it is not only the input and output of innovation processes but moreover the solution to problems (Potts 2001). This resource is allowing firms to innovate and keep pace with national and international competitors. It is helping to generate technological progress, economic growth and prosperity. Therefore, understanding and managing the creation and diffusion of knowledge within and outside of firms and innovation networks is of utmost importance to make full use of this precious resource.

1.1 Knowledge and its Diffusion in Innovation Networks

How knowledge has been created and managed by entrepreneurs, firms and policy makers within the last decades strongly depends on the underlying understanding and definition of knowledge. In mainstream neo-classical economics, knowledge has been understood and treated as an intangible good, exhibiting public good features as non-excludability and non-rivalry in consumption (Solow 1956, 1957; Arrow 1972). These (alleged) public good features of knowledge have been assumed to cause different problems. As other actors cannot be excluded from the consumption of a public good, new knowledge freely flows from one actor to another, causing spillover effects. In this situation, some actors can benefit from the new knowledge without having invested in its creation, i.e. a typical free-riding problem emerges (Pyka et al. 2009). Therefore, the knowledge creating actor cannot fully appropriate the returns resulting from his research activities (Arrow 1972), leading to market failure, i.e. a situation in which the investment in R&D is below the social optimum. In this mainstream neo-classical world, knowledge falls like *manna from heaven* (Solow 1956, 1957). Knowledge instantly flows from one actor to another (at no costs) and therefore, there is no need for learning. This understanding and definition of knowledge has influenced policy making for a long period. Policies inspired by the concept of knowledge as a public good have mainly focused on the mitigation of potential externalities, for instance by incentive creation through R&D subsidies and knowledge production by the public sector (Smith 1994; Chaminade and Esquist 2010). While policies changed to a certain extent when the understanding of knowledge changed, nowadays, innovation policies as R&D subsidies (especially for the public sector) in socially desirable fields are still common practice (see chapter 5 on this topic).

Challenged by the fact that the mainstream neo-classical understanding lacks in giving an adequate and comprehensive definition of knowledge, (evolutionary or neo-Schumpeterian) innovation economists and management scientists tried providing a much more appropriate analysis of knowledge creation and diffusion by considering different features of knowledge, affecting its creation and diffusion. Following this understanding, knowledge can instead be seen as a *latent* public good (Nelson 1989), exhibiting many non-public good features. These features have a substantial impact on how to best manage the valuable resource knowledge. Nowadays we know that knowledge is far from being a pure public good. Knowledge is characterised by cumulativeness (Foray and Mairesse 2002; Boschma 2005), relatedness (Morone and Taylor 2010), path dependency (Dosi 1982; Rizzello 2004), tacitness (Polanyi 2009), stickiness (von Hippel 1994; Szulanski 2002), dispersion (Galunic and Rodan 1998b), context specificity and locality (Galunic and Rodan 1998b). Therefore, the neo-Schumpeterian approach especially emphasises the role of knowledge and learning (Hanusch and Pyka 2007; Malerba 2007). In line with the neo-Schumpeterian approach, anyone that has ever prepared for an exam, written a doctoral thesis, or even tried to cook a dish from a famous cook, would agree upon the fact that knowledge does not fall like *manna from heaven* and does not freely flow from one actor to another without the other actor actively acquiring the knowledge (learning). Instead it is the case that the named non-public good characteristics of knowledge substantially influence learning and the exchange and diffusion of knowledge between actors and within a network.

Inspired by communication theory, how the characteristics of knowledge influence its exchange and diffusion can be understood by using the famous Shannon-Weaver-Model of communication (Shannon 1948; Shannon and Weaver 1964). Following the idea of this model, not only information transfer but also knowledge transfer can (at least to a certain extent) be seen as a systemic process in which knowledge is transmitted from a sender to a receiver (see, e.g. Schwartz 2005). How knowledge can be transferred from one actor to another depends both on the characteristics of the sender and the receiver and on the characteristics of knowledge itself. When talking about knowledge and the impacts of its characteristics on knowledge exchange, the questions are: (i) is it possible to send the knowledge?, (ii) can the receiver re-interpret the knowledge?, and, (iii) can the knowledge be used by the receiver?

Characteristics of knowledge that influence knowledge diffusion and (i) whether it is possible to send the knowledge, are tacitness, stickiness and dispersion. Knowledge is not equal to information. Essential parts of knowledge are tacit, i.e. very difficult to be codified and to be transferred (Galunic and Rodan 1998a). Tacit knowledge is rival and excludable and therefore not public (Polanyi 1959). Even if the sender of the knowledge is willing to share, the tacitness makes it sometimes impossible to send this knowledge. Besides, knowledge and its transfer can be sticky (von Hippel 1994; Szulanski 2002), i.e. the transfer of this knowledge requires significantly more effort than the transfer of other knowledge. According to Szulanski (2002), both the knowledge and the process of knowledge exchange might be sticky. Reasons can be the kind and amount of knowledge itself but also attributes of the sender or receiver of knowledge. The dispersion of knowledge also influences the possibility of sending knowledge. Galunic and Rodan (1998a) explain dispersed knowledge by using the example of a jigsaw puzzle. The authors state that knowledge is distributed if all actors receive a photocopy of the picture of the jigsaw puzzle. At the same time, the knowledge is dispersed if every actor receives one piece of the jigsaw puzzle, meaning that everybody only holds pieces of the knowledge but not the 'whole' picture. Dispersed knowledge (or systems-embedded knowledge) is difficult to be sent, as detecting dispersed knowledge can be quite problematic (Galunic and Rodan 1998a).

Characteristics of knowledge and actors that influence (ii) whether the receiver can re-interpret the knowledge, are the cumulative nature of knowledge or the knowledge relatedness, agents' skills or cognitive distances and their absorptive capacities. New knowledge always is a (re-)combination of previous knowledge (Schumpeter 1912). The more complex and industry-specific the knowledge is, the higher the importance of the own knowledge stock and knowledge relatedness. To understand and integrate new knowledge, agents need absorptive capacities (Cohen and Levinthal 1989, 1990). The higher the cognitive distance between two actors, the more difficult it is for them to exchange and internalise knowledge. So, the 'optimal' cognitive distance can be decisive for learning (Nooteboom et al. 2007).

Characteristics of knowledge that influence (iii) whether the knowledge can actually be used by the receiver are the context-specific or local character of knowledge. Even if the knowledge is freely available, public good features of knowledge might not be decisive and the knowledge might be of little or no use to the receiver. We have to keep in mind that knowledge itself has no value, it only becomes valuable to someone if the knowledge can be used to, e.g. solve specific problems (Potts 2001). Hence, knowledge has different values to different actors and, following this assumption, more knowledge is not always better. Actors need the right knowledge in the right context and have to be able to combine this knowledge in the right way. The valuable resource knowledge might only be relevant and of use in the narrow context for and in which it was developed (Galunic and Rodan 1998a).

Making use of this model from communication theory quite impressively shows why an adequate, comprehensive understanding and definition of knowledge and its characteristics is of utmost importance when analysing and managing knowledge diffusion between actors and within networks. With an inadequate understanding and definition of knowledge, policy makers will not be able to manage and foster knowledge creation and diffusion. This can, for instance, be seen by policies inspired by a somewhat linear understanding of knowledge and innovation processes, heavily supporting basic research but failing to transfer the results into practice and producing successful innovations.

It is safe to state that the improved understanding and definition of knowledge positively influenced innovation policies (see, e.g. study 3 in this thesis). By applying a more realistic understanding of the characteristics of knowledge and how these influence knowledge creation and diffusion, researchers and policy makers were able to shift their focus on systemic problems instead of the correction of market failures (Chaminade and Esquist 2010). Understanding the importance of networks and their structures for knowledge diffusion performance allows for creating network structures that foster knowledge diffusion. However, researchers and policy makers alike so far mainly focus on the creation and diffusion of information or mere techno-economic knowledge. This intense focus neglects other important characteristics and types of knowledge and therefore is not able to give valid policy recommendations, e.g. for innovation policies aiming at fostering transformation endeavours. Especially the politically desired transformation towards a sustainable knowledge-based Bioeconomy (SKBBE) has been identified to be in need of more than the production and diffusion of techno-economic knowledge (Urmetzer et al. 2018). Inspired by sustainability literature, three other types of knowledge have been identified to be relevant for such transformations (Abson et al. 2014). These are systems knowledge, normative knowledge, and transformative knowledge. In chapter 4, the concept of so-called *dedicated knowledge*, incorporating besides mere techno-economic knowledge also systems, normative, and transformative knowledge is presented.

Since the effect of network structure on knowledge diffusion performance is strongly affected by what actually diffuses, analysing and incorporating different kinds of knowledge is important. Therefore, the first step in this direction is done in study 3 (chapter 4). Study 3 puts special emphasis on different types of knowledge necessary to foster the transformation towards a sustainable knowledge-based Bioeconomy (SKBBE). It shows that innovation policies so far put no sufficient attention on what actually diffuses throughout innovation networks.

As the collection and generation of (new) knowledge give such competitive advantages, there is a keen interest of firms and policy makers on how to foster the creation and diffusion of (new) knowledge. Firms can get access to new knowledge, either by internal knowledge generation processes, as, e.g. intra-organisational learning, or by access to external knowledge sources, e.g. inter-organisational cooperation (Malerba 1992). Nowadays strong focus on inter-organisational cooperation can be explained by the fact that "invention activity is far from being the outcome of isolated agents' efforts but that of interactive and collective processes" (Carayol and Roux 2009, p. 2). In nearly all industries and technological areas, we observe a pronounced intensity of R&D cooperation and the emergence of innovation networks with dynamically changing compositions over time (Kudic 2015). At the same time, we know that the economic actors' innovativeness is strongly affected by their strategic network positioning and the structural characteristics of the socio-economic environment in which the actors are embedded. Networks provide a natural infrastructure for knowledge exchange and provide the pipes and prisms of markets by enabling information and knowledge flow (Podolny 2001).

It comes as no surprise, that innovation networks and how knowledge diffusion within (and outside of) these networks takes place have become the centre of attention within the last decades (Valente 2006; Morone and Taylor 2010; Jackson and Yariv 2011; Lamberson 2016). Diffusion literature in this context has been identified to mainly focus on four different areas or key questions.

These are:

a) What diffuses?

b) How does it diffuse?

c) Where does it diffuse?

d) What are the effects (or performance) of the diffusion process and how are they measured? (see Schlaile et al. 2018)

In line with this, the four studies presented in this thesis focus to different extends on these four questions. Study 1 and 2 focus on how different network structures influence knowledge diffusion performance (key question c) and d)), for different diffusion mechanisms (key question b)). Study 3 focuses on what actually diffuses within the network (key question a)), and study 4 combines findings from study 1 and 2 with those of study 3, namely how network structure influences knowledge diffusion in general and how network structure influences knowledge diffusion of special types of knowledge, in particular.

These four key areas show that knowledge diffusion research can take various forms with varying results. Especially when analysing the effect of network properties on knowledge diffusion performance, as done in this thesis, the identified effects are manifold and even ambiguous. This is why, dependent on a), b), and c), different studies identified different network characteristics and structures as fostering or being 'optimal' for knowledge diffusion performance (see, e.g. Morone et al. (2007) vs. Lin and Li (2010)).

While sometimes disagreeing in what actually is the best structure for diffusion performance, agent-based simulation models within the last 15 years confirmed that certain network characteristics and structures seem to be relatively important for diffusion. These are the networks' average path lengths, the networks' average or global clustering coefficients, the networks' sizes and the networks' degree distributions (Morone and Taylor 2004; Cowan and Jonard 2004, 2007; Morone et al. 2007; Cassi and Zirulia 2008; Kim and Park 2009; Choi et al. 2010; Lin and Li 2010; Zhuang et al. 2011; Liu et al. 2015; Luo et al. 2015; Wang et al. 2015; Yang et al. 2015; Mueller et al. 2017; Bogner et al. 2018).

Concerning question a), what actually diffuses, most studies focus on analysing knowledge (rather oversimplified represented as numbers or vectors) in different network structures (Morone and Taylor 2004; Cowan and Jonard 2004, 2007; Morone et al. 2007; Cassi and Zirulia 2008; Kim and Park 2009; Lin and Li 2010; Zhuang et al. 2011; or study 1 and 2 in this thesis). Only a few authors investigate different kinds of knowledge (Morone et al. 2007, or study 3 in this thesis).

Regarding question b), how it diffuses, researchers either assumed knowledge exchange as a kind of barter trade, in which agents only exchange knowledge if this is mutually beneficial (Cowan and Jonard 2004, 2007; Morone and Taylor 2004; Cassi and Zirulia 2008; Kim and Park 2009). Alternatively they assume knowledge exchange as a gift transaction, i.e. for some reason agents freely give away their knowledge (Cowan and Jonard 2007; Morone et al. 2007; Lin and Li 2010; Zhuang et al. 2011; or study 2 and 4 in this thesis).

Concerning c), where it diffuses, most studies focus on knowledge diffusion in different archetypical network structures, as, e.g. small-world structures, random structures or regular structures. Most of the time the investigated structures are static (Cowan and Jonard 2004, 2007; Morone et al. 2007; Cassi and Zirulia 2008; Kim and Park 2009; Lin and Li 2010; or study 1 and 2 in this thesis), while sometimes researchers also investigate dynamic network structures or network structures evolving over time (Morone and Taylor 2004; Zhuang et al. 2011, or study 4 in this thesis).

As the effects of network characteristics and structures on knowledge diffusion performance depend on many different aspects, researchers found ambiguous effects of network characteristics and structures on diffusion. Most studies measure d), the effect of the diffusion process, as efficiency and equity of knowledge diffusion, i.e. the mean average knowledge stocks of all agents over time as well as the variance of knowledge levels (Cowan and Jonard 2004, 2007; Morone and Taylor 2004; Morone et al. 2007; Cassi and Zirulia 2008; Kim and Park 2009; Lin and Li 2010; Zhuang et al. 2011; and study 1 and 2 of this thesis) (sometimes complemented by an analysis of individual knowledge levels (Zhuang et al. 2011; and study 1 and 2 of this thesis)). However, d), the actual performance differs.

Many researchers agree that small-world network structures (Watts and Strogatz 1998) are favourable (if not best) for knowledge diffusion performance (Cowan and Jonard 2004; Morone and Taylor 2004; Morone et al. 2007; Cassi and Zirulia 2008; Kim and Park 2009, and study 1 of this thesis). Nonetheless, this is not always the case and depends on different aspects. While Cowan and Jonard found that small-world structures lead to the most efficient diffusion of knowledge, these structures at the same time lead to most unequal knowledge distribution (Cowan and Jonard 2004). Morone and Taylor found that small-world networks only provide optimal patterns for diffusion if some 'barriers to communication' are removed (Morone and Taylor 2004). Cassi and Zirulia state the small-world networks only foster diffusion performance for a certain level of opportunity costs for using the network (Cassi and Zirulia 2008). Moreover, other studies found that other network structures provide better patterns for knowledge diffusion, in general. These are for instance scale-free network structures (Lin and Li 2010), or even random network structures (Morone et al. 2007). Besides, many researchers agree that how network structures affect diffusion performance also depends on, e.g. agents' absorptive capacities (Cowan and Jonard 2004), agents' cognitive distances (Morone and Taylor 2004; and study 2 in this thesis), on the diffusion mechanism (Cowan and Jonard 2007; and study 1 and 2 in this thesis), on the special kind of knowledge and its relatedness (Morone et al. 2007), on the costs of using the network (Cassi and Zirulia 2008), and many more. "Analysing the structure of the network independently of the effective content of the relation could be therefore misleading." (Cassi et al. 2008, p. 285). Summing up, it is impossible to make general statements and give valid policy recommendations about network structures 'optimal' for knowledge diffusion.

As knowledge diffusion performance is affected by so many different, interdependent aspects, Table 1.1 in the Appendix gives an overview of those studies conducting experiments on knowledge diffusion used for and in my thesis. A more general comprehensive overview, however, goes beyond the scope of this introduction. Such a rather general overview can, for instance, be found in Valente (2006), Morone and Taylor (2010), Jackson and Yariv (2011), or Lamberson (2016).

1.2 Analysing Knowledge Diffusion in Innovation Networks

Analysing knowledge diffusion can be quite a challenging task. As learning, knowledge exchange and knowledge diffusion mainly take place between connected agents in different types of networks, a method needed and used in studies analysing knowledge diffusion within networks is social network analysis (SNA).

Social network analysis aims at describing and exploring "patterns apparent in the social relationships that individuals and groups form with each other. (...) It seeks to go beyond the visualisation of social relations to an examination of their structural properties and their implications for social action" (Scott 2017, p. 2). Since knowledge diffuses throughout networks, many studies analyse how the underlying network structures or properties of agents within the network influence knowledge diffusion (Ahuja 2000; Cowan and Jonard 2004, 2007; Mueller et al. 2017; Bogner et al. 2018, to name just a few). Applying the network perspective "allows new leverage for answering standard social and behavioural science research questions by giving precise formal definition to aspects of the political, economic, or social structural environment." (Wasserman and Faust 1994, p. 3). Hence, the network perspective allows not only for analysing, e.g. face-to-face knowledge exchange between two agents, but rather to focus on knowledge systems and therefore to examine knowledge spread and diffusion throughout the whole network.

Due to the impossibility of actually measuring knowledge and its diffusion, approaches in diffusion literature either use empirical methods, as measuring patents (Ahuja 2000; Nelson 2009), or questionnaires (Reagans and McEvily 2003). Or they focus on using experiments, ranging from laboratory experiments (Morone et al. 2007), to quasi-experiments in form of different models, such as percolation models (Silverberg and Verspagen 2005; Bogner 2015) or other agent-based models (ABMs) (Cowan and Jonard 2004, 2007; Mueller et al. 2017; Bogner et al. 2018). The studies presented in this doctoral thesis analyse knowledge diffusion through agent-based models (study 1 and 2) and by analysing network structures and potential diffusion performance by deducing from theoretical considerations in social network analysis (study 4).

The advantage of using agent-based models for analysing knowledge diffusion results from the fact that ABM can help to not only understand agents' or individuals' behaviours, but also to understand aggregate behaviour and how the behaviour and interaction of many individual agents lead to large-scale outcomes (Axelrod 1997). This helps understanding fundamental processes that take place. "Agent-based modeling is a way of doing thought experiments. Although the assumptions may be simple, the consequences may not be at all obvious." (Axelrod 1997, p. 4). According to Axelrod "ABM [...] is a third way of doing science" (Axelrod 1997, p. 3) in addition to deduction and induction.

Many scientists argue that traditional modelling tools in economics are no longer sufficient for analysing innovation processes, especially if we want to analyse innovations in an increasingly complex and interdependent world (Dawid 2006; Pyka and Fagiolo 2007). This is another reason why the method of agent-based modelling has become that famous. Dawid (2006) explains this by the fact that ABM is able to incorporate the particularities of innovation processes, such as the unique nature of knowledge and the heterogeneity of actors' knowledge. Agent-based simulation allows for modelling and explaining 'true', non-reversible path dependency, feedbacks, herding-behaviour and global phenomena as, for instance, the creation of knowledge and its diffusion (Pyka and Fagiolo 2007). Therefore, the method of agent-based modelling (ABM) is an approach that becomes more and more important, especially in modelling and studying complex systems with autonomous, decision making agents that interact with each other and with their environment (North and Macal 2007), as agents that repeatedly exchange knowledge being arranged according to a particular network algorithm.

1.3 Structure of this Thesis

Given the importance of understanding and even managing knowledge exchange between different actors, this doctoral thesis aims to use methods as social network analysis and agent-based modelling, in addition to theoretical considerations, to explore how different network structures influence knowledge diffusion in different settings. Therefore, the overall research question of this doctoral thesis is "What are the effects of different network structures on knowledge diffusion performance in R&D networks?" This research question can be subdivided in nine research questions covered in the four studies presented in this thesis. These are:

- Covered in study 1: What are the effects of different network structures on knowledge diffusion performance in informal networks in which knowledge is exchanged as a barter trade? How does the embeddedness of actors and especially the existence of 'stars' affect individual as well as overall diffusion performance?

- Covered in study 2: What are the effects of different network structures on knowledge diffusion performance in formal R&D networks in which knowledge diffuses freely between the actors, however, is limited by the different cognitive distances of these actors? Which cognitive distance between actors is best in the respective network structure?
- Covered in study 3: Which types and characteristics of knowledge are instrumental creating policies fostering a transformation towards a sustainable knowledge-based Bioeconomy (SKBBE)? What are the policy-relevant implications of this extended perspective on the characteristics of knowledge?
- Covered in study 4: What is the structure of the publicly funded R&D network in the German Bioeconomy? From a theoretical point of view, how does this network structure influence knowledge diffusion of both mere techno-economic knowledge as well as *dedicated knowledge*? Does policy making allow for or even create network structures that adequately support the creation and diffusion of dedicated knowledge in R&D networks?

To answer the named research questions, the structure of this doctoral thesis is as follows (see also Figure 1.1):

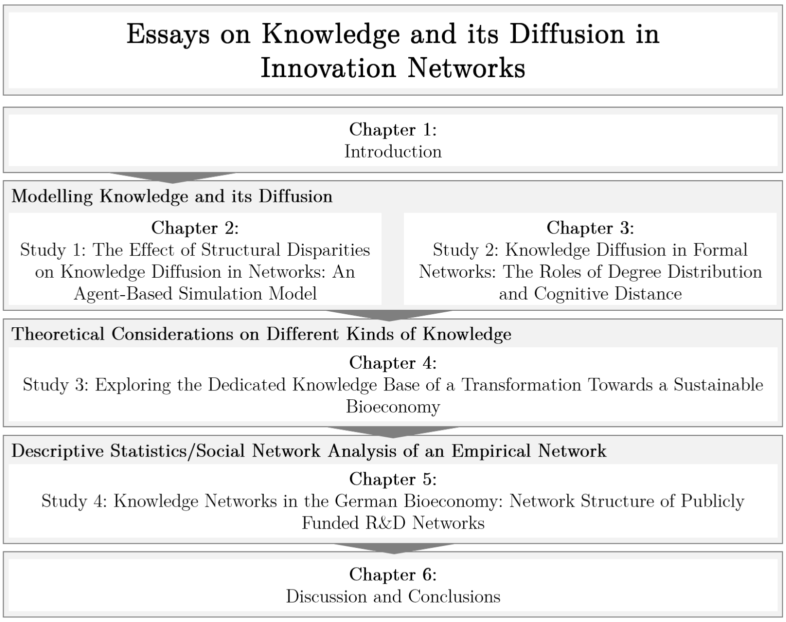

FIGURE 1.1: Structure of my doctoral thesis.

First, chapter 1 gives an introduction to the topics covered, the research questions answered the and methods used.

In chapter 2, study 1 analyses the effect of different structural disparities on knowledge diffusion by using an agent-based simulation model. It focuses on how different network structures influence knowledge diffusion performance. This study especially emphasises the effect of an asymmetric degree distribution on knowledge diffusion performance. Study 1 complements previous research on knowledge diffusion by showing that (i) besides or even instead of the average path length and the average clustering coefficient, the (asymmetry of) degree distribution influences knowledge diffusion. In addition, (ii) especially small, inadequately embedded agents seem to be a bottleneck for knowledge diffusion in this setting, and iii) the identified somewhat negative network structures on the macro level appear to result from the myopic linking strategies of the actors at the micro level, indicating a trade-off between 'optimal' structures at the network and the actor level.

In chapter 3, study 2 uses an agent-based simulation model to analyse the effect of different network properties on knowledge diffusion performance. As study 1, study 2 also focuses on the diffusion of knowledge, however, in contrast to study 1, this study analyses this relationship in a setting in which knowledge is diffusing freely throughout an empirical formal R&D network as well as through the four benchmark networks already investigated in study 1. Besides, the concept of cognitive distance and differences in learning between agents in the network are taken into account. Study 2 complements study 1 and further previous research on knowledge diffusion by showing that (i) the (asymmetry of) degree distribution and the distribution of links between actors in the network indeed influence knowledge diffusion performance to a large extent. In addition, (ii) the extent to which a skewed degree distribution dominates other network characteristics varies depending on the respective cognitive distances between agents.

In chapter 4, study 3 analyses how so-called *dedicated knowledge* can contribute to the transformation towards a sustainable, knowledge-based Bioeconomy. In this study, the concept of dedicated knowledge, i.e. besides mere-techno economic knowledge also systems knowledge, normative knowledge and transformative knowledge, is first introduced. Moreover, the characteristics of dedicated knowledge which are influencing knowledge diffusion performance are analysed and evaluated according to their importance and potential role for knowledge diffusion. In addition, it is analysed if and how current Bioeconomy innovation policies account for dedicated knowledge. This study complements previous research on knowledge and knowledge diffusion by taking a strong focus on different types of knowledge besides techno-economic knowledge (often overemphasised in policy approaches). It shows that i) different types of knowledge necessarily need to be taken into account when creating policies for knowledge creation and diffusion, and ii) that especially systems knowledge so far has been only insufficiently considered by current Bioeconomy policy approaches.

In chapter 5, study 4 analyses the effect of different structural disparities on knowledge diffusion by deducing from theoretical considerations on network structures and diffusion performance. This study focuses on how different network structures influence knowledge diffusion performance by analysing an empirical R&D network in the German Bioeconomy over the last 30 years by means of descriptive statistics and social network analysis. The first part of the study presents the descriptive statistics of the publicly funded R&D projects and the research conducting actors within the last 30 years. The second part of the study shows the network characteristics and structures of the network in six different observation periods. These network statistics and structures are evaluated from a knowledge diffusion point of view. The study tries to answer whether the artificially generated network structures seem favourable for the diffusion of both mere techno-economic knowledge as well as dedicated knowledge. Study 4 especially complements previous research on knowledge diffusion by (i) analysing an empirical network over such a long period of time (i), and (ii) by showing that even though a network and its structure might be favourable for the diffusion of information or mere techno-economic knowledge, this does not imply it also fosters the creation and diffusion of other types of knowledge (i.e. dedicated knowledge) necessary for the transformation towards a sustainable knowledge-based Bioeconomy (SKBBE).

In chapter 6, the main results of this doctoral thesis are summarised and discussed, and an outlook on possible future research avenues is given.

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Appendix

Study	What diffuses?	How does it diffuse?	Where does it diffuse?	Special focus on	What are the effects (or performance) of the diffusion process and how are they measured?	Main results?
Agent-based model of knowledge diffusion in networks by Cowan and Jonard (2004)	Knowledge (being represented as a vector of numbers).	Barter trade diffusion mechanism.	In three different theoretical networks exhibiting different network properties (random, small-word, scale-free).	Average path length, average clustering coefficient, effect of asymmetry of degree distribution, effect of absorptive capacities on effect of asymmetric degree distribution.	Knowledge diffusion performance measured as mean average/variance of knowledge stock over time and at different periods in time.	Small-world structures lead to most efficient (and most unequal) diffusion, path length and clustering efficient not most decisive, but asymmetry of degree distribution. Absorptive capacities influence knowledge diffusion.
Agent-based simulation model by Morone and Taylor (2004)	Knowledge (being represented as a number).	Barter trade diffusion mechanism.	Diffusion in a dynamically changing network structure, exhibiting, e.g. small-world properties.	Average path length, average clustering coefficient, cognitive distance, effect of re-wiring on resulting network structure on convergence of knowledge, 'ignorance trap' mechanisms.	Mean/variance of average knowledge stock.	Small-world dynamics lead to most equal and efficient knowledge diffusion, but sometimes only if 'barriers to communication' are removed. Dependent on differences in knowledge levels, small-world structures support diffusion differently.
Agent-based model of knowledge diffusion in networks by Cowan and Jonard (2007)	Knowledge as sets of ideas (represented as set of numbers).	Barter trade diffusion mechanism and knowledge exchange as gift transaction.	In an industrial R&D network exhibiting different network properties.	Average path length, average clustering coefficient, effect of asymmetry of degree distribution dependent on diffusion mechanism, different roles of 'traders' and 'givers', different kinds of knowledge (scarce vs. abundant).	Knowledge diffusion performance as efficiency in knowledge distribution (size of average output of ideas), both from individual aggregate view.	Effect of asymmetric degree distribution depends on diffusion mechanism (positive effect if stars are givers, negative effect if stars are traders). For individual performance, clustered ego-networks better, for overall performance dense neighbourhoods preferable. Network with structural holes performs better if knowledge is scarce, rather clustered networks perform better if knowledge is abundant.
Laboratory experiment and agent-based model by Morone et al. (2007)	Knowledge (represented as number).	Knowledge exchange as gift transaction.	In three different theoretical networks exhibiting different network properties (regular, small-world, random).	Knowledge relatedness and cumulativeness, cognitive maps entailing different kinds of (more or less specialised) knowledge.	Mean/variance of average knowledge stock, knowledge dispersion.	Small-world better than regular networks, but worse than random networks. The bigger the network size, the faster the diffusion (independent from network architecture). 'Best' learning strategy depends on desired type of knowledge.
Agent-based simulation model by Cassi and Zirulia (2008)	Knowledge (represented as a vector of numbers).	Barter trade diffusion mechanism.	In three different theoretical networks exhibiting different network properties (regular, small-world, random).	Cost-benefit comparison of knowledge exchange (trade), effect of cost-benefit considerations on effect of network structure.	Mean/variance of knowledge levels and use of network.	Optimal network structure dependent on opportunity cost of using the network. Small-world network structure not always best.
Agent-based model of knowledge diffusion in networks by Kim and Park (2009)	Knowledge (as a function of previous knowledge (number)).	Barter trade diffusion mechanism.	In three different theoretical networks exhibiting different network properties (regular, small-world, random).	Average path length, average clustering coefficient, asymmetry of degree distribution, learning and forgetting.	Impact of network structure on performance, focusing on average knowledge stock and knowledge variance.	Small-world structures best for diffusion, path length and clustering efficient not most decisive factor.
Agent-based model of knowledge diffusion in networks by Lin and Li (2010)	Knowledge (as a function of previous knowledge (number)).	Knowledge exchange as gift transaction.	In four different theoretical networks exhibiting different network properties (regular, random, small-world, scale-free).	Average path length, average clustering coefficient, effect of asymmetry of degree distribution and systems size on knowledge diffusion.	Average knowledge levels and knowledge growth rate over time.	Path length and clustering efficient not most decisive, but asymmetry of degree distribution. Scale-free networks optimal for knowledge diffusion performance as stars rapidly collect and redistribute new knowledge.
Agent-based network model of knowledge accumulation and diffusion by Zhuang et al (2011)	Knowledge (as a function of previous knowledge (number)).	Knowledge exchange as gift transaction.	Diffusion in a dynamically changing network structure exhibiting different network characteristics.	Dynamic network structure and effect of different link selection strategies, different in- and out-degrees, effect of degree distribution on knowledge accumulation and diffusion.	Average knowledge level of all agents as well as per-capita knowledge at time t.	Diffusion performance affected by network size and number of neigbours (the higher, the faster diffusion the knowledge accumulation). Timing affects diffusion efficiency (gaining knowledge from overall network more efficient in the long run). "
Agent-based model of knowledge diffusion in networks by Mueller et al. (2017)	Knowledge (being represented as a vector of numbers).	Barter trade diffusion mechanism.	In informal networks exhibiting different network properties (regular, small-world, scale-free, evolutionary).	Average path length, average clustering coefficient, effect of asymmetry of degree distribution, effect of absorptive capacities.	Performance as mean average/variance of knowledge stock over time and at different periods in time as well as mean average knowledge stock of certain actor groups.	Small-world networks perform best, path length and clustering efficient not most decisive, but asymmetry of degree distribution. Inadequately embedded agents as bottleneck for diffusion, 'traditional' linking strategies or linking strategies beneficial on the actor level lead to negative diffusion properties on the overall network level.
Agent-based model of knowledge diffusion in networks by Bogner et al. (2018)	Knowledge (being represented as a vector of numbers).	Knowledge exchange as a gift transaction.	In formal R&D networks exhibiting different network properties (regular, small-world, scale-free, evolutionary) as well as in an empirical R&D network.	Average path length, average clustering coefficient, effect of asymmetry of degree distribution, role of cognitive distance on knowledge diffusion.	Performance as mean average/variance of knowledge stock over time/at different periods in time as well as mean average knowledge stock of groups.	Random or small-world networks perform best, path length and clustering efficient not most decisive, but degree distribution. 'Traditional' linking strategies/linking strategies beneficial on the actor level lead to negative diffusion properties on the overall network level.

TABLE 1.1: Overview of agent-based models on knowledge diffusion.

Chapter 2

The Effect of Structural Disparities on Knowledge Diffusion in Networks: An Agent-Based Simulation Model

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Abstract

We apply an agent-based simulation approach to explore how and why typical network characteristics affect overall knowledge diffusion properties. To accomplish this task, we employ an agent-based simulation approach (ABM) which is based on a 'barter trade' knowledge diffusion process. Our findings indicate that the overall degree distribution significantly affects a network's knowledge diffusion performance. Nodes with a below-average number of links prove to be one of the bottlenecks for efficient transmission of knowledge throughout the analysed networks. This indicates that diffusion-inhibiting overall network structures are the result of the myopic linking strategies of the actors at the micro level. Finally, we implement policy experiments in our simulation environment in order to analyse the consequences of selected policy interventions. This complements previous research on knowledge diffusion processes in innovation networks.

Keywords

innovation networks; knowledge diffusion; agent-based simulation; scale-free networks

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The content of the text has not been altered. For reasons of consistency, the language and the formatting have been changed slightly.

2.1 Introduction

By now it is well-recognised that knowledge is a key resource that allows firms to innovate and keep pace with national and international competitors. We also know from previous research that the generation of novelty is a collective process (Pyka 1997). Firms frequently engage in bi- or multilateral cooperation to exchange knowledge, learn from each other and innovate (Grant and Baden-Fuller 2004). However, when it comes to more complex cooperation structures, the transfer of knowledge among the actors involved becomes a highly multifaceted phenomenon. It goes without saying that the structural configuration of a network is likely to affect knowledge exchange processes at the micro level and the systemic level. At the same time, it is important to note that the link between the individual exchange process, the network structure and the systemic diffusion properties is still not fully understood. Accordingly, at the very heart of this paper, we seek to contribute to an in-depth understanding of how and why different network topologies affect knowledge diffusion processes in innovation networks.

Scholars from various scientific disciplines have addressed network change processes (Powell et al. 2005) and structural properties of networks, such as core-periphery structures (Borgatti and Everett 1999), fat-tailed degree distributions (Barabási and Albert 1999) and small-world network properties (Watts and Strogatz 1998). Previous research provides evidence that structural network characteristics affect both the innovation outcomes at the firm level (Schilling and Phelps 2007) and at higher aggregation levels (Fleming et al. 2007), as well as the knowledge transfer processes among the actors involved (Morone and Taylor 2010). At the same time, we know that knowledge exchange and learning processes are closely related to firm-level innovation outcomes. Empirical studies show that a firm's network position affects its innovative performance (Powell et al. 1996; Ahuja 2000; Stuart 2000; Baum et al. 2000; Gilsing et al. 2008). Additionally, the knowledge transfer and diffusion properties of a system directly affect the ability of the actors involved to innovate. Uzzi et al. (2007), for instance, reveal a positive relationship between small-world properties and the creation of novelty and innovation at higher aggregation levels.

Against this backdrop, it is astonishing that research on how knowledge diffusion processes affect existing network topologies is still rather scarce. There is an ongoing debate in the literature about what constitutes the most effective collaborative network structures. In particular, researchers focus on how different network characteristics may foster a fast and uniform diffusion of knowledge and spur on collective innovation. However, there has been a strong interest in network characteristics, such as path length and cliquishness (most notably: Cowan and Jonard 2004; Lin and Li 2010; Morone et al. 2007). Interestingly, a number of closely related studies indicate other network characteristics that also influence diffusion processes (Cowan and Jonard 2007; Kim and Park 2009; Mueller et al. 2014). We are primarily interested in understanding how the exchange of knowledge is organized in complex socio-economic systems. This is not only of academic interest; it also enables us to understand how innovation is generated in real economic systems.

In this paper, we set up an agent-based network simulation model analysing how and why the degree distribution within a network can be harmful to network performance and how firms and policy makers can intervene. First, we investigate the relationship between network structure and diffusion performance on both the overall network level and the micro level. We are particularly interested in identifying the determinants and intertwined effects that may hinder efficient diffusion of knowledge in a system. Then we use our simulation environment to evaluate a set of hypothetical policy interventions. In other words, we go beyond the mere analysis of network structure and diffusion performance and create policy experiments in which policy makers can evaluate different scenarios to improve diffusion performance both on the firm and on the network level.

The remainder of this paper is organised as follows: In Sect. 2.2. we give an overview of the literature pertaining to knowledge exchange processes in networks and to network formation algorithms, placing a particular emphasis on barter trade processes in informal networks. In Sect. 2.3., we conduct a simulation-based analysis of knowledge diffusion in four structurally distinct networks. As part of this analysis, we explore how different characteristics affect network performance and how harmful network structures can be prevented. In addition, we conduct a policy experiment which allows us to analyse and evaluate different scenarios both on the network and on the firm level. Our results are then discussed in Sect. 2.4. together with some remarks on limitations and fruitful avenues for further research.

2.2 Knowledge Exchange and Network Formation Mechanisms

The following section provides the theoretical foundation of the simulation model. We continue with a brief overview of the literature on knowledge exchange processes in networks. Then we introduce and discuss the knowledge barter trade diffusion model typically applied in simulation experiments. Finally, we present four network formation algorithms which allow us to reproduce different combinations of frequently observed real-world network topologies in our simulation environment.

2.2.1 Theoretical Background

Economic growth and prosperity are closely related to innovation processes which are fuelled by the ability of the actors involved to access, apply, recombine and generate new knowledge. Consequently, the term 'knowledge-based economy' has become a catchphrase. Knowledge-based economies are "directly based on the production, distribution and use of knowledge" (OECD 1996, p. 7). This recognition led to a growing interest in knowledge generation and diffusion among practitioners, politicians and scholars alike.

However, it is important to note that information and knowledge is not freely available or homogeneously distributed among the actors of a real-world economy. The classical-neoclassical notion of knowledge as a ubiquitous public good does not reflect everyday reality. Instead, innovators are constantly searching for new ideas, opportunities, and markets. The neo-Schumpeterian approach to economics (Hanusch and Pyka 2007) emphasises the role of innovators and explicitly acknowledges the nature of information and knowledge. Malerba (2007) argues that knowledge and learning are key building blocks of the neo-Schumpeterian approach. At the same time, this approach accounts for the firms' ability to store and generate new stocks of knowledge by referring to the concept of organisational routines by Nelson and Winter (1982).

The traditional idea that knowledge can be acquired without any restrictions and obstacles has been replaced by other, more realistic concepts and explanatory approaches. According to Malerba (1992), firms can gain access to new knowledge via internal processes (e.g. intra-organisational learning) or by external knowledge channels (e.g. modes of inter-organisational cooperation). We particularly focus on the latter channel. It has been argued that networks provide the pipes and prisms of markets (Podolny 2001) while enabling the flow of information and knowledge. The ties between the nodes in such networks can be both formal and informal (Pyka 1997). This paper particularly focuses on firms' external knowledge channels and analyses informal cooperation and network structures.

In line with our previous considerations, Herstad et al. (2013, p. 495) point to the fact that "[...] innovation is shifting away from individual firms towards territorial economies and the distributed networks by which they are linked". Inter-organisational knowledge exchange is of growing importance for the competitiveness of firms and sectors (Herstad et al. 2013) such that innovation processes nowadays take place in complex innovation networks in which actors with diverse capabilities create and exchange knowledge (Levén et al. 2014). Networks are the prerequisite for the exchange of knowledge. As these systems are becoming more and more complex, the linkage between the underlying network structure and knowledge creation and diffusion has to be analysed and understood thoroughly.

The natural question that arises in this context is what do we know from previous research on the issues raised above. To start with, several studies have focused on the efficiency of knowledge transfer in networks with either regular, random or small-world structures (see Cowan and Jonard 2004; Morone et al. 2007; Kim and Park 2009; Lin and Li 2010). So for example, Cowan and Jonard (2004) use a barter trade diffusion process to investigate the efficiency of different network structures. Their model shows that, unlike fully regular or random structures, small-world structures lead to the most efficient (as well as the most unequal) knowledge diffusion within informal networks. Building on these findings, Morone et al. (2007) use a simulation model to analyse the effects of different learning strategies of agents, network topologies, and the geographical distribution of agents and their relative initial levels of knowledge. Interestingly the results show that, in contrast to the conclusions drawn by Cowan and Jonard (2004), small-world networks do perform better than regular networks, but consistently underperform compared with random networks.

A new aspect in this debate was introduced by Cowan and Jonard (2007). The study is based on the theoretical discussion on structural holes (Burt 1992) and social capital (Coleman 1988). Cowan and Jonard introduce a simulation model with a barter trade knowledge exchange process in which the authors analyse the effects of network randomness and the existence of stars (i.e. firms with a high number of links) on a systemic and individual level. Their results show that the existence of stars can either be positive or negative for the diffusion of knowledge depending on whether stars are givers or traders of knowledge. The aspect of different degree distributions of networks is also stressed by Lin and Li (2010). The authors analysed how different network structures affect knowledge diffusion in a scenario in which agents freely give away knowledge. Their analysis reveals that networks with an asymmetric degree distribution, namely scale-free networks, provide optimal patterns for knowledge transfer.

Even though previous research has found that network structures - more precisely degree distribution - do affect diffusion performance, the rationale behind this effect is unclear. We neither know why exactly the degree distribution affects diffusion performance nor do we know under which conditions this effect varies.

2.2.2 Informal Knowledge Exchange within Networks

Informal cooperation is the rule rather than the exception. The same holds when it comes to more complex systems. Ties in innovation networks not only reflect formal contracts but also informal relationships (Hanson and Krackhardt 1993; Pyka 1997). Nonetheless, the broad majority of network studies are based on data from formalised cooperation agreements. The rationale behind this is straightforward: econometric network studies depend on reliable raw data sources (e.g. patent data) that allow the cooperation behaviour of a well-specified population of actors to be replicated. Irrespective of how good these raw data sources are, the informal dimension of cooperation is hardly reflected in this kind of data. Morone and Taylor (2004, p. 328) conclude in this context: "informal processes of knowledge diffusion have been insufficiently investigated both at the theoretical level as well as the empirical level". Therefore, a lot more research is required to further investigate knowledge exchange in informal networks.

We follow Cowan and Jonard (2004) in modelling knowledge exchange between actors as a barter trading process and knowledge as an individual vector of different knowledge categories. In informal networks, knowledge exchange is highly dependent on agents that freely share their knowledge. Givers of knowledge will only do so as they expect to receive something back in return. Hence, informal knowledge exchange has the character of a barter exchange (Cowan and Jonard 2004). Following this idea, agents in our networks are linked to a small, fixed number of other actors with whom they repeatedly exchange knowledge if, and only if, trading is mutually beneficial for both actors, i.e. they receive something in return. Thus, in our paper, knowledge exchange is modelled as follows:

The model starts with a set of agents $I = (1, ..., N)$. Any pair of agents $i, j \in I$ with $i = j$ can be either directly connected (indicated by the binary variable $X(i, j) = 1$) or not (indicated by the binary variable $X(i, j) = 0$). An agent's neighbourhood N_i is defined as the set $N_i = j \in I$ with $x(i, j) = 1$, i.e. the set of all other agents in the network to which agent i is directly connected. The network $G_{n,p} = x(i, j); i, j \in I$ is therefore "the list of all pairwise relationships between agents" (Cowan and Jonard 2004, p. 1560). The distance $d(i, j)$ between two agents i and j is defined as the length of the shortest path connecting these agents, with a path in $G_{n,p}$ between i and j characterised as the set of pairwise relationships $[(i, i_1), ..., (i_k, j)]$ for which $x(i, i_1) = ... = x(i_k, j) = 1$.

Every agent $i \in I$ is endowed with a knowledge vector $v_{i,c}$ with $i = 1, ..., N; c = 1, ..., K$ for the K knowledge categories. Knowledge is exchanged between agents in a barter exchange process. Agents follow simple behavioural rules in a sense that they trade knowledge if trading is mutually beneficial. An exchange therefore takes place if two agents are directly linked and if both agents can receive new knowledge from the other respective agent regardless of the amount of knowledge they actually receive. This assumption allows us to incorporate the realistic idea that agents can only assess whether or not the potential partner has some relevant knowledge to share and is unable to assess *a priori* how much can be precisely gained from the knowledge exchange. This is in line with the special nature of knowledge in that its exact value can only be assessed after its consumption (if at all).

In a more formal description, two conditions have to be fulfilled. Let $j \in N_i$ and assume there is a number of knowledge categories $n(i,j) = (c : v_{i,c} > v_{j,c})$ in which agent i's knowledge strictly dominates agent j's knowledge. As we already know, agent j will only be interested in trading with agent i if $n(i,j) > 0$ and *vice versa*. Hence, the barter exchange takes place and agents i and j exchange knowledge if and only if $j \in N_i$, and $min[n(i,j), n(j,i)] > 0$. This is also called a "double coincidence of wants" (Cowan and Jonard 2004, p. 1562). If the 'double coincidence of wants' condition holds, the agents exchange knowledge in as many categories of their knowledge vector as are mutually beneficial. If the number of categories in which the agents strictly dominate each other is not equal among the trading agents (i.e. $n(i,j) \neq n(j,i)$), the number of categories in which the agents exchange knowledge is equal to $min[n(i,j), n(j,i)]$, while the decision as to which categories the agents eventually exchange knowledge in is randomly chosen with a uniform probability. In addition to the special nature of knowledge mentioned above, the model also incorporates the fact that the internalisation of knowledge is difficult and the assimilation of knowledge is only partly possible due to the different absorptive capacities of the agents. This means that only a constant share of α with $0 < \alpha < 1$ can actually be assimilated by the receiver.[1] Therefore, for each period in time, the knowledge stock of an agent can either increase to an amount that is unknown before the exchange (if an exchange takes place) or stay constant (if no exchange takes place).

Agents in the model mutually learn from one another and, in doing so, knowledge diffuses through the network and the mean knowledge stock of all agents within the network $\bar{v} = \sum_{i=1}^{N} v_i / I$ increases over time. As knowledge is considered to be non-rival in consumption, an economy's knowledge stock can only increase or stay constant since an agent will never lose knowledge by sharing it with other agents. Assume, for instance, that $n(i,j) = n(j,i) = 1$ and that agent j's knowledge strictly dominates agent i's knowledge in category c_1 and that agent i's knowledge strictly dominates agent j's knowledge in category c_2. In this situation agent i will receive knowledge from agent j in category c_1 (with his knowledge in category c_2 being unaffected) and agent j will receive knowledge from agent i in category c_2 (with its knowledge in category c_1 being unaffected). Therefore, after the trade, the knowledge of agent i changes according to $v_{i,c1}(t+1) = v_{i,c1}(t) + \alpha(v_{j,c1}(t) - v_{i,c1}(t))$ and the knowledge of agent j changes according to $v_{j,c1}(t+1) = v_{j,c1}(t) + \alpha(v_{i,c1}(t) - v_{j,c1}(t))$. As agents exchange their knowledge for as long as this trade is mutually advantageous, the barter trade process takes place until all trading possibilities are exhausted, i.e. "there are no further double coincidences of wants: $\forall i, j \in I : min(n(i,j), n(j,i)) = 0$" (Cowan and Jonard 2004, p. 1562).

2.2.3 Algorithms for the Creation of Networks

To investigate the structural effects of different network topologies on knowledge diffusion we apply four structurally distinct algorithms to construct network topologies. The four resulting network topologies are: (i) Erdős-Rényi random network ER, (ii) Barabási-Albert network BA, (iii)Watts-Strogatz network WS, and (iv) Evolutionary network EV. While ER, BA, and WS networks are well-known,

[1] Notably, in the model, absorptive capacities are similar for all firms and endogenously given. Hence, they can be considered as an industry level parameter rather than an agent-level parameter. An alternative approach has been conceptualised and applied by Savin and Egbetokun (2016).

EV networks are considered because of their realistic network formation strategy and because of their unique network characteristics.[2]

We begin by briefly addressing ER networks (Erdős and Rényi 1959). The attachment logic behind the Erdős-Rényi (n, M) algorithm is quite simple. Each of the n nodes attracts ties with the same probability p which ultimately creates M randomly distributed links between the nodes. The resulting random graphs are characterised by short path length, low cliquishness and a relatively symmetric degree distribution following a Poisson or normal degree distribution (Erdős and Rényi 1960; Bollobás et al. 2001).

Next, we look at BA networks. Barabási and Albert (1999) introduced a preferential attachment mechanism, which better explains the structures of real-world networks compared to random graphs. That is, the degree distribution of links among nodes approximately approaches a right-skewed power law where a large number of nodes have only a few links and a small number of nodes are characterised by a large number of links. This is usually described by the following expression: $P(k)\tilde{}k^{-y}$, in which the probability $P(k)$ that a node in the network is linked with k other nodes decreases according to a power law. The BA algorithm is based on the following logic: nodes with above average degree attract links at a higher rate than nodes with fewer links. More precisely, the algorithm starts with a set of 3 connected nodes. New nodes are added to the network one at a time. Each new node is then connected to the existing nodes with a probability that is proportional to the number of links that the existing nodes already have. This process of growth and preferential attachment leads to networks which are characterised by small path length, medium cliquishness, highly dispersed degree distributions - which approximately follows a power law-, and the emergence of highly connected hubs.

Watts and Strogatz (1998) stressed that biological, technical and social networks are typically neither fully regular nor fully random but exhibit a structure that is somewhere in between. In their seminal study, they proposed a simple algorithm which enabled them to reproduce so-called small-world networks. The algorithm defines the randomness of a network using the parameter p that describes the probability that links within a regular ring network lattice are redistributed randomly. The authors found that, within a certain range of randomness, the resulting networks show both a high tendency for clustering, like a regular network and at the same time, short average paths lengths, like in a random graph.[3]

Finally, our last network algorithm is the EV algorithm originally proposed by Mueller et al. (2014). The algorithm was developed to create dynamic networks in a well-defined population of firms. We employ the EV algorithm to study knowledge diffusion processes[4] for at least two reasons: it is based on a quite realistic linking strategy of the actors at the micro level and it allows network topologies to be generated which combine the characteristics of WS and BA networks. The

[2] At this point it would have been possible to decide in favour of other algorithms and the resulting network topologies as for example core-periphery structures (Borgatti and Everett 1999; Cattani and Ferriani 2008; Kudic et al. 2015).

[3] The exact rewiring procedure works as follows: The starting point is a ring lattice with n nodes and k links. In a second step, each link is then rewired randomly with the probability p. By altering the parameter p between $p = 0$ and $p = 1$, i.e. the network can be transformed from regularity to disorder.

[4] In this paper we analyse diffusion processes in existing networks. In the case of the EV algorithm, we assume that the linking process is repeated 100 times. To create comparable networks with a pre-defined number of links we further assume that links are deleted after two time steps of the rewiring process.

underlying idea of the algorithm is straightforward. The EV algorithm is based on the notion that innovating actors typically face a scarcity of information about potential cooperation partners. As a consequence, actors are continuously adapting their partner selection behaviour to address this information deficit problem. The trade-off between the need for reliable information and the cost of the search process is reflected in a two-stage selection process in which each node chooses link partners based on both the transitive closure mechanism and preferential attachment aspects. For every time step, each agent defines a pre-selected group consisting of potential partners which they know via existing links, i.e. cooperation partners of their cooperation partners for which no link currently exists. If the size of this pre-selected group is smaller than a defined threshold, agents are added randomly to create a pre-selection of defined size. In a second step, agents then choose the potential partner with the highest degree centrality and form a link.

2.3 Numerical Model Analysis

Now we present the findings of our simulation analyses where we explore how different network topologies affect the diffusion of knowledge. First, we address the effect of network characteristics, such as path length and cliquishness, on network performance in terms of the average knowledge level $\bar{v}$ of all actors in the network. We then investigate how the distribution of links among these actors affects network performance. Finally, we run policy experiments for each of the four networks to gain an in-depth understanding of how policy interventions may affect the diffusion of knowledge.

2.3.1 Path Length, Cliquishness and Network Performance

The model is initialised with a standard set of parameters as follows: we assume a model population of $I = 100$ agents connected by 200 links for all networks. The agents and links within the network are placed according to the algorithms described above: (i) Watts-Strogatz, (ii) Random-Erdős-Rényi (n, M), (iii) Barabási-Albert and (iv) Evolutionary networks. In order to initiate the Watts-Strogatz networks, we assume a rewiring probability of $p = 0.15$. In order to initiate Evolutionary networks, we assume a pre-selected pool of five nodes. Figure 2.1 illustrates the networks produced by these formation algorithms.

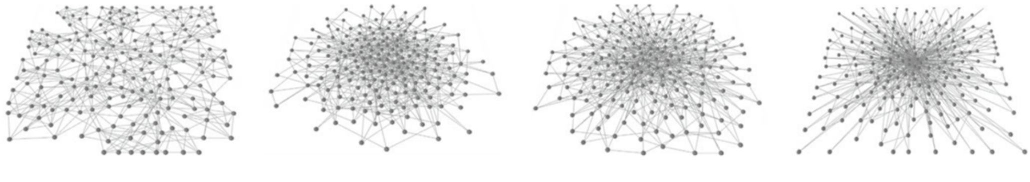


FIGURE 2.1: Visualisation of network topologies created in NetLogo. From left to right: visualisation of the Watts-Strogatz network, the random/Erdős-Rényi network, the Barabási-Albert network and the Evolutionary network algorithm.

Following Cowan and Jonard (2004), for each model run, each agent is equipped with a knowledge vector $v_{\mathrm{i,c}}$ with 10 different knowledge categories drawn from a uniform distribution, i.e. $v_{\mathrm{i,c}}(0) \sim U[0, 10]$. To enhance the knowledge diffusion, we also define 10 randomly chosen agents as ‘experts’, i.e. these agents are endowed with a knowledge level of 30 in one category. Unless stated otherwise, we assume a value of $\alpha = 0.1$ for the absorptive capacities. Finally, we assume that the knowledge levels of the agents in one category is similar if the difference in this respective category is <1%.

Figure 2.2 shows the average overall knowledge stock in the four networks over time, i.e. the mean average knowledge $\bar{v}$ of all agents within the network averaged over 500 simulation runs as well as the error bars of the respective results. The black part of the plot indicates that the knowledge stock $\bar{v}$ in the network is still growing (knowledge exchange is still taking place), while the grey part of the plot indicates that the knowledge stock $\bar{v}$ is no longer changing (knowledge stock has reached a steady state $\bar{v}*$, i.e. $\bar{v} = \bar{v}*$). The figure shows that the average knowledge stocks within the networks increase over time, however, there are significant differences between the four network topologies: WS networks perform best followed by ER networks, BA networks, and EV networks. It can also be seen that in the worse performing networks, the maximum knowledge stock $\bar{v}*$ is reached earlier than in the better performing networks. In the two best performing networks, knowledge is diffused for nearly twice as long as in the worst performing evolutionary networks.

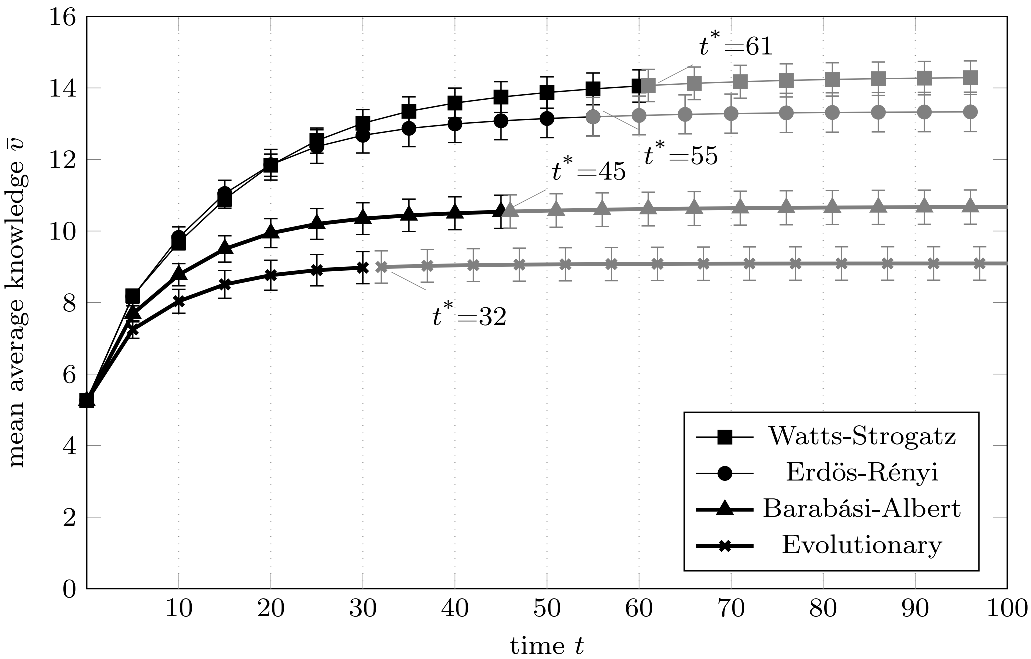


FIGURE 2.2: Mean average knowledge levels $\bar{v}$ of agents in the respective networks over time after 500 simulation runs.

In Table 2.1, we present network characteristics, i.e. average path length and global cliquishness of our four network topologies. Following the idea that path length and cliquishness are the main factors influencing the diffusion of knowledge, we now can investigate the relationship between these two characteristics and the diffusion performance shown in Fig. 2.2.

Our results reveal a positive relationship between path length and the average knowledge levels of nodes for the four network topologies. In fact, the networks with the lowest average path length are the networks that perform worst, i.e. the EV networks. However, the second network characteristic shown in Table 2.1 also fails to coherently explain the simulation results. While WS networks, which

TABLE 2.1: Average path length and global clustering coefficient (cliquishness) of the four network topologies over 500 simulation runs.

	Watts-Strogatz	**Erdős-Rényi**	**Barabási-Albert**	**Evolutionary**
Path length	4.49	3.45	2.99	2.74
Cliquishness	0.32	0.03	0.13	0.27

show the highest level of cliquishness, also result in the highest average knowledge levels, networks with the second best performance (ER networks) have the lowest average cliquishness. Moreover, the average path length of the BA and EV networks are quite similar, however, the average cliquishness of EV networks is twice the cliquishness of BA networks and yet BA networks still outperform EV networks. Interestingly, these patterns remain robust even for different values of absorptive capacities (see Fig. 2.3). To analyse the effect of different values of absorptive capacities (α), Fig. 2.3 depicts the average knowledge levels in the networks for different values of α. To be able to compare the results, we extend the number of steps analysed to 1000 which ensures that the diffusion process stops and reaches a final state in all cases.

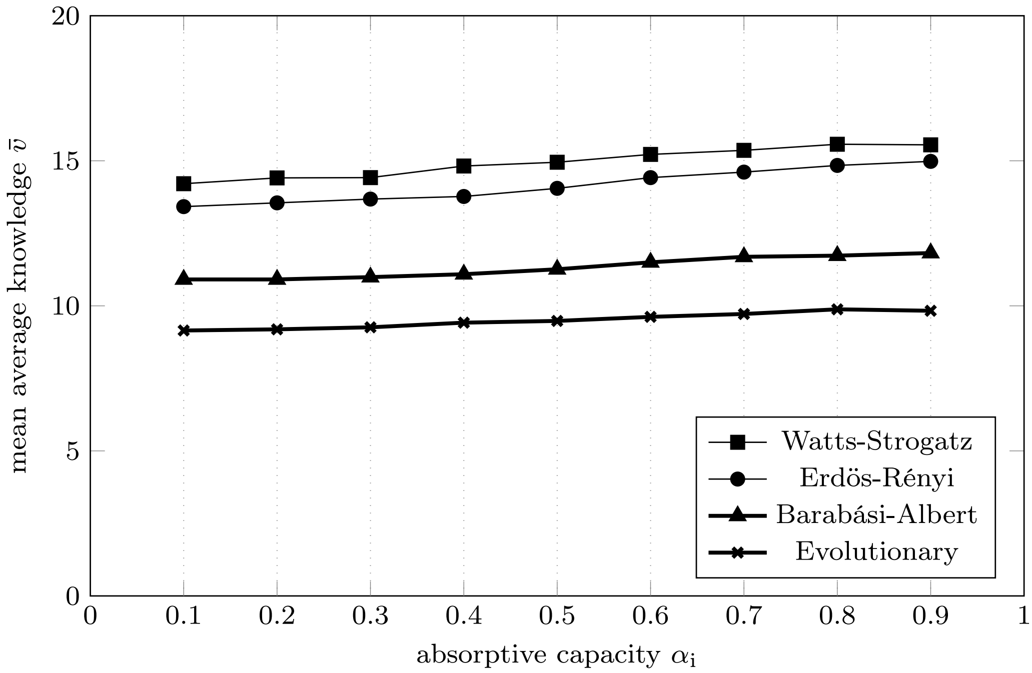


FIGURE 2.3: Mean average knowledge levels $\bar{v}$ of agents after 1000 steps for different levels of absorptive capacities.

These counter-intuitive results prompt the question of whether a network's path length and its cliquishness can fully explain the differences in the diffusion performance between the observed networks. Following the ideas of Cowan and Jonard (2007) and Lin and Li (2010), a network characteristic that may explain the differences in network performance is the distribution of links among agents.

In more detail, Cowan and Jonard (2007) found that, in a barter economy, knowledge diffusion performance can be negatively affected by the existence of 'stars', i.e. agents with a relatively high number of links (degree centrality) compared to other agents in the network. According to the authors, these stars negatively influence diffusion performance on the network level because stars have so many partners that they acquire all the knowledge they can in a very short time and learn much faster than their counterparts. This rapidly leads to a lack of 'double coincidences of wants' as the stars have so much knowledge that their partners have nothing left to offer as a barter object (i.e. $n_{(\text{i, star})} = \#(c : v_{(\text{i, c})} > v_{(\text{star, c})}) = 0 \rightarrow min[n_{(\text{i, star})}, n_{(\text{star,i})}] = 0$). This lack of double coincidences of wants blocks active trading links, stops the knowledge trading process within the network, and, thus, may even disconnect the entire network: "If the stars are traders, because they have many partners, they will rapidly acquire all the knowledge they need, and so stop trading. This blocks many paths between agents, and in the most extreme case, can disconnect the network." (Cowan and Jonard 2007, p. 108).

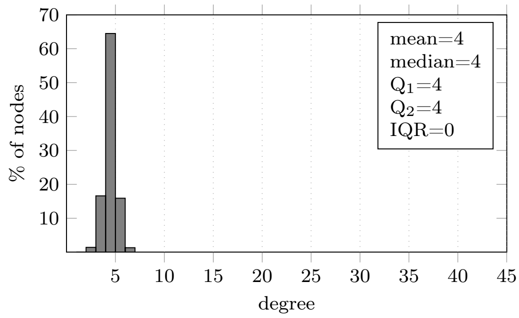
Encouraged by this explanation, we conducted several simulation experiments to see the extent to which a network's degree distribution actually affects diffusion processes. The main question that comes up at this point is whether the explanation given by Cowan and Jonard (2007) is sufficient to explain the differences in the simulation results. To address this issue we explored which nodes in a network stop trading early and why they do so. This helps us to get a deeper insight into why a skewed degree distribution hinders knowledge diffusion and whether the stars are responsible for a lower diffusion performance.

2.3.2 Degree Distribution and Network Performance

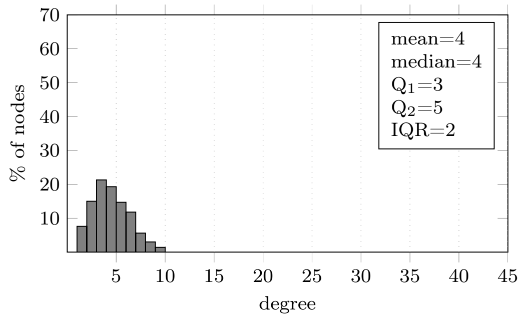
Next, we explore the relationship between degree distribution and network performance. The information depicted in Fig. 2.4 shows that the networks analysed in this paper do not only differ significantly in terms of their performance, but also with respect to the distribution of degrees. The worst performing networks, i.e. BA and EV networks, are networks that have a highly skewed and dispersed degree distributions which approximately follow a power law. Even though all networks by definition have the same average degree of four, BA and EV networks are characterised by a large number of small nodes (having only a few links) and a few nodes with an extremely high degree. In contrast, WS and ER networks have more symmetric degree distributions with only small deviations from the average degree of the network. These better performing networks are characterised by a less asymmetric degree distribution. The worse performing networks indeed have a more asymmetric degree distribution than the better performing networks.

To further analyse the effect of the degree distribution on diffusion performance, we show in Fig. 2.5 (left) the relationship between the variance of the degree distribution and the mean average knowledge level $\bar{v}$ in the respective networks achieved after 100 simulation steps. Additionally, Fig. 2.5 (right) also shows the cumulative number of non-traders in the network over time. In contrast to path length and cliquishness, we see that the variance of the degree distribution of networks shows a coherent effect on network performance. WS networks, which perform best, are characterised by the lowest variance in the nodes' degrees, while at the same time, showing the highest knowledge levels. The worst performing networks, i.e. EV networks, are also those networks with the highest variance in their degree distribution.

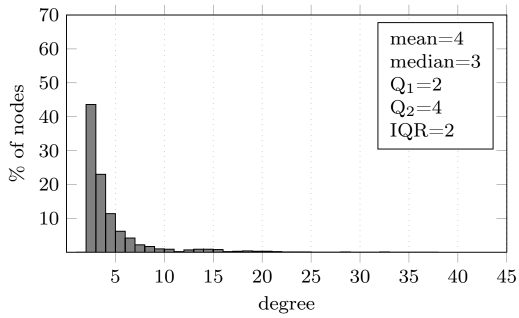
If we now look in more detail at the number of non-traders over time (Fig. 2.5 right), we can see that, in the worse performing networks, agents stop trading earlier than in the better performing networks, i.e. the diffusion process stops



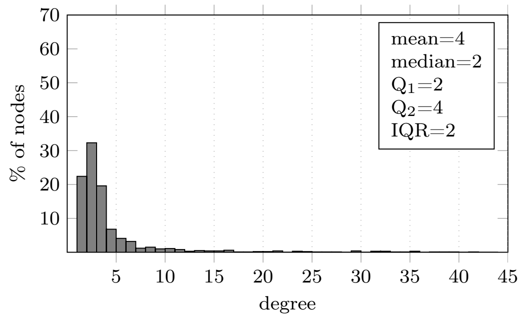
(A) Watts-Strogatz Networks



(B) Erdös-Rényi Networks

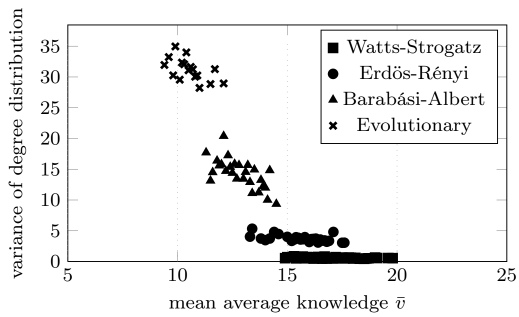


(C) Barabási-Albert Networks



(D) Evolutionary Networks

FIGURE 2.4: Average degree distribution of the agents in the respective networks.



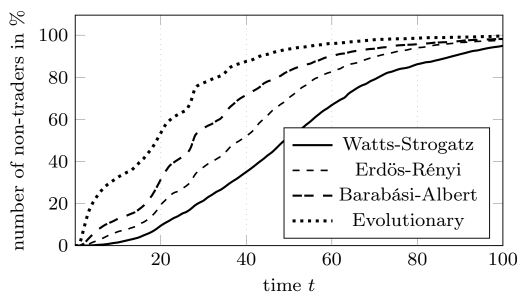


FIGURE 2.5: Relationship between the variance of the degree distribution and the mean average knowledge level $\bar{v}$ in the respective networks (left) and the cumulative number of non-traders over time (right).

earlier. Comparing EV and WS networks after 40 time steps we see that, while almost 90% of the agents in EV networks have already stopped trading, 65% of the agents in WS networks are still trading. Moreover, in EV networks, almost all agents stopped trading after 70 time periods, whereas in WS networks this occurs 30 time steps later.

Figure 2.5 provides evidence that the reason why networks with asymmetric degree distribution perform poorly is that agents stop trading early and, hence, disrupt the knowledge flow. However, the question at hand is: why?

To answer this question, Figs. 2.6 and 2.7 show the relationship between the nodes' degrees and the time when these nodes stop trading as well as the relationship between the nodes' degrees and their knowledge level acquired over an

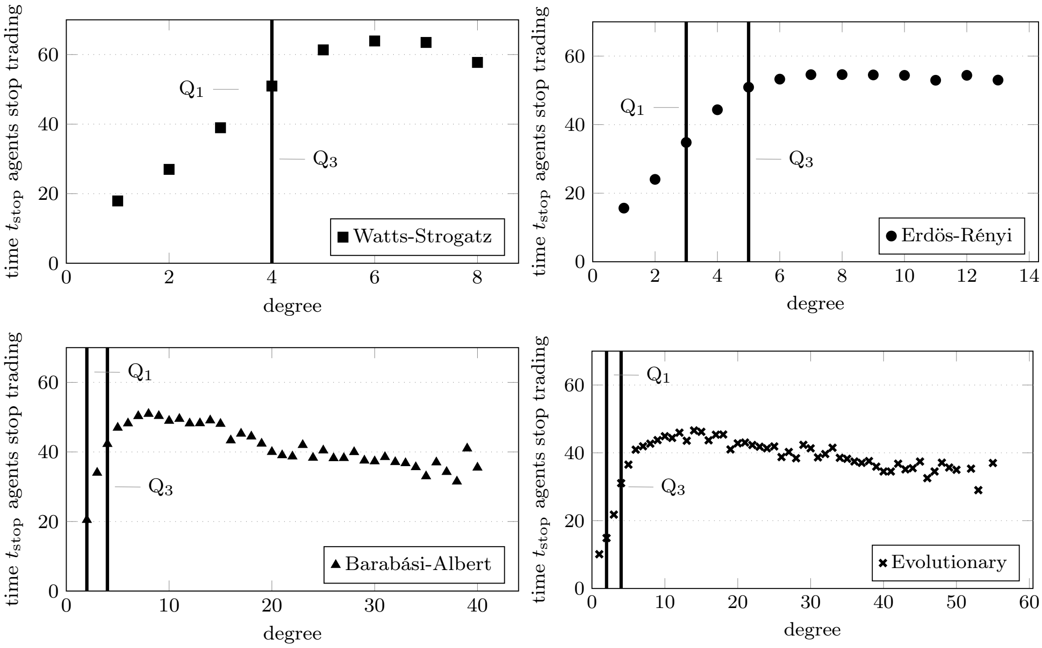


FIGURE 2.6: Relationship between the time the agents in the network stop trading and their degree. The vertical lines represent the 0.25 quartile (Q1) and the 0.75 quartile (Q3) of the degree distribution.

average of 500 simulation runs. Figure 2.6 shows that, in general, there is a positive relationship between the size of an agent and the time it stops trading, especially for networks with dispersed degree distribution (i.e. BA and EV networks). This positive relationship always holds for the first three quartiles (the lower 75%) of the distribution. So, in the lower 75% of the distribution, nodes actually stop trading earlier the fewer links they have. However, we see that, especially in networks with asymmetric degree distribution, this relationship fails for nodes with an extremely high number of links (the fourth quartile or the upper 25% of the distribution).

From this exploration, we can conclude that nodes with a high number of links do not stop trading first. In contrast, our results indicate that small nodes (the lower two quartiles of the distribution) stop trading first. Big nodes stop trading later, however, medium-sized nodes trade the longest. As a consequence, the poor performance of networks with a dispersed degree distribution can be explained by the sheer number of small nodes. Interestingly, as indicated by the quartiles of the BA and EV networks, it is important to note that when we speak of small nodes that stop trading earlier than big nodes, we are referring to the majority of nodes, i.e. over 50% of all nodes. If we now combine the information values provided by Figs. 2.6 and 2.2, we also see that nodes with a high degree actually stop trading after the increase in knowledge levels has reached its peak and almost no knowledge is traded within the network anymore.[5]

To further investigate why nodes stop trading, we illustrate, in Fig. 2.7, the relationship between a node's degree and the mean knowledge v_i the nodes reaches

[5]See also Fig. 2.2: The point in time the knowledge stock in the network has reached its steady state $\bar{v}*$ is $t* = 61$ for Watts–Strogatz networks, $t* = 55$ for Erdős–Rényi networks, $t* = 45$ for Barabási–Albert networks, and $t* = 32$ for networks created with the Evolutionary network algorithm.

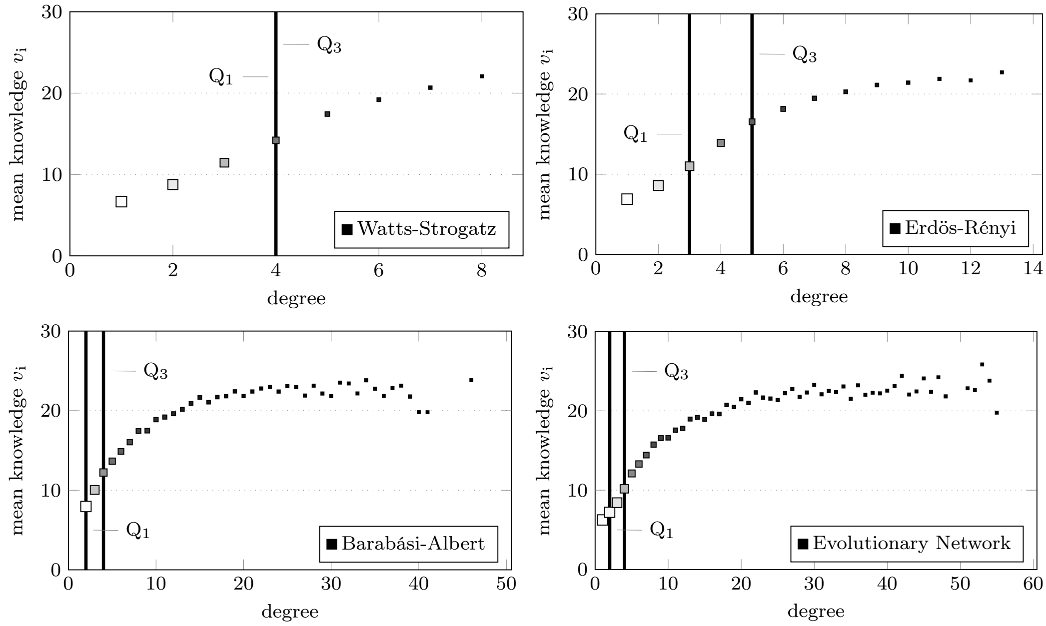


FIGURE 2.7: Relationship between the agents' mean knowledge levels v_i, their degree and the reason why agents eventually stopped trading (after 100 steps).

after 100 time steps averaged over 500 simulation runs. Additionally, the size and the colour of the marks indicate the reason why nodes do not trade knowledge. The data clearly shows a positive relationship between a node's degree and its acquired knowledge level v_i. So, in general, the more links a node has, the more knowledge it will receive. This positive effect, however, decreases for nodes with many links, indicating a saturation phenomenon for nodes with a high number of links in the network.

In addition to the relationship between degree and the time at which nodes stop trading, Fig. 2.7 also shows us why these nodes eventually stop exchanging knowledge.[6] While white marks indicate that nodes with the respective degree centrality stop because they could not offer knowledge to their trading partners, black marks indicate that these nodes stop trading because their partners do not offer them enough knowledge as a sufficient barter object. As the figure shows, we see that especially small nodes stop trading because they cannot offer knowledge to their partners. Nodes with a high degree stop trading because their partners cannot offer new knowledge. Medium-sized nodes (with grey marks), by contrast, stop trading because they have too much knowledge for their small partners and too little knowledge for their very large partners.

In summary, we can confirm the results of Cowan and Jonard (2007) that for barter trade diffusion processes the degree distribution of nodes is of decisive importance, even more important than other network characteristics such as path length and cliquishness. Based on our simulation results, we come to the conclusion that, in fact, nodes with a high number of links acquire much more knowledge than most of the other agents in the network (Fig. 2.7). They stop trading

[6]To determine why a node stops trading we define a variable for each node which contains the information on whether its unsuccessful trades failed because the respective node had insufficient knowledge or whether its trading partner actually had insufficient knowledge. The colour marking indicates the average results over a simulation run of 100 time steps.

because their partners have nothing left to offer, however, the difference in diffusion performance between the four network topologies cannot be solely explained by the 'star' argument. In fact, our results indicate a second effect which seems to dominate the diffusion processes in the networks. Very small agents with only few links are only able to receive very little knowledge and, hence, stop trading first. Considering the sheer number of small nodes in networks with a dispersed degree distribution we have to assume that these small nodes are responsible for disconnecting the network and interrupting the knowledge flow. This, in turn, negatively influences the effectiveness of the diffusion of knowledge within the entire network.

To tackle the question about whether the absolute degree of nodes in the network is the decisive factor influencing diffusion performance or whether the relative position (i.e. the difference between nodes and their partners) is most important, Fig. 2.8 shows the relationship between the node's knowledge level and its relative positions in the network (δ). As we see in Fig. 2.8, for the barter trade diffusion process, the node's relative position is of decisive importance. For all network topologies, nodes with an advantageous relative position (i.e. with a positive degree difference δ between nodes and their partners $\delta_{\mathrm{i}} > 0$) demonstrate a considerably higher knowledge level compared to nodes with fewer links ($\delta_{\mathrm{i}} < 0$). This effect is particularly strong for degree differences of $\delta_{\mathrm{i}} = -5$ to $+5$. However, we also see that more extreme degree differences do not considerably increase or decrease a node's knowledge level, which again indicates a saturation effect.

Our results demonstrate that neither path length nor cliquishness are fully sufficient for explaining the performance of knowledge diffusion in networks. Other factors, such as the degree distribution, have to be considered in order to fully understand the relevant processes within networks. In contrast to the findings of Cowan and Jonard (2007), our results show that the dissimilarities between nodes - especially for dispersed networks with scale-free structures - can create gaps in knowledge levels. These gaps create a situation where small nodes, which make up the majority of nodes in these networks, do not gain knowledge fast enough to keep pace with the other nodes in the networks. Hence, the many small agents rapidly fall behind and stop trading, which disrupts and disconnects the network and the knowledge flow. Comparing medium-sized nodes and big nodes, however, we also see that stars play a key role in networks.

2.3.3 Policy Experiment

From a policy perspective, it is important to note that network topologies can be systematically shaped and designed. In other words, the structural configuration can be manipulated by policy maker and other authorities in order to increase the knowledge diffusion efficiency of the system. Against the backdrop of Sect. 2.3.2 the question, however, arises as to how the system can be manipulated to gain a performance increase on a systemic and on an individual level. Our policy experiment is conducted as a comparative analysis in which we add new links to an existing network. The general idea behind this is straightforward. We first define three subgroups within the population of nodes and then systematically analyse the effect of adding new links within and between the predefined subgroups.[7] In

[7] In the policy intervention, we define 'stars' as those 10% of all nodes that have the highest degree centrality, whereas 'small' is defined as those 10% of the distribution that have the lowest degree centrality. 'Medium' agents are those 80% of the distribution that are neither 'stars' nor 'small'.

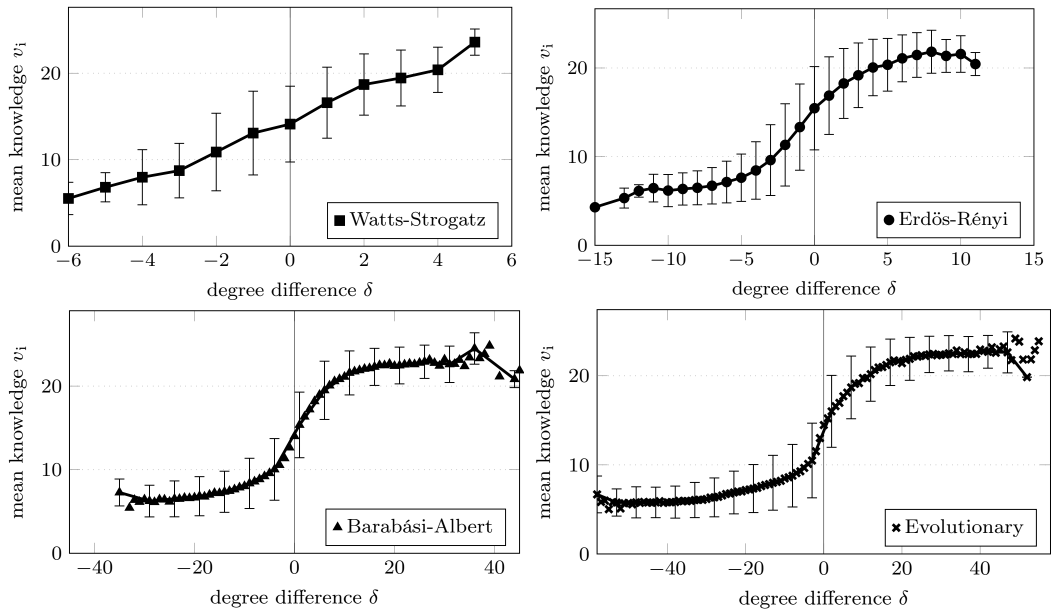


FIGURE 2.8: Relationship between agents' mean knowledge levels v_i and the degree difference δ between them and their partners (after 100 steps). Where $\delta_i > 0$, indicating node i has more links than its partners and $\delta_i < 0$, indicating node i has fewer links than its partners.

this section we present an exemplary policy experiment in which we analyse the effect of six interventions.

As a baseline scenario, we assume a situation where we have no intervention at all, i.e. the number of links in the network does not change, which is indicated by the horizontal reference line in the plots. This 'no intervention' scenario is used as a reference or control scenario for the actual policy interventions. Intervention 1, 'stars-to-stars', shows the diffusion performance in a situation in which we equally distributed 20 additional links between stars. Intervention 2, 'stars-to-medium', shows the diffusion performance in a situation in which we distributed 20 new links between stars and medium nodes. Intervention 3, 'stars-to-small', shows the diffusion performance in a situation in which we distributed 20 new links between stars and small nodes. Intervention 4, 'medium-to-medium', shows the diffusion performance in a situation in which we equally distributed 20 new links between medium nodes. Intervention 5, 'small-to-medium', shows the diffusion performance in a situation in which we distributed 20 new links between small and medium nodes. Finally, intervention 6, 'small-to-small', shows the diffusion performance in a situation in which we equally distributed 20 new links between small nodes.

As shown in Fig. 2.9, all interventions applied to 'stars' (1, 2 and 3) actually may have a negative (or, at best, a marginally positive) impact on network performance. This is interesting because additional links should improve the network's performance as they create new trading possibilities. However, for networks with a symmetric degree distribution, these additional links limit knowledge flow. The explanations for this can be found when we look at the degree distribution of the

To measure the performance of the policy interventions we measure the steady-state knowledge stock $\bar{v}*$ for every policy after 100 simulation steps and over 500 simulation runs.

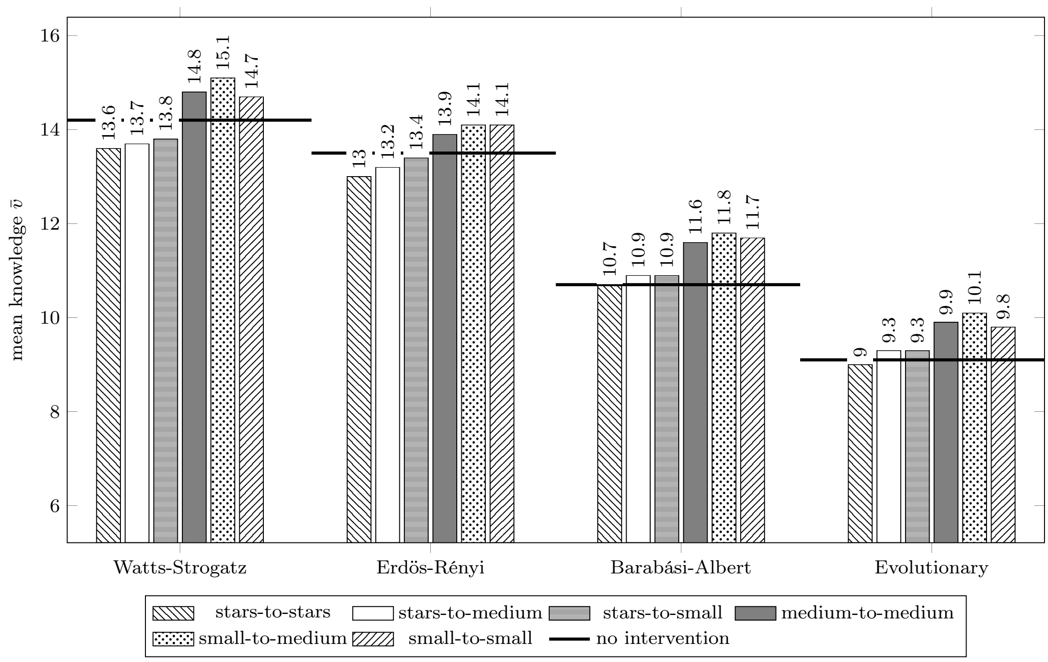


FIGURE 2.9: Effect of different policy interventions on mean average knowledge levels $\bar{v}$.

networks. Although additional links in the network open new trading possibilities, they also increase the asymmetry of the degree distribution. This leads to the effects described in Sect. 2.3.2. On the one hand, small nodes stop trading early because they have too little knowledge. On the other hand, nodes with a high number of links stop trading because they do not find partners with sufficient knowledge levels. On the overall network level, policy interventions supporting 'stars' or 'picking-the-winner' strategies, therefore, never seem to be recommendable as they increase the asymmetry of the networks.

If we now analyse all interventions applied to small nodes (3, 5 and 6),we see that the overall effect is positive (or in the worst case there is no effect). Interventions aiming at small nodes do not increase the asymmetry in the degree distribution, but rather reduce it. This, in turn, relativises the effects discussed in Sect. 2.3.2. Interestingly, the best performing intervention at the system level is not a 'small-to-small' intervention - as one may presume based on the findings in Sect. 2.3.2 - but rather interventions creating links between small and medium-sized nodes.

While the experiment in Fig. 2.9 analysed the implications of our findings on an aggregated network level, we also have to consider the individual level. Let us start with recalling that the disparate structure of the network itself is only the result of the myopic linking strategies of its actors. In BA and EV networks, one key element of the actors' strategies is preferential attachment, according to which linking up to other high degree actors is likely to increase the individual knowledge stock. Yet this linking strategy leads to the network characteristics discussed above which hinder the diffusion process on the network level, and this, in turn, prevents smaller nodes from gaining knowledge. To put it another way, the limiting network characteristics, which hinder the knowledge diffusion at both the actor and the network level, are actually caused by the behaviour of small nodes which aim to receive knowledge from larger nodes. Hence, in contrast to how small nodes actually behave in BA and EV networks, the optimal strategy for

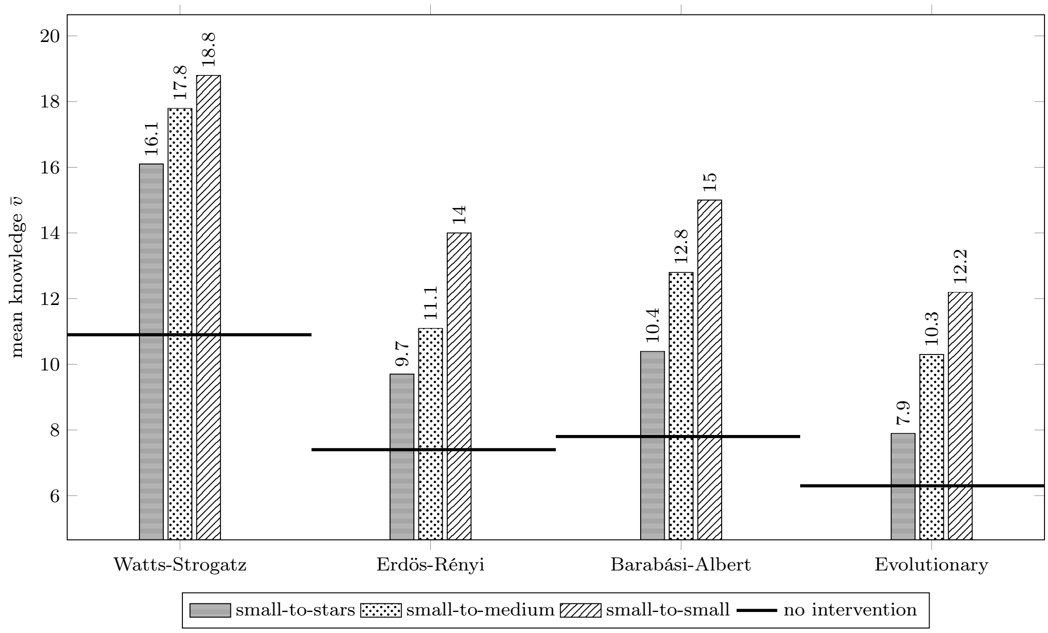


FIGURE 2.10: Effect of different policy interventions on the mean average knowledge levels $\bar{v}^{\text{small}}$ of the 10% smallest agents.

gaining knowledge might actually be to link up with other small nodes.

By looking at Fig. 2.10 we see that this actually holds. Although on the global scale the linking of small and medium nodes performed best, at the individual level and, more specifically, for small nodes, the best strategy to gain an individually superior knowledge level is to connect with nodes that are most similar to them, i.e. to follow a strategy inspired by structural homophily.

2.4 Discussion and Conclusions

Economic actors - or to use the more technical term 'agents' - in economies are becoming increasingly connected. Most scholars in the field of interdisciplinary innovation research would agree that "networks contribute significantly to the innovative capabilities of firms by exposing them to novel sources of ideas, enabling fast access to resources, and enhancing the transfer of knowledge" (Powell and Grodal 2005, p.79). However, systems in which economic actors are involved are anything but static or homogenously structured and - even more important in this context - structural properties affect the diffusion performance of the entire system. We consciously restricted this analysis on four distinct network topologies in our attempts to learn more about knowledge diffusion in networks. To reiterate, the four applied algorithms and analysed network topologies mirror, at best, a small selection of structural particularities of networks.

Previous research has significantly enhanced our understanding of knowledge diffusion processes in complex systems. Some scholars have studied the effect of small-world networks - characterised by short path lengths and high cliquishness - and their effect on the diffusion of knowledge. Others have added some additional explanations to the debate by showing that a network's degree distribution seems to play a decisive role in efficiently transferring knowledge throughout the pipes and prisms of a network.

Inspired by the insights of these studies, we were curious to understand which network characteristic dominates the knowledge diffusion efficiency both at the overall network level as well as at the individual level. Accordingly, we employ an agent-based simulation approach, implemented four network formation algorithms and integrated a barter trade knowledge process to analyse how and why structural properties affect diffusion efficiency. Our analysis shows that 'small-world' properties do not matter in the analysed settings. Instead, our results indicate that the degree distribution has a pronounced effect on the outcome of the simulation. In fact, our simulation results show that a highly asymmetric degree distribution has a negative impact on the overall network performance. This is not really surprising but fully in line with the explanation given in Cowan and Jonard (2007).

Our analysis shows that, consistent with the findings of Cowan and Jonard (2007), a highly asymmetric degree distribution actually has a negative impact on the overall network performance. However, we find that this negative effect cannot solely be explained by the existence of stars. Our results show that stars neither acquire more knowledge than, e.g. medium-sized agents, nor do they stop trading earlier. In fact, our findings indicate that stars often only stop trading after the network has almost reached its steady-state knowledge stock. The group of agents that actually has a very low level of knowledge and stops trading long before most of the knowledge has already been diffused throughout the network, is the group of very small, inadequately embedded agents.

More precisely, our results support the idea that the difference between large and small nodes is actually what hinders efficient knowledge diffusion. Because the dissimilarities in the degree distribution are the direct result of the individual linking strategies (e.g. preferential attachment), we conclude that the limiting network characteristics, which hinder knowledge diffusion in the network, are actually caused by the individual and myopic pursuit of knowledge by small nodes. Hence the optimal strategy for small nodes to gain knowledge is to link up with other small nodes. This - as outlined above - turns out to foster efficient knowledge diffusion within the network. In contrast, other strategies hamper knowledge diffusion in the system.

Finally, we conducted a policy experiment to stress the implications of these findings. The experiment revealed that, on an individual level, links between small nodes and other small nodes are best on the global level, the best strategy would be to support links between small and medium-sized nodes. Obviously, individual, optimal linking strategies of actors (i.e. small-to-small), and policy interventions that aim to enhance the diffusion performance at the systemic level (i.e. small-to-medium), are not fully compatible. This, however, has far-reaching implications. Policy makers need to implement incentive structures that enable small firms to overcome their myopic - and at first glance - superior linking strategy. In other words, if it succeeds in collectively fostering superior linking strategies, the diffusion efficiency of the system increases noticeably to the benefit of all actors involved.

All in all, our simulation comes to the conclusion that policy makers must be aware of the complex relationship between degree distribution and network performance. More precisely, our results support the idea that, in the case of research funding, always 'picking-the-winner' - without knowing the exact underlying network structure - can be harmful. Efficient policy measures depend on the respective network structure as well as on the overall goal in mind.

Our work prompts the following two policy recommendations: Firstly, without knowing the exact underlying network structure, it is almost impossible for policy intervention to influence network structure to increase knowledge diffusion performance. Our policy experiment shows that some policy measures can even be harmful to some network structures. The second policy recommendation is that, if the practical relevance of our results can be confirmed by further research, policy makers should be conscious of the dissimilarity of the agents' links in informal networks instead of always 'picking the winner'. This would imply that the very small agents, in particular, have to be sufficiently integrated into the network. In order to confirm our results, and to obtain a deeper understanding of the explanation of our results, further research is required, especially on network structures that evolve over time.

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Chapter 3

Knowledge Diffusion in Formal Networks: The Roles of Degree Distribution and Cognitive Distance

Chapter 3

Knowledge Diffusion in Formal Networks: The Roles of Degree Distribution and Cognitive Distance

Abstract

Social networks provide a natural infrastructure for knowledge creation and exchange. In this paper, we study the effects of a skewed degree distribution within formal networks on knowledge exchange and diffusion processes. To investigate how the structure of networks affects diffusion performance, we use an agent-based simulation model of four theoretical networks as well as an empirical network. Our results indicate an interesting effect: neither path length nor clustering coefficient is the decisive factor determining diffusion performance but the skewness of the link distribution is. Building on the concept of cognitive distance, our model shows that even in networks where knowledge can diffuse freely, poorly connected nodes are excluded from joint learning in networks.

Keywords

agent-based simulation; cognitive distance; degree distribution; direct project funding; Foerderkatalog; German energy sector; innovation networks; knowledge diffusion; publicly funded R&D projects; random networks; scale-free networks; simulation of empirical networks; skewness; small-world networks.

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The content of the text has not been altered. For reasons of consistency, the language and the formatting have been changed slightly.

3.1 Introduction

Knowledge transfer between agents and knowledge diffusion within networks strongly depend on the underlying structure of these networks. While in the literature some structural characteristics of networks, such as the properties of small-world networks, are assumed to foster fast and efficient knowledge diffusion, other network structures are assumed to rather harm diffusion performance. So far, research on knowledge diffusion focused mainly on path length and clustering coefficient as the decisive network characteristics determining the diffusion of knowledge in networks. With this work, we aim to stress the importance of a network characteristic that is too often neglected: the degree distribution of the network. We particularly aim to analyse the effects of skewness of degree distributions. More specifically, we aim to show that in networks exhibiting few well-connected nodes and a majority of nodes with only a few links, the diffusion of knowledge is hampered and nodes with relatively few links may irrevocably fall behind.

Recent studies have shown ambiguous effects on knowledge exchange and diffusion. Some studies found that the skewness of degree distributions may hamper diffusion of knowledge, whereas others come to contrasting conclusions (e.g. see Cowan and Jonard, 2004, 2007; Kim and Park, 2009; Lin and Li, 2010; Mueller et al., 2016). More specifically, the literature suggests that in cases where knowledge diffuses freely throughout the network, the skewness of degree distributions can have a positive effect on the overall knowledge diffusion level. Nodes with a relatively high number of links rapidly absorb and collect knowledge from the network and simultaneously distribute this knowledge among all nodes. In contrast, it has also been argued that in cases of a knowledge barter trade, a skewed degree distribution can lead to the interruption of the diffusion process for all nodes in the network. Building on the concept of cognitive distance (Boschma, 2005; Morone and Taylor, 2004; Nooteboom, 1999, 2008; Nooteboom et al., 2007) our analysis aims to investigate whether this pattern also holds if we assume that knowledge diffuses freely but that learning, i.e. the capability to absorb new knowledge from other nodes, depends on nodes' cognitive proximity and follows an inverted u-shape. To stress the relevance of our work also for the empirical case, our analysis includes an empirical research and development (R&D) network in the German energy sector. Additionally, we apply four network algorithms found in the literature with unique network characteristics.

The structure of our paper is as follows: we start with a glimpse on relevant literature on knowledge diffusion within networks. We then describe the knowledge diffusion model used in our simulation and characterise the empirical R&D network. In the third section, we introduce benchmark networks and present the model setup and parametrisation. Finally, we discuss the results of our simulation both on the network and on the actor level. The last section of this paper summarises our findings and gives an outlook on further research avenues.

3.2 Modelling Knowledge Exchange and Knowledge Diffusion in Formal R&D Networks

3.2.1 Network Structure, Learning and Knowledge Diffusion Performance in Formal R&D Networks

Networks play a central role in the exchange of knowledge and the diffusion of innovations. As, for example, Powell and Grodal (2005, p.79) note: "Networks contribute significantly to the innovative capabilities of firms by exposing them to novel sources of ideas, enabling fast access to resources, and enhancing the transfer of knowledge". Interorganisational knowledge exchange within and across innovation networks is of growing importance for the competitiveness of firms, sectors, and countries (Herstad et al., 2013).

With the emergence of network science (e.g. Barabási, 2016), an increasing number of scholars started to focus on analysing the interplay between network characteristics and the diffusion of knowledge and innovation between and within organisations as well as individuals (see also Cointet and Roth, 2007; Cowan, 2005; or Luo et al., 2015, for an overview). While some studies rather capture the interplay between networks and knowledge diffusion using micro measures (e.g. actor-related centrality measures) (see, e.g. Ahuja, 2000; Bell, 2005; Björk and Magnusson, 2009; Chiu, 2009; Gilsing et al., 2008; Ibarra, 1993; Owen-Smith and Powell, 2004; Soh, 2003; Tsai, 2001; Whittington et al., 2009), other studies focus on capturing the interplay between networks and knowledge diffusion by means of macro measures (such as network structure or global values including path length, clustering, degree distribution, etc.) (see, e.g. Cassi and Zirulia, 2008; Cowan and Jonard, 2004, 2007; Kim and Park, 2009; Lin and Li, 2010; Mueller et al., 2014; Reagans and McEvily, 2003; Zhuang et al., 2011, to name but a few).

On the micro level, learning by exchanging and internalising knowledge has been shown to depend on many different aspects. Researchers in this area analysed, for example, the effects of actors'

- absorptive capacities (Cohen and Levinthal, 1989, 1990),
- their centrality (e.g. Björk and Magnusson, 2009; Chiu, 2009; Whittington et al., 2009), or
- their cognitive distance (Boschma, 2005; Morone and Taylor, 2004; Nooteboom, 1999, 2008; Nooteboom et al., 2007) on learning.

For example, with regard to the first point, learning and knowledge diffusion have been found to depend strongly on the actors' individual absorptive capacities (e.g. Savin and Egbetokun, 2016). Second, several studies on centrality have identified a positive link between actors' centrality and knowledge and innovation (see, e.g. Ahuja, 2000; Bell, 2005; Björk and Magnusson, 2009; Chiu, 2009; Gilsing et al., 2008; Ibarra, 1993; Owen-Smith and Powell, 2004; Soh, 2003; Tsai, 2001; Whittington et al., 2009). Central actors in an innovation network have better access to resources, greater influence and a better bargaining position due to their position in the network. This becomes particularly relevant for the 'preferential attachment' aspect (Barabási and Albert, 1999) of link formation strategies. Finally, concerning cognitive distance, studies have shown that if and how actors are able to learn and integrate knowledge from each other depends on the relatedness of their knowledge stocks or their cognitive distance (e.g. Nooteboom, 1999, 2008; Nooteboom et al., 2007). As Nooteboom concisely puts it: "Cognitive proximity enables understanding. But there must also be novelty, and hence sufficient cognitive distance, since otherwise the knowledge is redundant: nothing new is learned" (Nooteboom 1999, p.140).[1]

On the macro level, the picture is similarly complex and knowledge diffusion is also determined by various interdependent aspects. Important objects of investigation are, for example, the effects of path length and cliquishness of networks (Cowan and Jonard, 2004; Lin and Li, 2010; Morone et al., 2007, to name just a few), or degree distribution of networks (Cowan and Jonard, 2007; Kim and Park, 2009; Mueller et al., 2016) on knowledge diffusion.

It is assumed that a short path length increases diffusion efficiency, as it improves the speed of knowledge diffusion processes. Moreover, a high cliquishness is also assumed to increase diffusion efficiency.[2] However, previous studies suggest that these two network characteristics cannot exclusively explain knowledge diffusion performance. Instead, these studies stress that the degree distribution is also of decisive importance (Cowan and Jonard, 2007; Kim and Park, 2009; Mueller et al., 2016).

Depending on the underlying learning and diffusion mechanism, a skewed degree distribution has been identified to have ambiguous effects on knowledge exchange and diffusion. Some studies found that in situations where knowledge can diffuse freely throughout the network, knowledge exchange is most efficient in networks with some well-connected nodes with many links (Cowan and Jonard, 2007; Lin and Li, 2010). Following this idea, well-connected nodes absorb and collect knowledge from the network and simultaneously distribute it among the nodes in the network, thereby serving as some kind of 'knowledge funnel'. As opposed to this, other studies show that if knowledge is not diffusing freely through the network (e.g. as a consequence of exchange restrictions as in a barter trade) skewed degree distributions may hamper learning on a network and on an agent level. In this case, nodes with only a few links are only able to receive very little knowledge and, hence, stop trading quickly. This, in turn, disconnects the network, hereby interrupting knowledge flows between most nodes (e.g. Cowan and Jonard, 2004, 2007; Kim and Park, 2009; Mueller et al., 2016).

3.2.2 Modelling Learning and Knowledge Exchange in Formal R&D Networks

With our model, we aim to show whether the pattern described above holds if we assume that sharing knowledge is not restricted by a barter trade but that learning, i.e. the capability of absorbing new knowledge from others, depends on the cognitive distance between nodes. While the particularities of the knowledge exchange mechanism are relevant for informal networks, the distinctive properties of learning are relevant for both, informal and formal networks: In contrast to informal networks, actors in a formal network often have an official agreement on knowledge exchange and intellectual property rights (IPR) (see, e.g. Hagedoorn, 2002; Ingham and Mothe, 1998). Consequently, the assumption of a barter trade

[1] At which cognitive distance agents can still learn from each other also depends on the specificity, variety, and homogeneity of knowledge within a sector. For example, knowledge in the service sector is rather homogeneous and less specific than, for instance, in the biotech sector. Consequently, we would assume the maximum cognitive distance at which agents can still learn from each other to be much higher in the service sector than in the biotech sector.

[2] See also the discussion on structural holes (Burt, 1992) and social capital (Coleman, 1988).

for knowledge exchange is not feasible. Instead, we assume in our model that all actors in the networks exchange knowledge freely with their adjacent partners. However, even though all agents freely give away their knowledge, there is a restriction on the extent of the knowledge exchange. Building on the works of Nooteboom (1999), Morone and Taylor (2004), Nooteboom et al. (2007), and others, we focus on the importance of actors' cognitive distance. Actors can learn from each other (defined as receiving and also integrating new knowledge) as long as their knowledge stocks are neither too close nor too different from their partners' knowledge stocks.[3] Consequently, in a formal R&D network of publicly funded project partners, as in the empirical R&D network example analysed below, the most suitable and plausible assumption is that knowledge can only be integrated depending on actors' cognitive distance.

Building on these theoretical deliberations, we model learning and knowledge exchange as follows: Each network is equipped with a set of actors $I = (1, ..., N)$, where N denotes the number of actors in the network at time t . Every agent $i \in I$ is endowed with a knowledge vector $v_{\mathrm{i,c}}$ with $i = 1, ..., N; c = 1, ..., K$ for the K knowledge categories. Each time step $t = 1, .., T$, knowledge is exchanged in all knowledge categories between all actors in the network that are directly linked. Knowledge is always exchanged between all directly connected actors $i, j \in I$ with $i \neq j$, which means that j receives knowledge from i in all knowledge categories where i outperforms j, and i receives knowledge from j in all knowledge categories where j outperforms i. However, the mere fact that knowledge is exchanged if actors are directly linked does not mean that these actors actually learn from each other and integrate the knowledge they receive.

As already explained above, whether or not actors can integrate external knowledge depends on the cognitive distance between them and their partners. To be more specific, we assume a global maximum cognitive distance Δ_{max} that reflects the highest cognitive distance which still allows actors to learn from each other. Within this range, learning takes place following an inverted u-shape (following, e.g. Nooteboom, 1999, 2009; Morone and Taylor, 2004, and Nooteboom et al., 2007, illustrated in Figure 3.1). So, even though connected agents always exchange knowledge in all knowledge categories $c = 1, ..., K$ in their knowledge vector $v_{\mathrm{i,c}}$, an agent i's knowledge stock only increases in those categories in which $(c_{\mathrm{i}} - c_{\mathrm{j}}) \leq \Delta_{\mathrm{max}}$ holds. In this case, actor i's knowledge stock increases according to $(1 - ((c_{\mathrm{i}} - c_{\mathrm{j}})/\Delta_{\mathrm{max}})) \times ((c_{\mathrm{i}} - c_{\mathrm{j}})/\Delta_{\mathrm{max}})$. If otherwise, actors are unable to integrate knowledge and, therefore, cannot increase their knowledge level μ_{i} in the respective knowledge category c.

Following these ideas, actors in the model mutually learn from each other and knowledge diffuses through the network. Thereby, the mean knowledge stock of all actors within the network $\mu = \bar{v} = \sum_{i=1}^{N} v_{\mathrm{i}}/I$ increases over time. As knowledge is considered to be non-rival in consumption, an economy's knowledge stock can only increase or stay constant since an actor will never lose knowledge by sharing it with other actors. In our analysis, we assume network structures to be better performing than other network structures if the overall knowledge stock is higher and increases faster over time.

[3]Of course, the actual meaning of 'too close' and 'too different' is open to discussion and will heavily influence learning and knowledge diffusion.

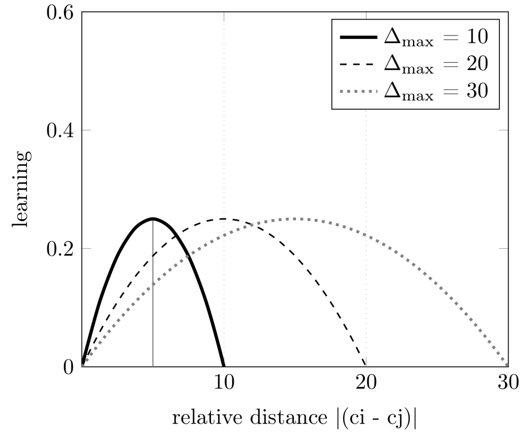

FIGURE 3.1: Knowledge gain for different $\Delta_{\max}$.

3.2.3 The R&D Network in the Energy Sector: An Empirical Example

To stress the relevance of our work also for the empirical case, our analysis includes an empirical R&D network in the German energy sector that is based on data gathered from the database of joint R&D projects funded by the German federal government.[4] We choose this network as an empirical example of a formal collaboration network characterised by a skewed degree distribution. From the project database, we extracted all research collaborations between research partners in the energy sector in 2015. We then constructed a network of actors engaging in research projects. Possible actors (nodes) in the network include firms conducting research, universities, municipal utilities, and research organisations. Correspondingly, links between nodes represent joint projects funded by the government in 2015. In more detail, the subsidised R&D innovation network in the German energy sector is a purposive project-based network with many different participants of complementary skills. Project-based networks fundamentally differ from informal or business networks (Grabher and Powell, 2004). We can assume that project networks exhibit a higher level of hierarchical coordination than other networks and include both inter-organisational and interpersonal relationships (Grabher and Powell, 2004). In contrast to informal networks, formal project-based networks are created for a specific purpose and aim to accomplish specific project goals. Collaboration in these networks is characterised by a project deadline and, therefore, of limited duration.

In our empirical R&D network, we have 1401 actors and 4218 links (BMBF Bundesministerium für Bildung and Forschung, 2016). The most central actors with the highest number of links are research institutes, universities, and some large-scale enterprises. It is important to note that the links between the actors in the innovation network are used for mutual knowledge exchange. To guarantee this mutual exchange, funded actors have to sign agreements, guaranteeing their willingness to share knowledge, which is a prerequisite for funding (Broekel and Graf, 2012). This leads to a challenging situation where - in contrast to informal networks - the question is not whether knowledge exchange takes place, but how.

A unique feature of the empirical R&D network is a tie formation process which follows a two-stage mechanism. At the first stage, actors jointly apply for funding. As research and knowledge exchange is strongly related to trust,

[4]An important contribution to the analysis of this database is made, e.g. by Broekel and Graf (2012).

this implies a high probability that actors either already know each other (e.g. from previous research) or that they have at least heard of each other (e.g. from a commonly shared research partner). Consequently, at the first stage, actors' application for funding follows a transitive closure mechanism (see, e.g. Uzzi, 1997; Wasserman and Faust, 1994). At the second stage, the government evaluates research proposals and grants funds for a small subset of proposed projects.

For both stages, it is reasonable to assume that, to some extent, a 'picking-the-winner' strategy is at work. For example, at stage one, it is likely that actors choose other actors that already successfully applied for funding or that are well known for their valuable knowledge. Second, as already indicated above, from all applications received, the German federal government will only choose a small set of projects and research partnerships they will support. One central criterion for the positive evaluation of research proposals is prior experience in research projects, which again relates to 'picking-the-winner' strategies. As Broekel and Graf already found in 2012, the structure of publicly funded R&D networks differs significantly from firm-dominated research networks (Broekel and Graf, 2012). According to the authors, R&D networks - such as the empirical R&D network in the energy sector - tend to be smaller, denser, and, as already explained above, more centralised, i.e. characterised by a highly skewed degree distribution where "the bulk of linkages is concentrated on a few actors" (Broekel and Graf, 2012, p.346).

3.3 Simulation Analysis

3.3.1 Four Theoretical Networks

In order to analyse the effect of the skewness of the degree distribution on the diffusion of knowledge, we investigate the performance of the knowledge diffusion process in terms of the mean average knowledge levels μ and knowledge equality (variance of knowledge levels σ^2) over time. We are well aware that previous literature has also pointed to the fact that network structure and diffusion processes are in a dynamic, interdependent (or, co-evolutionary) relationship (e.g. Luo et al., 2015). As Canals (2005, pp.1–2) already noted a decade ago: "The use of the idea of networks as the turf on which interactions happen may be very useful. But knowledge diffusion is also a mechanism of network building". Weng (2014, p.118) argues in the same vein that "(n)etwork topology indeed affects the spread of information among people (...) Meanwhile, traffic flow, in turn, influences the formation of new links and ultimately alters the shape of the network". Consequently, the network topology cannot solely be regarded as the 'independent variable' influencing knowledge diffusion but also as the result of previous diffusion processes and, hence, as a 'dependent variable'.

Nevertheless, using static network structures for the analysis instead can, to some extent, be justified with the complexity of analysing the influence of network structures within a dynamic framework as well as the temporary stability of formal networks. To analyse the effects of a skewed degree distribution on the diffusion of knowledge, we have to investigate this aspect in a more 'isolated' fashion by means of focusing on static networks before introducing interdependencies between diffusion processes and network structure. Additionally, it may be reasonable to argue that formal networks such as the R&D network in the energy sector are, at least temporarily, static: Due to contractual restrictions, for the duration of projects, the links within the network are fixed. New links only occur with new projects.

Additionally, we apply four network algorithms found in the literature. These networks are used as a benchmark to evaluate the influence of different network characteristics. The four networks that serve as a benchmark are

- random or Erdős-Rényi (n, M) networks (ER) (Erdős and Rényi, 1959),
- small-world or Watts-Strogatz networks (WS) (Watts and Strogatz, 1998),
- scale-free or Barabási-Albert networks (BA) (Barabási and Albert, 1999), and
- networks created by a so-called evolutionary network algorithm (EV) (Mueller et al., 2014).

While the network formation mechanisms of the first three networks are well-known from network literature (e.g. Barabási, 2016; Newman, 2010), the fourth algorithm is rather unknown and, therefore, is briefly explained in the following: The EV algorithm, originally proposed by Mueller et al. (2014), is an algorithm for the creation and representation of dynamic networks. It is based on a two-stage selection process in which nodes in the network choose link partners based on both the transitive closure mechanism and preferential attachment aspects. For every time step, each node follows a transitive closure strategy and defines a pre-selected group consisting of potential partners which they know via existing links, e.g. cooperation partners of their cooperation partners. In a second step, actors then follow a preferential attachment strategy and choose the potential partner with the highest degree centrality to form a link (for more details, see Figure 3.2 and Mueller et al., 2014). To create a static network for the analysis of the diffusion processes, for each simulation run, we analyse diffusion in the network emerging after 100 repetitions of the above-described process.

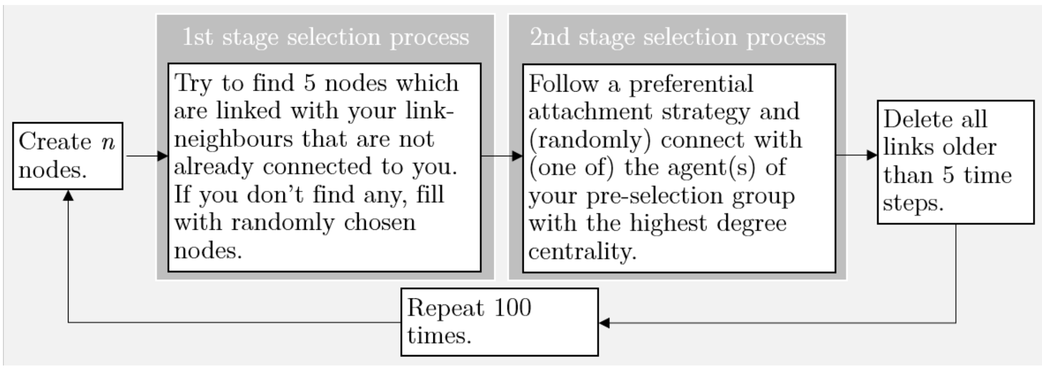

FIGURE 3.2: Flow-chart of the evolutionary network algorithm.

All benchmark networks exhibit unique configurations of network characteristics assumed relevant for knowledge diffusion performance. Random graphs (ER) are characterised by short path length, low clustering coefficient, and a relatively symmetric degree distribution following a Poisson or normal degree distribution. WS networks exhibit both a high tendency for clustering like regular networks and, at the same time, relatively short average path lengths. They are also characterised by a rather symmetric degree distribution. BA networks are characterised by small path length, medium cliquishness, highly skewed degree distributions (which approximately follow a power law and exhibit few well-connected nodes).

Networks created by the evolutionary algorithm combine characteristics of both WS and BA networks and have relatively low path lengths, high cliquishness, and a skewed degree distribution with a few well-connected nodes.

3.3.2 Model Setup and Parametrisation

To analyse the diffusion processes in the five networks we apply an agent-based simulation model built with the open source software NetLogo.[5] In order to get comparable network topologies, we focus hereafter on the biggest component of the R&D network, which leaves us with a connected network of 1401 nodes and 4218 links. The standard setting of our model is depicted in Table 3.1.

TABLE 3.1: Standard parameter setting.

Model population N	1401
Number of links L	4218
Number of knowledge categories c	10
Initial knowledge endowment	Random float $(0 < x < 30)$
Max. knowledge differences between agents Δ_{max}	$0 < \Delta_{max} < 30$

In Table 3.2 and Figure 3.3 we see the resulting network characteristics of the R&D network and our theoretical models which have been created with the same number of nodes and links as the R&D network.[6] As stated before, introducing theoretical networks does not aim at recreating the R&D network with its particular network characteristics. Instead, we are looking for a large set of different network topologies with different combinations of characteristics to analyse and potentially isolate dominant factors for the diffusion of knowledge that is able to explain possible differences in performance.

As shown in Table 3.2 and Figure 3.3, the empirical R&D network exhibits a relatively high path length, an extremely high clustering coefficient, and a skewed degree distribution. EV networks combine a short path length, a relatively high clustering coefficient, and the most skewed degree distribution. In contrast to this, for example, ER networks are characterised by short path length, small clustering coefficient but simultaneously similar degree centralities of nodes. Looking in more detail at the degree distributions of our five networks (see Figure 3.3), we see that the R&D network (the same holds for BA and EV networks) shows a fat-tailed degree distribution with a small number of highly connected nodes and a high number of small nodes with few links. In contrast to this, the WS and ER algorithms produce networks with nodes of relatively similar degree centrality.

3.3.3 Knowledge Diffusion Performance in Five Different Networks

In this section, we analyse the knowledge diffusion performance of all five networks. Analysing the mean average knowledge stock μ indicates how much knowledge agents have gained over time. We use the variance of knowledge levels σ^2 as an indicator if the knowledge between agents is equally distributed.

[5] We used version 5.3.1. The software can be downloaded at: https://ccl.northwestern.edu/netlogo/.

[6] To reduce random effects, we show the average results for 500 simulation runs for each of the benchmark networks.

TABLE 3.2: Network characteristics of our five networks.

Networks	**Path length**	**Average clustering coefficient**
R&D	5.3	0.72
Erdős-Rényi	~ 4.2	~ 0.005
Watts-Strogatz	~ 5.6	~ 0.30
Barabási-Albert	~ 3.6	~ 0.02
Evolutionary	~ 2.9	~ 0.32

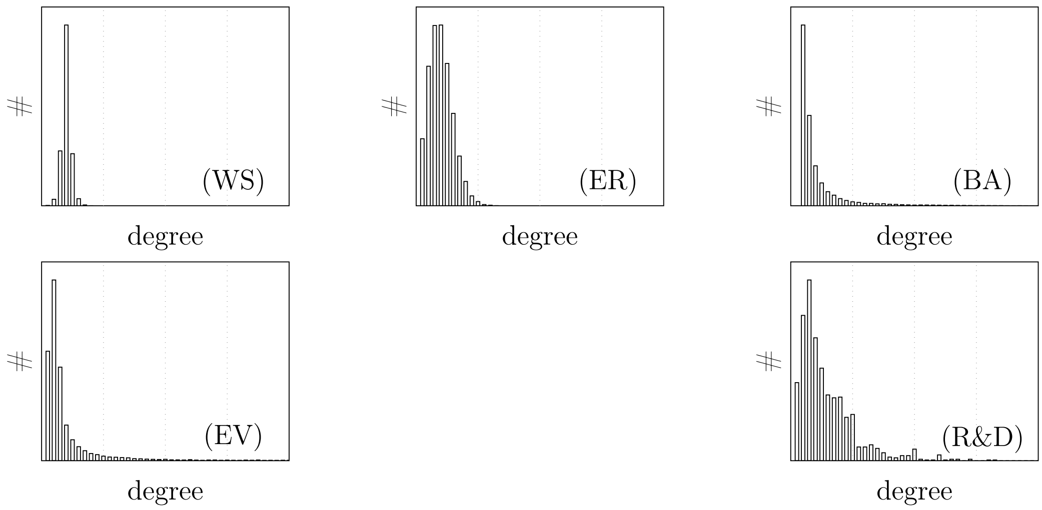

FIGURE 3.3: Average degree distribution of the actors in the theoretical networks as well as in the empirical R&D network in the energy sector in 2015.

Figure 3.4 shows the mean average knowledge levels as well as the variance of knowledge levels in a setting with maximum cognitive distance $\Delta_{\text{max}} = 7$ (l.h.s.) and $\Delta_{\text{max}} = 15$ (r.h.s.) over time (75 simulation time steps).

In line with previous studies (e.g. see Mueller et al., 2016), our results first indicate that path length and clustering coefficient cannot consistently be identified as the decisive factors influencing performance. Neither are the better performing networks characterised by a lower path length and a higher clustering coefficient (see Table 3.2) nor can we find another linear relationship between the average knowledge levels obtained over time and these two network characteristics.

Instead, our simulation results indicate that the skewness of the degree distribution is the dominant factor for explaining the differences in performances. Networks in which nodes have relatively similar numbers of links (WS and ER networks) consequently outperform networks with a skewed degree distribution (BA, EV, and the R&D network). The mean knowledge level in those outperforming networks rises faster and reaches a higher level. At the same time, better performing networks always show a lower variance in knowledge levels, while worse performing networks show a higher variance in knowledge levels.

The explanation for this pattern can be found in the knowledge exchange mechanism addressed in this paper. At the beginning of the diffusion process, nodes with a relatively high number of links have the chance to learn quickly and

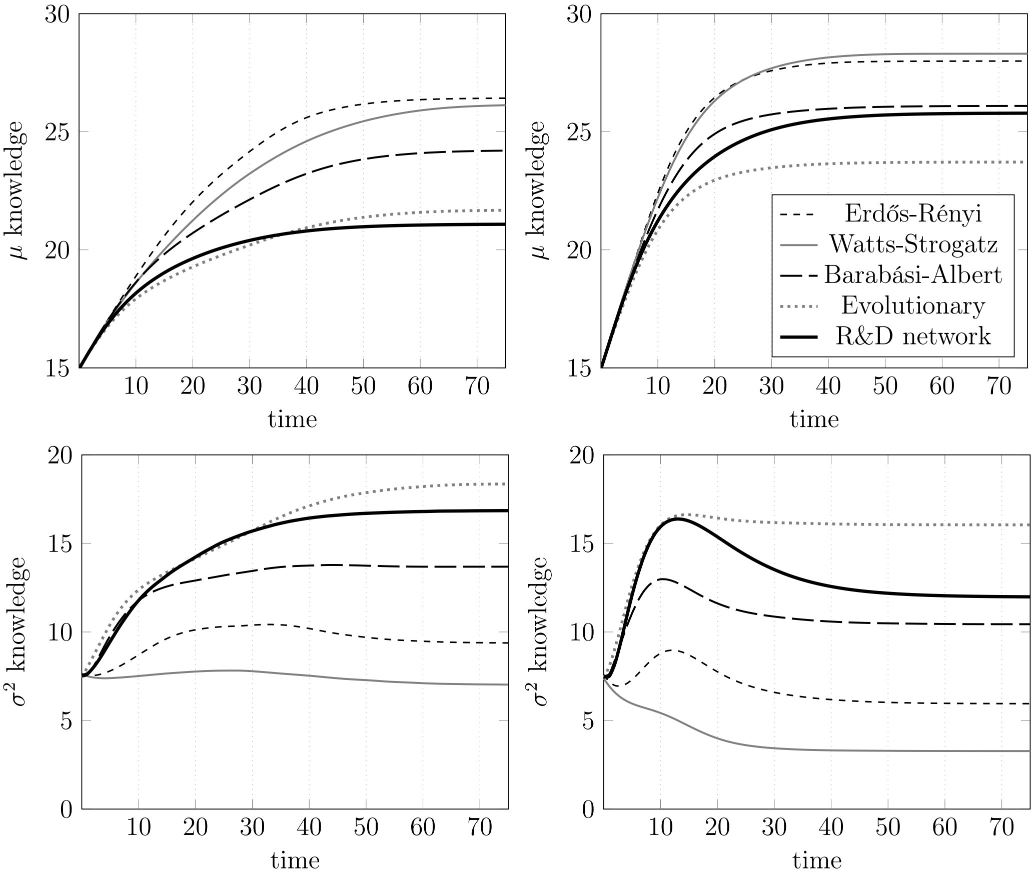

FIGURE 3.4: Mean knowledge levels μ and variance of the average knowledge levels σ^2 in a setting with $\Delta_{max} = 7$ (l.h.s) and $\Delta_{max} = 15$ (r.h.s.) over time.

eventually acquire very high knowledge levels (as they simply have more partners to choose from). Consequently, in these networks, already at early stages of the diffusion process, we observe a gap in the knowledge levels between the well and poorly connected nodes which hinders a widespread knowledge diffusion. Over time, this gap is, to some extent, bridged and poorly connected nodes catch up. In WS and ER networks, however, actors are characterised by relatively similar degree centralities. In this case, all nodes learn equally fast and, therefore, no notable gap in the knowledge levels emerges. This pattern also explains the different variances in knowledge levels between the five networks. The fast learning of highly connected nodes at the beginning of the simulation first increases the variance of knowledge levels (consequently the best performing networks show the lowest variances in knowledge levels). At the later stages, the catching up process of small nodes leads to converging knowledge levels. This catching up process, however, is strongly determined by the underlying network topology and the maximum cognitive distance Δ_{max}.

To investigate the effects of varying degrees of Δ_{max}, Figure 3.5 shows the average knowledge stocks of nodes as well as the variance of their knowledge stocks at two points in time for $0 < \Delta_{max} < 30$. On the left-hand side, we see the mean and variance of knowledge levels after the diffusion process already stopped (i.e. after 70 steps). On the right-hand side, we see the results while the diffusion process is still running (i.e. after 15 steps).

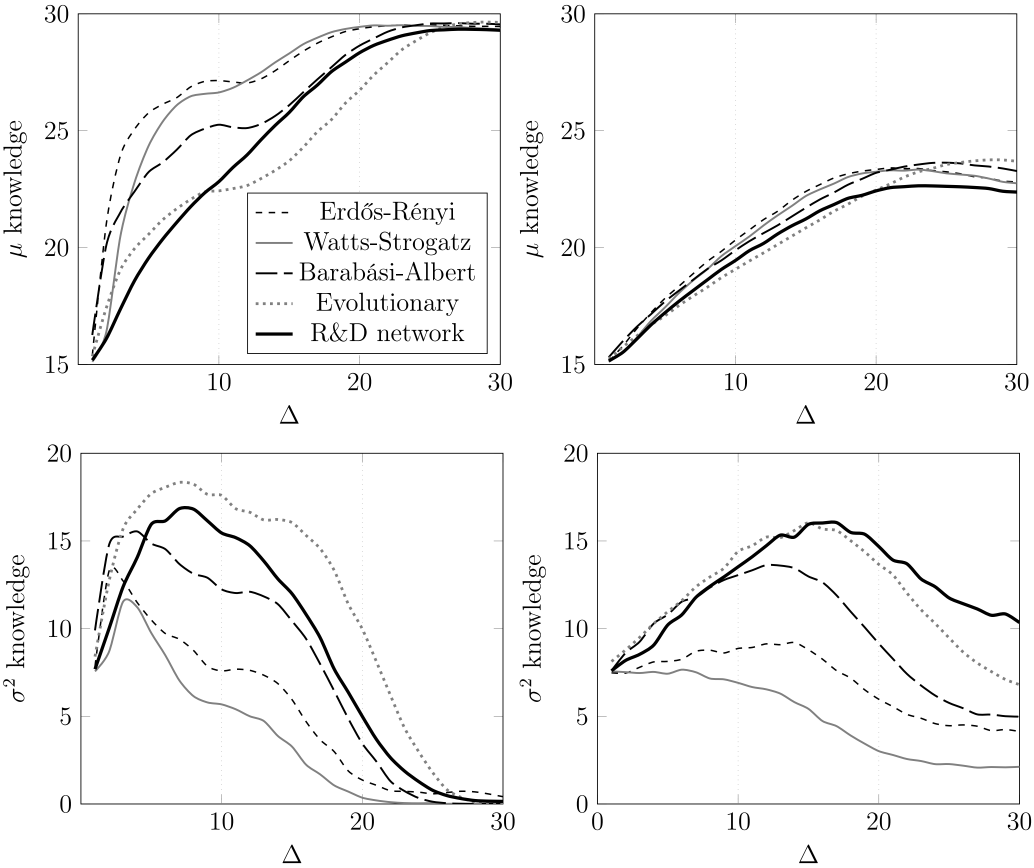

FIGURE 3.5: Mean knowledge levels μ and variance of the average knowledge levels σ^2 at time step $t = 70$ (l.h.s.) and $t = 15$ (r.h.s.).

Starting with the mean knowledge levels after knowledge diffusion has stopped (after 70 steps), we see a positive relationship between the maximum cognitive distance Δ_{max} and the knowledge levels reached within the network. Additionally, for extreme values of the maximum cognitive distance Δ_{max}, the effect of network characteristics can be neglected. For extremely small values of Δ_{max}, the networks show no knowledge diffusion and for extremely high values of Δ_{max} knowledge levels in all networks reach their maximum. Figure 3.5 also confirms our previous results (see Figure 3.4) that the relative performance of a network (compared to other networks for a similar parameter setting) is in a strong relationship with the maximum cognitive distance. So, for example, while for small values of Δ_{max} the R&D network performs worst, for high values of Δ_{max} the EV network performs worst. The same pattern holds if we look at the speed of diffusion as indicated by the average knowledge levels after 15 time steps (r.h.s.).

Counterintuitively, the results in Figure 3.5 show that for all levels of Δ_{max} the skewness of the degree distribution is the decisive factor determining the performance of diffusion. However, we also see that the extent to which a skewed degree distribution dominates other network characteristics varies. For high Δ_{max} the ranking of the average knowledge levels at the end of the simulation follows the reverse order of the skewness of the degree distribution. For smaller values of Δ_{max}, however, we see that also the path length of networks influences the performance. In this case, the general division between networks with and without skewed degree distribution still holds, but we see that networks with short path length perform better than networks with longer path lengths. In this situation, for example, EV networks (characterised by short path lengths) outperform the R&D network despite its highly skewed degree distribution. Finally, Figure 3.5 shows that, in some cases, an increasing maximum cognitive distance Δ_{max} has no dominant or even some negative effects on the diffusion of knowledge. In most of our networks, we see a plateau effect for $\Delta_{\text{max}} = \sim 10$ where an increase in the maximum cognitive distance Δ_{max} only leads to marginal changes in the knowledge levels reached (Figure 3.5, l.h.s.). In this situation, the knowledge differences between nodes simply surpass the feasible range of knowledge levels in which learning is possible. At the same time, we see in Figure 3.5 (r.h.s.) that for high Δ_{max} the mean knowledge levels of nodes may also drop. This indicates that for extremely high values of Δ_{max} learning is considerably slower than for medium values of Δ_{max}. This effect can be explained by the underlying knowledge diffusion process used in our model. As also depicted in Figure 3.1, the amount of new knowledge and, with that, the speed of knowledge diffusion in a network, strongly depends on the cognitive distances between nodes and Δ_{max}. In other words, for high values of the maximum cognitive distance ($\Delta_{\text{max}} > 20$) for which we observe a fully diffused knowledge, any increase in the maximum cognitive distance is shifting the learning curve to the right and, hence, reduces the abilities of nodes to integrate new knowledge from their link neighbours.

3.3.4 Actor Degree and Performance in the R&D Network in the Energy Sector

To get a complete picture of the processes involved, we focus in this section on the knowledge levels of the agents at the agent level. Figure 3.6 visualises the learning race between nodes over time. More precisely, we show the histogram of the average knowledge levels gained for the time steps $t = 5$, $t = 20$ and $t = 50$.

As knowledge is randomly distributed among nodes before the first model run, in the beginning (step 0), we see an equal distribution of values within the knowledge vectors for all five networks. Already after 5 steps, we see that in all networks some nodes achieve the maximum possible values[7], while others are stuck with medium levels. This process continues over time (step 20) and for the later stages of the simulation (step 50) we clearly see two groups of nodes emerging: on the one hand, there are nodes with the maximum knowledge level possible; on the other hand, there are some nodes with only medium levels of knowledge or lower. Between these groups, we see a clear gap. As the maximum knowledge level is fixed, it becomes evident that the different numbers of nodes with only low or medium levels of knowledge are responsible for the different outcomes of the five network topologies (see Section 3.3.3). Put differently, we see that in networks where nodes exhibit similar degree centralities (as WS and ER networks) fewer nodes are cut off from the learning race and, hence, a large number of nodes can catch up in the long run. In contrast to this, we see that in networks with skewed degree distributions (as in BA, EV, and in the R&D network) the structural imbalance considerably discriminates small nodes.

To give further evidence, Figure 3.7 shows the relationship between actors' degree centrality and their knowledge levels μ_i for different values of Δ_{max} after the diffusion finally stopped (70 steps (l.h.s.)) as well as after 15 steps (r.h.s.).

[7]For a better visualisation, we clipped the columns for values higher than 500.

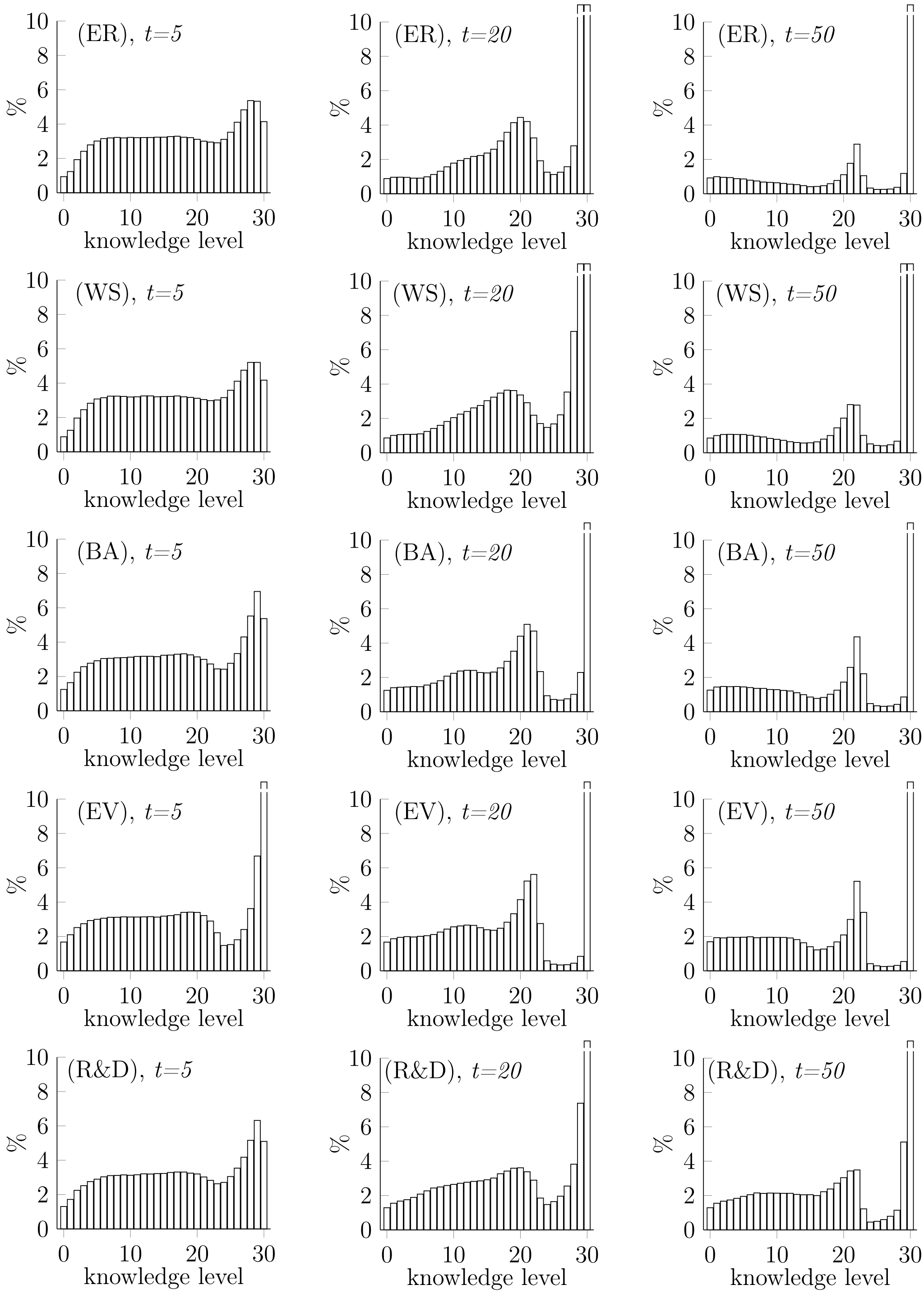

FIGURE 3.6: Histogram of knowledge levels for $\Delta_{max} = 7$.

Figure 3.7 depicts the relationship between actors' degree centrality and their knowledge level μ_i. Depending on the Δ_{max}, we see a positive relationship between degree and knowledge. However, this positive relationship is not always as pronounced as expected. While the diffusion process still is running (r.h.s.) and for smaller values of Δ_{max}, we actually see a positive relationship between agents' degree and their knowledge level. For agents with more links, though, we see a saturation effect for which a higher degree centrality does not lead to a higher

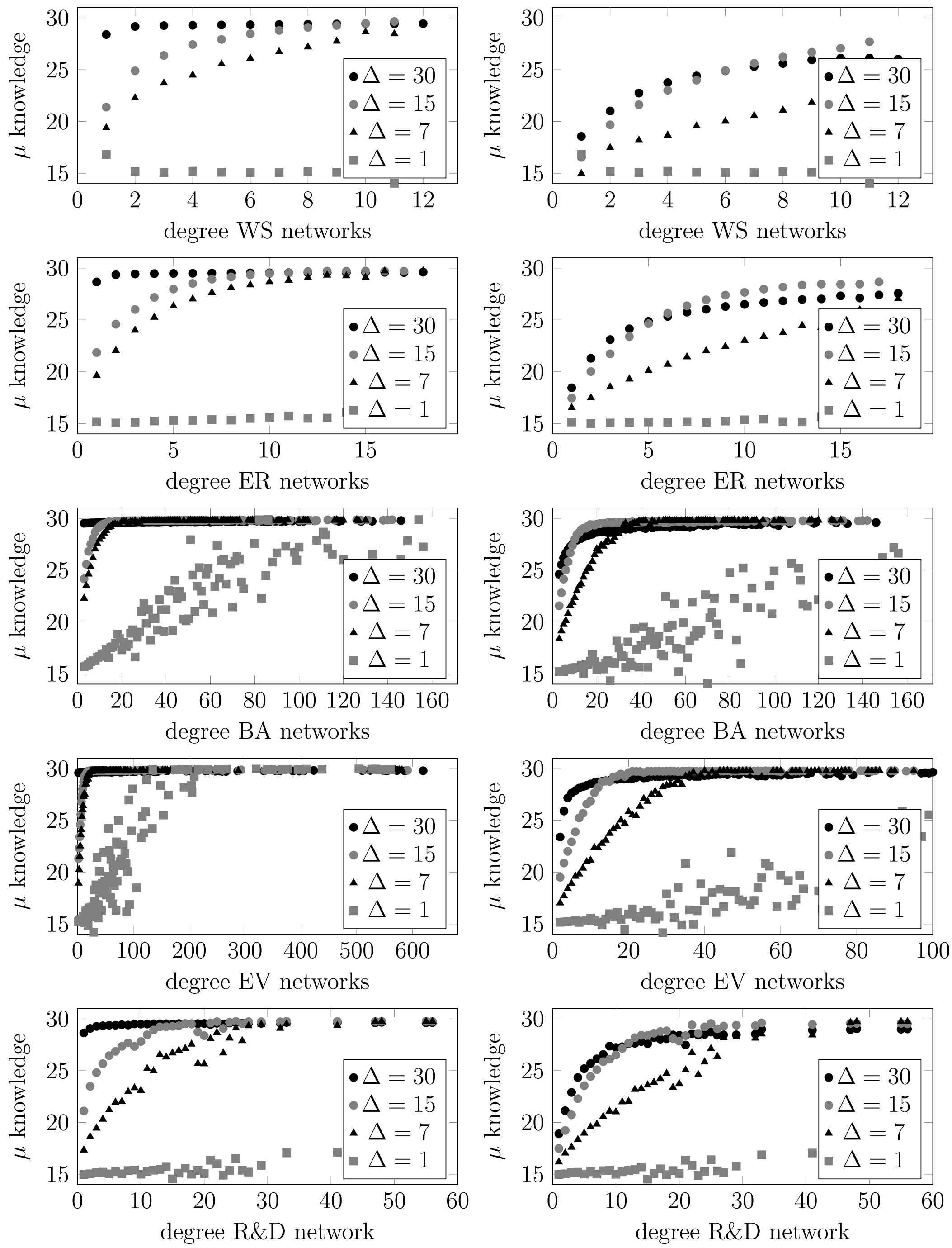

FIGURE 3.7: Relationship between actors' mean knowledge levels μ_i and their degree centralities for different values of Δ_{max} at time step $t = 70$ (l.h.s.) and at time step $t = 15$ (r.h.s.).

knowledge level. At the end of the diffusion process (l.h.s.), the number of agents for which there is a positive relationship between degree and knowledge level is even smaller. These results confirm our previous statements. There is a learning race in which, for more skewed network structures, small nodes are left behind and, hence, are responsible for the different performances of the networks.

3.4 Summary and Conclusions

In this paper, we have built on previous work studying the diffusion of knowledge in networks. We contribute to this field by proposing a model that allows us to analyse knowledge diffusion in four theoretical networks and an empirical network. Here, we investigate how the structure of the networks, as well as the cognitive distance of the agents, affect diffusion performance. Our results support the idea that the performance of the knowledge diffusion process strongly depends on the skewness of degree distributions. Networks with a skewed distribution of links perform worse, as they foster a knowledge gap between nodes relatively early on. While for informal networks this has already been stressed by Cowan and Jonard (2007) and Mueller et al. (2017), our model focuses on formal networks. Our results imply that networks with a skewed degree distribution perform considerably worse than networks in which nodes exhibit similar degree centralities. Well-connected nodes forge ahead and leave poorly connected nodes behind. This discrepancy then leads to disrupted knowledge exchange.

Although our model uses a simplified representation of knowledge and learning, the observed patterns can already raise awareness for the following issue: Policy makers are very keen on network structures that foster knowledge diffusion performance. Yet, to a certain extent, our simulation results question whether the purposely created networks are actually able to support fast and efficient knowledge diffusion. Often, these networks are generated in a way that focuses on creating links with incumbent actors, thereby leading to an artificially skewed degree distribution. In our model, it is exactly these network structures that hinder knowledge diffusion.

Nevertheless, for the exact interpretation of the results, we have to bear in mind that our simulation builds on a very strict and simplified perspective that should be considered and amended in future research endeavours: First, the diffusion process in our simulation takes place on static networks. Thereby, we have assumed a unidirectional relationship between network structure and the efficiency of knowledge diffusion. In reality, however, network structure and diffusion processes are in a dynamic, interdependent (co-evolutionary) relationship. In other words, relationships among cooperation partners are often also depending on the individual and goal-oriented behaviour of heterogeneous actors. In our model, this would lead to the simple question: if nodes cannot learn from each other, why are they connected and why will they stay connected in the future? Second, our model assumes that something as vague, relational, and tacit as knowledge can be modelled via vectors of numbers. As simulation results always depend on the specifics of how knowledge and its diffusion process are conceptualised, other, more realistic knowledge representations (e.g. knowledge as a network as proposed by Schlaile et al., 2018) should be incorporated in the model. Third, knowledge creation and diffusion are also interdependent processes. Consequently, future research should not analyse knowledge diffusion in an isolated fashion but rather extend the model in ways that can account for the complex and often path-dependent processes of knowledge creation, recombination, and variation.

Despite these and various other potential extensions of the model, this paper shows that there exist so far under-explored effects that are at stake within knowledge diffusion processes in networks and that future research is needed.

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Chapter 4

Exploring the Dedicated Knowledge Base of a Transformation towards a Sustainable Bioeconomy

Chapter 4

Exploring the Dedicated Knowledge Base of a Transformation towards a Sustainable Bioeconomy

Abstract

The transformation towards a knowledge-based Bioeconomy has the potential to serve as a contribution to a more sustainable future. Yet, until now, Bioeconomy policies have been only insufficiently linked to concepts of sustainability transformations. This article aims to create such link by combining insights from innovation systems (IS) research and transformative sustainability science. For a knowledge-based Bioeconomy to successfully contribute to sustainability transformations, the IS' focus must be broadened beyond techno-economic knowledge. We propose to also include systems knowledge, normative knowledge, and transformative knowledge in research and policy frameworks for a sustainable knowledge-based Bioeconomy (SKBBE). An exploration of the characteristics of this extended, *'dedicated' knowledge* will eventually aid policy makers in formulating more informed transformation strategies.

Keywords

sustainable knowledge-based Bioeconomy; innovation systems; sustainability transformations; dedicated innovation systems; economic knowledge; systems knowledge; normative knowledge; transformative knowledge; Bioeconomy policy

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The content of the text has not been altered. For reasons of consistency, the language and the formatting have been changed slightly.

4.1 Introduction

In the light of so-called wicked problems (e.g. [1,2]) underlying the global challenges that deeply affect social, environmental, and economic systems, fundamental transformations are required in all of these sustainability dimensions. Therefore, solution attempts need to be based on a systemic consideration of the dynamics, complementarities, and interrelatedness of the affected systems [3].

A relatively new and currently quite popular approach to sustainability transformations addressing at least some of these problems is the establishment of a bio-based economy: the Bioeconomy concept relies on novel and future methods of intelligent and efficient utilization of biological resources, processes, and principles with the ultimate aim of substituting fossil resources (e.g. [4–11]). It is therefore frequently referred to as knowledge-based Bioeconomy [11–13]. Whereas the idea of a Bioeconomy is promoted both by academia and in policy circles, it remains unclear what exactly it is comprised of, how to spur the transformation towards a knowledge-based Bioeconomy, and how it will affect sustainable development [14,15]. While the development and adoption of novel technologies that help to substitute fossil resources by re-growing biological ones certainly is a condition *sine qua non*, a purely technological substitution process will hardly be the means to confront the global challenges [3,16–20]. It must be kept in mind that a transformation towards a sustainable Bioeconomy is only one important contribution to the overall transformation towards sustainability. We explicitly acknowledge that unsustainable forms of bio-based economies are conceivable and even - if left unattended - quite likely [21]. All the more, we see the necessity of finding ways to intervene in the already initiated transformation processes to afford their sustainability.

For successful interventions in the transformation towards a more sustainable Bioeconomy, a systemic comprehension of the underlying dynamics is necessary. The innovation system (IS) perspective developed in the 1980s as a research concept and policy model [22–26] offers a suitable framework for such systemic comprehension. In the conventional understanding, according to Gregersen and Johnson, an IS "can be thought of as a system which creates and distributes knowledge, utilizes this knowledge by introducing it into the economy in the form of innovations, diffuses it and transforms it into something valuable, for example, international competitiveness and economic growth" ([27], p. 482). While welcoming the importance attributed to knowledge by Gregersen and Johnson and other IS researchers (e.g. [28–32]), particularly in the context of a knowledge-based Bioeconomy, in this article, we aim to re-evaluate the role and characteristics of knowledge generated and exploited through IS. We argue that knowledge is not just utilized by and introduced in economic systems, but it also shapes (and is shaped by) societal and ecological systems more generally. Consequently, especially against the backdrop of the required transformation towards a sustainable knowledge-based Bioeconomy (SKBBE), that which is considered as something valuable goes beyond an economic meaning (see also [33], on a related note). For this reason, it is obvious that the knowledge base for an SKBBE cannot be a purely techno-economic one. We rather see a need for exploring additional types of knowledge and their characteristics necessary for fostering the search for truly transformative innovation [16].

From the sustainability literature, we know that at least three types of knowledge are relevant for tackling (wicked) problems related to transformations towards sustainability: Systems knowledge, normative knowledge, and transformative knowledge [34–38]. Undoubtedly, these knowledge types need to be centrally considered and fostered for a transformation towards an SKBBE.

In the course of this paper, we aim to clarify the meaning and the characteristics of knowledge necessary for sustainability-oriented interventions in the transformation towards a Bioeconomy. To reach this aim, we will explore the following research questions:

- Based on a combination of IS research with the sustainability science perspectives, what are the characteristics of knowledge that are instrumental for a transformation towards an SKBBE?
- What are the policy-relevant implications of this extended perspective on the characteristics of knowledge?

The article is structured as follows: Section 4.1. sets the scene by reviewing how knowledge has been conceptualised in economics. Aside from discussing in which way the understanding of the characteristics of economic knowledge has influenced innovation policy, we introduce the three types of knowledge (systems, normative, and transformative) relevant for governing sustainability transformations. Section 4.3. specifies the general meaning of these three types of knowledge, highlights their relevance and instrumental value for transformations towards an SKBBE, and relates them to the most prevalent characteristics of knowledge. Subsequently, Section 4.4. presents the policy-relevant implications that can be derived from our previous discussions. The concluding Section 4.5. summarises our article and proposes some avenues for further research.

4.2 Knowledge and Innovation Policy

The understanding of knowledge and its characteristics vary between different disciplines. Following the Oxford Dictionaries, knowledge can be defined as "[f]acts, information, and skills acquired through experience or education" or simply as "theoretical or practical understanding of a subject" [39]. The Cambridge Dictionary defines knowledge as the "understanding of or information about a subject that you get by experience or study, either known by one person or by people generally" [40]. A more detailed definition by Zagzebski ([41], p. 92) states that "[k]nowledge is a highly valued state in which a person is in cognitive contact with reality. It is, therefore, a relation. On one side of the relation is a conscious subject, and on the other side is a portion of reality to which the knower is directly or indirectly related". Despite this multitude of understandings of knowledge, most researchers and policy makers probably agree with the statement that knowledge "is a crucial economic resource" ([28], p. 27). Therefore, the exact understanding and definition of knowledge and its characteristics strongly affect how researchers and policy makers tackle the question of how to best deal with and make use of this resource. Policy makers intervene in IS to improve the three key processes of knowledge creation, knowledge diffusion, and knowledge use (its transformation into something valuable). Policy recommendations derived from an incomplete understanding and representation of knowledge, however, will not be able to improve the processes of knowledge flow in IS and can even counteract the attempt to turn knowledge into something genuinely valuable.

4.2.1 Towards a More Comprehensive Conceptualisation of Knowledge

A good example that highlights the importance of how we define knowledge is the understanding and treatment of knowledge in mainstream neoclassical economics. Neoclassical economists describe knowledge as an intangible good with public good features (non-excludable, non-rivalrous in consumption). Due to the (alleged) non-excludable nature of knowledge, new knowledge flows freely from one actor to another (spillover) such that other actors can benefit from new knowledge without investing in its creation (free-riding) [42]. In this situation, the knowledge-creating actors cannot fully benefit from the value they created, that is, the actors cannot appropriate the returns that resulted from their research activity (appropriability problem) [43]. There is no need for learning since knowledge instantly diffuses from one actor to another and the transfer of knowledge is costless. As Solow is often accredited with pointing out, knowledge falls "like *manna from heaven*" (see, e.g. [44,45] with reference to [46,47]), and it can instantly be acquired and used by all actors [48].

In contrast to mainstream neoclassical economics, (evolutionary or neo-Schumpeterian) innovation economists and management scholars consider other features of knowledge, thus, providing a much more appropriate analysis of knowledge creation and innovation processes. Innovation economists argue that knowledge can rather be seen as a latent public good [48] that exhibits many non-public good characteristics relevant for innovation processes in IS. Since these more realistic knowledge characteristics strongly influence knowledge flows, their consideration improves the understanding of the three key processes of knowledge creation, knowledge diffusion, and knowledge use (transforming knowledge into something valuable) [27]. In what follows, we present the latent public good characteristics of knowledge and structure them according to their relevance for these key processes in IS. Note that for the agents creating, diffusing, and using knowledge, we will use the term knowledge carrier in a similar sense as Dopfer and Potts ([49], p. 28), who wrote that "the micro unit in economic analysis is a knowledge carrier . . . acquiring and applying knowledge".

Characteristics of knowledge that are most relevant in the knowledge creation process are the cumulative nature of knowledge (e.g. [50,51]), path dependency of knowledge (e.g. [52,53]), and knowledge relatedness (e.g. [54,55]). As the creation of new knowledge or innovation results from the (re-)combination of previously unconnected knowledge [56,57], knowledge has a cumulative character and can only be understood and created if actors already have a knowledge stock they can relate the new knowledge to [54,58]. The more complex and industry-specific knowledge gets, the higher the importance of prior knowledge and knowledge relatedness (see also the discussions in [55,59]).

Characteristics of knowledge that are especially important for the knowledge diffusion process are tacitness, stickiness, and dispersion. Knowledge is not equal to information [60,61]. In fact, as Morone [62] also explains, information can be regarded as that part of knowledge that can be easily partitioned and transmitted to someone else; information requires knowledge to become useful. Other parts of knowledge are tacit [63], that is, very difficult to be codified and to be transported [64]. Tacit knowledge is excludable and, therefore, not a public good [65]. So, even if the knowledge carrier is willing to share, tacitness makes it sometimes impossible to transfer this knowledge [66]. In addition, knowledge and its transfer can be sticky [67,68], which means that the transfer of this knowledge requires significantly more effort than the transfer of other knowledge. According to Szulanski [67], both knowledge and the process of knowledge exchange can be sticky. The reasons may be the kind and amount of knowledge itself but also attributes of the knowledge carriers. Finally, the dispersion of knowledge also influences the possibility of diffusing knowledge. Galunic and Rodan [64] explain dispersed knowledge by using the example of a jigsaw puzzle. The authors state that knowledge is distributed if all actors receive a photocopy of the picture of the jigsaw puzzle. In contrast, knowledge is dispersed if every actor receives one piece of the jigsaw puzzle, meaning that everybody only holds pieces of the knowledge but not the 'whole' picture. Dispersed knowledge (or systems-embedded knowledge) is difficult to be transferred from one to the other actor (as detecting dispersed knowledge can be problematic, too [64]), thus hindering knowledge diffusion.

Characteristics of knowledge (and knowledge carriers) that influence the possibility to use the knowledge within an IS, that is, to transform it into something valuable, are the context specificity and local characteristics of knowledge. Even if knowledge is freely available in an IS, the public good features of knowledge are not necessarily decisive, and it might be of little or no use to the receiver. We have to keep in mind that knowledge itself has no value; it only becomes valuable to someone if the knowledge can be used, for example, to solve certain problems [69]. Assuming that knowledge has different values for different actors, more knowledge is not always better. Actors need the right knowledge in the right context at the right time and have to be able to combine this knowledge in the right way to utilize the knowledge. The 'resource' knowledge might only be relevant and of use in the narrow context for and in which it was developed [64]. Moreover, to understand and use new knowledge, agents need absorptive capacities [70,71]. These capacities vary with the disparity of the actors exchanging knowledge: the larger the cognitive distance between them, the more difficult it is to exchange and internalise knowledge. Hence, the cognitive distance can be critical for learning and transforming knowledge into something valuable [72,73].

Note that while we have described the creation, diffusion, and use of knowledge in IS as rather distinct processes, this does not imply any linear character or temporal sequence of these processes. Quite the contrary, knowledge creation, diffusion, and use and the respective characteristics of knowledge may overlap and intertwine in a myriad of ways. For example, due to the experimental nature of innovation in general and the fundamental uncertainty involved, there are path dependencies, lock-ins (for example, in terms of stickiness), and feedback that lead to evolutionary cycles of variation/recombination, selection, and transmission or retention of knowledge. Moreover, the vast literature on knowledge mobilisation, knowledge translation, and knowledge transfer (e.g. [74–77]) suggests that there can be various obstacles between the creation, diffusion, and use of knowledge, and that so-called knowledge mediators or knowledge brokers may be required to actively guide these interrelated processes (see also [78], on a related discussion). Consequently, we caution against reading the 'trichotomy' of creation, diffusion, and use as connoting that knowledge will be put to good use by the carriers in the end so long as the conditions, such as social network structures, for diffusion are right. In fact, the notion of 'optimal' network structures for diffusion may be misguided against the backdrop of the (in-)compatibility of knowledge, cognitive distance, and the dynamics underlying the formation of social networks [58].

4.2.2 How Knowledge Concepts have Inspired Innovation Policy Making

Depending on the underlying concept of knowledge, different schools of thought influenced innovation policies in diverse ways (see also [60,79,80]). Following the mainstream neoclassical definition, the (alleged) public good characteristics of knowledge may result in market failure and the appropriability problem. As a consequence, policies have mainly focused on the mitigation of potential externalities and the elimination of inefficient market structures. This was done, for example, by incentive creation (via subsidies or intellectual property rights), the reduction of market entry barriers, and the production of knowledge by the public sector [81]. As Smith also states, "policies of block funding for universities, R&D subsidies, tax credits for R&D etc. [were] the main instruments of post-war science and technology policy in the OECD area" ([82], p. 8).

Policies changed (at least to a certain extent) when the understanding of knowledge changed. Considering knowledge as a latent public good, the main rationale for policy intervention is not market failure, but rather systemic problems [81,83]. Consequently, it can be argued that the mainstream neoclassical perspective neglects the importance (and difficulty) of facilitating knowledge creation, knowledge diffusion, and knowledge use in IS (see also [79,80], on a related note). Western innovation policies are often based on the IS approach and inspired by the more comprehensive understanding of knowledge and its implications for innovation. They generally aim at solving inefficiencies in the system (for example, infrastructural, transition, lock-in/path dependency, institutional, network, and capabilities failures as summarised by [83]). These inefficiencies are tackled, for example, by supporting the creation and development of different institutions in the IS as well as fostering networking and knowledge exchange among the system's actors [81]. Since "knowledge is created, distributed, and used in social systems as a result of complex sets of interactions and relations rather than by isolated individuals" ([84], p. 2), network science [85] especially has provided methodological support for policy interventions in innovation networks [86–88].

It is safe to state that innovation policies have changed towards a more realistic evaluation of innovation processes over the last decades [89], although in practice, they often still fail to adequately support processes of knowledge creation, diffusion, and use. Even though many policy makers nowadays appreciate the advanced understanding of knowledge and innovation, what Smith wrote more than two decades ago is arguably still valid to some extent, namely that "linear notions remain powerfully present in policy thinking, even in the new innovatory context" ([82], p. 8). Such a non-systemic way of thinking is also reflected by the strongly disciplinary modus operandi which is most obviously demonstrated by the remarkable difficulties still present in concerted actions at the level of political departments.

4.2.3 Knowledge Concepts in Transformative Sustainability Science

Policy adherence to the specific knowledge characteristics identified by economists has proven invaluable for supporting IS to produce innovations. However, to what end? So far, innovation has frequently been implicitly regarded as desirable per se [3,90,91] and, by default, creating something valuable. However, if IS research shall be aimed at contributing to developing solution strategies to global sustainability challenges, a mere increase in innovative performance by improving the flow of economically relevant knowledge will not suffice [3]. In times of globally effective wicked problems challenging our current production and consumption patterns, it is evident that research into knowledge creation and innovation cannot be a task for economists or any other isolated discipline alone (see also [92], on a related discussion). Additional types of knowledge particularly relevant for addressing wicked problems have been proposed by sustainability science in general and transformational sustainability research in particular [36]. Solution options for the puzzle of reconciling economic development with sustainability goals have been found to require three kinds of knowledge: First, systems knowledge, which relates to the understanding of the dynamics and processes of ecological and social systems (including IS); second, normative knowledge, which determines the desired (target) states of a system; and third, transformative knowledge, which builds on systems and normative knowledge to inform the development of strategies for changing systems towards the desired state [34–38]. Although there are alternative terms for these three types of knowledge (such as explanatory knowledge, orientation knowledge, and action-guiding knowledge, as used in [93]), for the sake of terminological consistency with most recent publications, we adopt the terms systems knowledge, normative knowledge, and transformative knowledge.

The fundamental significance of these three kinds of knowledge (systems, normative, and transformative) for sustainability transformations has been put forward by a variety of research strands from theoretical [34,35] to applied planning perspectives [94,95]. Explorations into the specific characteristics in terms of how such knowledge is created, diffused, and used within IS, however, are missing so far. For the particular case of a dedicated transformation towards an SKBBE, we seek to provide some clarification as a basis for an improved governance towards desired ends.

4.3 Dedicated Knowledge for an SKBBE Transformation

A dedicated transformation towards an SKBBE can be framed with the help of the newly introduced concept of *dedicated innovation system (DIS)* [3,16,96], which goes beyond the predominant focus on technological innovation and economic growth. DIS are dedicated to transformative innovation [97,98], which calls for experimentation and (co-)creation of solution strategies to overcome systemic inertia and the resistance of incumbents. In the following, we specify in what ways the IS knowledge needs to be complemented to turn into *dedicated knowledge* instrumental for a transformation towards an SKBBE. Such dedicated knowledge will thus have to comprise economically relevant knowledge as regarded in IS as well as systems knowledge, normative knowledge, and transformative knowledge. Since little is known regarding the meaning and the nature of the latter three knowledge types, we need to detail them and illuminate their central characteristics. This will help to fathom the processes of knowledge creation, diffusion, and use, which will be the basis for deriving policy-relevant implications in the subsequent Section 4.4.

4.3.1 Systems Knowledge

Once the complexity and interdependence of transformation processes on multiple scales are acknowledged, systemic boundaries become quite irrelevant. In the context of an SKBBE, systems knowledge must comprise more than the conventional understanding of IS in terms of actor configurations, institutions, and interrelations. As already stressed by Grunwald ([99], p. 154), "sufficient insight into natural and societal systems, as well as knowledge of the interactions between society and the natural environment, are necessary prerequisites for successful action in the direction of sustainable development". Although the IS literature has contributed much to systems knowledge about several levels of economic systems, including technological, sectoral, regional, national, and global IS, the interplay between IS, the Earth system (e.g. [100,101]), and other relevant (sub-)systems (e.g. [102–106]) must also be regarded as a vital part of systems knowledge in the context of sustainability and the Bioeconomy. On that note, various authors have emphasised the importance of understanding systemic thresholds and tipping points (e.g. [107–110]) and network structures (e.g. [111,112]), which can thus be considered important elements of systems knowledge. In this regard, it may also be important to stress that systems knowledge is (and must be) subject to constant revision and change, because, as Boulding ([113], p. 9) already emphasised, "we are not simply acquiring knowledge about a static system which stays put, but acquiring knowledge about a whole dynamic process in which the acquisition of the knowledge itself is a part of the process".

To give a prominent example which suggests a lack of systems knowledge in Bioeconomy policies, we may use the case of biofuels and their adverse effects on land-use and food supply in some of the least developed countries [114,115]. In this case, the wicked problem addressed was climate change due to excessive CO_2 emissions and the solution attempt was the introduction of bio-based fuel for carbon-reduced mobility. However, after the first boom of biofuel promotion, emissions savings were at best underwhelming or negative since the initial models calculating greenhouse gas savings had insufficiently considered the effects of the biofuel policies on markets and production: whereas the carbon intensity of biofuel crop cultivation was taken into account, the overall expansion of the agricultural area and the conversion of former grasslands and forests into agricultural land was not [114,115]. These indirect land-use change (ILUC) effects are estimated to render the positive effects of biofuel usage more than void, which represents a vivid example for how (a lack of) comprehensive systems knowledge can influence the (un)sustainability of Bioeconomy transformations.

In accordance with much of the IS literature's focus on knowledge and the common intellectual history of IS and evolutionary economics (e.g. [23]), it becomes clear that an economic system, in general, and a (knowledge-based) Bioeconomy, in particular, may also be regarded as "a coordinated system of distributed knowledge" ([69], p. 413). Potts posits that "[k]nowledge is the solution to problems. A solution will consist of a rule, which is a generative system of connected components" ([69], p. 418f.). The importance of rules is particularly emphasised by the so-called rule-based approach (RBA) to evolutionary economics developed by Dopfer and colleagues (e.g. [49,116–121]). According to the RBA, a "rule is defined as the idea that organizes actions or resources into operations. It is the element of knowledge in the knowledge-based economy and the locus of evolution in economic evolution" ([49], p. 6). As Blind and Pyka also elucidate, "a rule represents knowledge that enables its carrier to perform economic operations, i.e. production, consumption and transactions. The distinction between generic rules and operations based on these rules is essential for the RBA" ([122], p. 1086). According to the RBA, these generic rules may be further distinguished into subject and object rules: subject rules are the cognitive and behavioural rules of an economic agent, whereas object rules are social and technical rules that represent the organizing principles for social and technological systems [49,118]. The latter include, for example, Nelson-Winter organisational routines [123] and Ostrom social rules (e.g. [124–126]). From this brief summary of the RBA, it already becomes clear that an understanding of the bioeconomic systems' rules and their interrelations is an instrumental element of systems knowledge. Or, as Meadows puts it, "[p]ower over the rules is real power" ([127], p. 158).

Since it can be argued that the creation, diffusion, and use of systems knowledge is the classical task of the sciences [93,99], most of the characteristics of latent public goods (as outlined above) can be expected to also hold for systems knowledge in terms of its relatedness, cumulative properties, and codifiability. Special features to be considered when dealing with systems knowledge in the context of a transformation towards an SKBBE will be twofold: First, systems knowledge may be quite sticky, that is, it may require much effort to be transferred. This is owed to the fact that departing from linear cause-and-effect thinking and starting to think in systems still requires quite some intellectual effort on the side of the knowledge carrier (see also [128], on a related note). Second, systems knowledge can be expected to be strongly dispersed among different disciplines and knowledge bases of great cognitive distances, such as - with recourse to the example of ILUC - economics, agricultural sciences, complexity science, and other (social and natural) sciences.

4.3.2 Normative Knowledge

According to Abson and colleagues ([35], p. 32), "[n]ormative knowledge encompasses both knowledge on desired system states (normative goals or target knowledge...) and knowledge related to the rationalization of value judgements associated with evaluating alternative potential states of the world (as informed by systems knowledge...)". In the context of an SKBBE, it becomes clear that normative knowledge must refer not only to directionality, responsibility, and legitimacy issues in IS (as discussed in [3]) but also to the targets of the interconnected physical, biological, social, political, and other systems (e.g. [102]). Thereby, for the transformation of knowledge into "something valuable" within IS (cf. [27]), the dedication of IS to an SKBBE also implies that the goals of "international competitiveness and economic growth" (cf. [27]) must be adjusted and re-aligned with what is considered something valuable in conjunction with the other interconnected (sub-)systems (for example, social and ecological ones) (see also [129,130] on the related discussion about orientation failure in IS).

Yet, one of the major issues with prior systemic approaches to sustainability transformations, in general, seems to be that they tend to oversimplify the complexity of normative knowledge and value systems by presuming a consensus about the scale and importance of sustainability-related goals and visions [131]. As, for instance, Miller and colleagues [132] claim, "[i]nquiries into values are largely absent from the mainstream sustainability science agenda" ([132], p. 241). However, sustainability is a genuinely normative phenomenon [93] and knowledge related to norms, values, and desired goals that indicate the necessity for and direction of change is essential for the successful systemic change towards a sustainable Bioeconomy (and not just any Bioeconomy for the sake of endowing the biotechnology sector). Norms, values, and narratives of sustainability are regularly contested and contingent on diverse and often conflicting and (co-)evolving worldviews [3,131–138].

Similar ambiguity can be observed in the context of the Bioeconomy (e.g. [15,139]). When taking the complexity of normative knowledge seriously, it may even be impossible to define globally effective rules, norms, or values (in terms of a universal paradigm for an SKBBE) [21]. Arguably, it may be more important to empower actors within IS to "apply, negotiate and reconcile norms and principles based on the judgements of multiple stakeholders" ([140], p. 12). The creation of normative knowledge for an SKBBE can thus be expected to depend on different initial conditions such as the cultural context, whereas the diffusion of a globally effective canon of practices for an SKBBE is highly unlikely (see also [141]). Normative knowledge for an SKBBE is, therefore, intrinsically local in character despite the fact that sustainable development is a global endeavour.

Moreover, the creation of normative knowledge is shaped by cultural evolutionary processes (e.g. [138,142–149]). This means, for example, that both subject rules that shape the sustainability goals of the individual carriers (for example, what they consider good or bad) and object rules that determine what is legitimate and important within a social system or IS are subject to path dependence, competition, and feedback at the level of the underlying ideas (e.g. [58,131,150,151]). The diffusion of normative knowledge about the desired states of a system is therefore always contingent on its context specificity and dependent on cultural evolution. In Boyd and Richerson's words, "people acquire beliefs, attitudes, and values both by teaching and by observing the behavior of others. Culture is not behavior; culture is information . . . that, together with individuals' genes and their environments, determines their behavior" ([145], p. 74). While many object rules are codifiable as laws and formal institutions, most subject rules can be assumed to remain tacit so that normative knowledge consists of a combination of tacit and codified knowledge. Of course, "people are not simply rule bound robots who carry out the dictates of their culture" ([145], p. 72), but rules can often work subconsciously to evolve institutions (e.g. [152]) and shared paradigms that span the "bounded performative space" of an IS (see, e.g. [3], on a related note).

Consequently, when referring to normative knowledge and the constituting values and belief systems, we are not only dealing with the competition and evolution of knowledge at the level of rules and ideas driven by (co-)evolutionary processes across the societal sub-systems of individuals, the market, the state, civil society, and nature [106]. To a great extent, the cognitive distances of competing carriers within sub-systems and their conflicting strategies can also pose serious impediments to normative knowledge creation, diffusion, and use. This complex interrelation may, thus, be understood from a multilevel perspective with feedback between worldviews, visions, paradigms, the Earth system, regimes, and niches [153].

4.3.3 Transformative Knowledge

Transformative knowledge can, in the context of this article, be understood as knowledge about how to accelerate and influence the ongoing transformation towards an SKBBE. As, for instance, Abson and colleagues [35] explain this type of knowledge is necessary for the development of tangible strategies to transform systems (based on systems knowledge) towards the goals derived from normative knowledge. Theoretical and practical understanding must be attained to afford transitions from the current to the desired states of the respective system(s), which will require a mix of codified and tacit elements. Creating transformative knowledge will encompass the acquisition of skills and knowledge about how to effect systemic changes, or, as Almudi and Fatas-Villafranca put it, how to deliberately shape the evolutionary processes in other sub-systems (a mechanism referred to as promotion [106]). Although wicked problems that necessitate these changes are most often global in nature, their solution strategies will have to be adapted to the local conditions [97]. While global concepts and goals for a Bioeconomy may be relatively easy to agree upon, the concrete measures and resource allocation will be negotiated and disputed at the regional and local scales [154]. This renders transformative knowledge in IS exceptionally local.

In line with the necessity for a change of goals and values, scholars of the educational sciences argue that effective transformative knowledge will also require a revision of inherited individual value frames and assumptions on the side of the knowledge carriers themselves [155]. This process of fundamentally challenging personal worldviews inherent in the absorption of truly transformative knowledge makes this type of knowledge extremely sticky and inhibited by lock-ins and path dependence. For a transformation from a fossil to a bio-based economy, the collective habituation to a seemingly endless and cheap supply of fossil resources and the ostensibly infinite capacity of ecosystems to absorb emissions and waste must be overcome. In line with findings from cultural evolution and the RBA, sustainability education research has also pointed to the importance of acknowledging that human action is driven not only by cognitive knowledge but also unconsciously by "deeper" levels of knowing such as norms, assumptions, values, or beliefs [156]. Consequently, only when being effective on these different levels of consciousness can transformative knowledge unfold its full potential to enable its carriers to induce behavioural change in themselves, a community, or the society. Put differently, the agents of sub-systems will only influence the replication and selection processes according to sustainable values in other sub-systems (via promotion) if they expect advantages in individual and social well-being [106].

Besides systems and normative knowledge, transformative knowledge thus requires the skills to affect deeper levels of knowing and meaning, thereby influencing more immediate and conscious levels of (cognitive and behavioural) rules, ideas, theories, and action [157,158]. Against this backdrop, it may come as no surprise that the prime minister of the German state of Baden-Wuerttemberg, member of the green party, has so far failed to push state policies towards a mobility transformation away from individual transport on the basis of combustion technology. In an interview, he made it quite clear that although he has his chauffeur drive him in a hybrid car on official trips, in his private life he "does what he considers right" by driving "a proper car" - namely a Diesel [159].

From what we have elaborated regarding the characteristics of transformative knowledge, we must conclude that its creation requires a learning process on multiple levels. It must be kept in mind that it can only be absorbed if the systemic understanding of the problem and a vision regarding the desired state are present, that is, if a certain level of capacity to absorb transformative knowledge is given. Furthermore, Grunwald [93] argues that the creation of transformative knowledge must be reflexive. In a similar vein, Lindner and colleagues stress the need for reflexivity in IS, and they propose various quality criteria for reflexive IS [130]. In terms of its diffusion and use, transformative knowledge is thought to become effective only if it is specific to the context and if its carriers have internalised the necessity for transformation by challenging their personal assumptions and values. Consequently, since values and norms have evolved via cultural evolution, transformative knowledge also needs to include knowledge about how to influence the cultural evolutionary processes (e.g. [133,160–163]). To take up Brewer's culture design approach, "change processes can only be guided if their evolutionary underpinnings are adequately understood. This is the role for approaches and insights from cultural evolution" ([160], p. 69).

4.4 Policy-Relevant Implications

4.4.1 Knowledge-Related Gaps in Current Bioeconomy Policies

The transformation towards an SKBBE must obviously be guided by strategies derived from using transformative knowledge which is, by definition, based on the other relevant types comprising dedicated knowledge. We suspect that the knowledge which guided political decision-makers in developing and implementing current Bioeconomy policies so far has, in some respect, not been truly transformative. Important processes of creating, diffusing, and using systems and, especially normative knowledge, have not sufficiently been facilitated. We propose how more detailed insights into the characteristics of dedicated knowledge can be used to inform policy makers in improving their transformative capacities. Based on the example of two common issues of critique in the current Bioeconomy policy approaches, we will substantiate our knowledge-based argument. Bioeconomy policies have been identified (i) to be biased towards economic goals and, therefore, take an unequal account of all three dimensions of sustainability [21,164–168]; and, to some extent related to it; (ii) to only superficially integrate all relevant stakeholders into policy making [21,165,169–173].

Bioeconomy policies brought forward by the European Union (EU) and several nations have been criticized for a rather narrow techno-economic emphasis. While using the term sustainable as an attribute to a range of goals and principles frequently, the EU Bioeconomy framework, for example, still overemphasises the economic dimension. This is reflected by the main priority areas of various political Bioeconomy agendas which remain quite technocratic: keywords include biotechnology, eco-efficiency, competitiveness, innovation, economic output, and industry in general [14,164]. The EU's proposed policy action along the three large areas (i) the investment in research, innovation and skills; (ii) the reinforcement of policy interaction and stakeholder engagement; and (iii) the enhancement of markets and competitiveness in Bioeconomy sectors ([174], p. 22), reveals a strong focus on fostering economically relevant and technological knowledge creation. In a recent review [175] of its 2012 Bioeconomy Strategy [174] the European Commission (EC) did indeed observe some room for improvement with regard to more comprehensive Bioeconomy policies by acknowledging that "the achievement of the interlinked Bioeconomy objectives requires an integrated (i.e. cross-sectoral and cross-policy) approach within the EC and beyond. This is needed in order to adequately address the issue of multiple trade-offs but also of synergies and interconnected objectives related to Bioeconomy policy (e.g. sustainability and protection of natural capital, mitigating climate change, food security)" ([175], p. 25).

An overemphasis on economic aspects of the Bioeconomy in implementation strategies is likely to be rooted in an insufficient stock of systems knowledge. If the Bioeconomy is meant to "radically change [Europe's] approach to production, consumption, processing, storage, recycling and disposal of biological resources" ([174], p. 8) and to "assure over the long term the prosperity of modern societies" ([4], p. 2), the social and the ecological dimension have to play equal roles. Furthermore, the systemic interplay between all three dimensions of sustainability must be understood and must find its way into policy making via systems knowledge. While the creation of systems knowledge within the individual disciplines does not seem to be the issue (considering, for example, advances in Earth system sciences, agriculture, and political sciences), its interdisciplinary diffusion and use seem to lag behind (see also [160], on a related note). The prevalent characteristics of this knowledge relevant for its diffusion have been found to be stickiness and dispersal (see Section 4.3.1 above). To reduce the stickiness of systems knowledge and, thus, improve its diffusion and transfer, long-term policies need to challenge the fundamental principles still dominating in education across disciplines and across school levels: linear cause-and-effect thinking must be abandoned in favour of systemic ways of thinking. To overcome the wide dispersal of bioeconomically relevant knowledge across academic disciplines and industrial sectors, policies must encourage inter- and transdisciplinary research even more and coordinate knowledge diffusion across mental borders. This, in turn, calls for strategies that facilitate connecting researchers across disciplines and with practitioners as well as translating systems knowledge for the target audience (e.g. [74]). Only then can systems knowledge ultimately be used for informing the creation processes of transformative knowledge.

TABLE 4.1: The elements of dedicated knowledge in the context of SKBBE policies.

Central Knowledge Types as Elements of Dedicated Knowledge	General Meaning	Sustainability and Bioeconomy-Related Instrumental Value	Most Prevalent Characteristics Regarding Creation, Diffusion and Use	Consideration by Current Bioeconomy Policy Approaches
Economically relevant knowledge	Knowledge necessary to create economic value.	Knowledge necessary to create economic value in line with the resources, processes, and principles of biological systems.	Latent public good, depending on the technology in question.	Adequately considered.
Systems knowledge	Descriptive, interdisciplinary understanding of relevant systems.	Understanding of the dynamics and interactions between biological, economic, and social systems.	Sticky and strongly dispersed between disciplines.	Insufficiently considered.
Normative knowledge	Knowledge about desired system states to formulate systemic goals.	(Knowledge of) Collectively developed goals for sustainable bioeconomies.	Intrinsically local, path-dependent, and context-specific; but sustainability as a global endeavour .	Partially considered.
Transformative knowledge	Know-how for challenging worldviews and developing tangible strategies to facilitate the transformation from current system to target system.	Knowledge about strategies to govern the transformation towards an SKBBE.	Local and context-specific, strongly sticky, and path-dependent.	Partially considered.

This brings us to the second issue of Bioeconomy policies mentioned above: the failure of Bioeconomy strategies to involve all stakeholders in a sincere and open dialogue on goals and paths towards (a sustainable) Bioeconomy [169,170,173]. Their involvement in the early stages of a Bioeconomy transformation is not only necessary for receiving sufficient acceptance of new technologies and the approval of new products [168,170]. These aspects - which, again, mainly affect the short-term economic success of the Bioeconomy - are addressed well across various Bioeconomy strategies. However, "[a]s there are so many issues, trade-offs and decisions to be made on the design and development of the Bioeconomy, a commitment to participatory governance that engages the general public and key stakeholders in an open and informed dialogue appears vital" ([168], p. 2603). From the perspective of dedicated knowledge, there is a reason why failing to integrate the knowledge, values, and worldviews of the people affected will seriously impede the desired transformation: the processes of creation, diffusion, and use of normative knowledge and transformative knowledge is contingent on the input of a broad range of stakeholders - basically, of everyone who will eventually be affected by the transformation. The use of normative knowledge (that is, the agreement upon common goals), as well as the use of transformative knowledge (that is, the definition of transformation strategies), have both been identified to be intrinsically local and context-specific (see Sections 3.2 and 3.3). A policy taking account of these characteristics will adopt mechanisms to enable citizens to take part in societal dialogue which must comprise three tasks: offering suitable participatory formats, educating people to become responsible citizens, and training transdisciplinary capabilities to overcome cognitive distances between different mindsets as well as to reconcile global goals with local requirements. In this respect, there has been a remarkable development at the European level: while the German government is still relying on the advice of a Bioeconomy Council representing only the industry and academia for developing the Bioeconomy policy [154], the recently reconstituted delegates of the European Bioeconomy Panel represent a variety of societal groups: "business and primary producers, policy makers, researchers, and civil society organisations" ([175], p. 13). Unsurprisingly, their latest publication, the Bioeconomy stakeholders' manifesto, gives some recommendations that clearly reflect the broad basis of stakeholders involved, especially concerning education, skills, and training [176].

For a structured overview of the elements of dedicated knowledge and their consideration by current Bioeconomy policy approaches, see Table 4.1.

4.4.2 Promising (But Fragmented) Building Blocks for Improved SKBBE Policies

Although participatory approaches neither automatically decrease the cognitive distances between stakeholders nor guarantee that the solution strategies agreed upon are based on the most appropriate (systems and normative) knowledge [95], an SKBBE cannot be achieved in a top-down manner. Consequently, the involvement of stakeholders confronts policy makers with the roles of coordinating agents and knowledge brokers [74,75,77,177]. Once a truly systemic perspective is taken up, the traditional roles of different actors (for example, the state, non-governmental organisations, private companies, consumers) become blurred (see also [178–180]), which has already been recognized in the context of environmental governance and prompted Western democracies to adopt more participatory policy approaches [181]. A variety of governance approaches exist, ranging from adaptive governance (e.g. [182–184]) and reflexive governance (e.g. [130,185]) to Earth system governance (e.g. [18,101,186]) and various other concepts (e.g. [107,187–190]). Without digressing too much into debates about the differences and similarities of systemic governance approaches, we can already contend that the societal roots of many of the sustainability-related wicked problems clearly imply that social actors are not only part of the problem but must also be part of the solution. Against this background, transdisciplinary research and participatory approaches such as co-design and co-production of knowledge have recently gained momentum with good reason (e.g. [37,191–198]) and are also promising in the context of the transformation towards an SKBBE. Yet, the question remains why only very few, if any, Bioeconomy policies have taken participatory approaches and stakeholder engagement seriously (see, e.g. [170,199], on a related discussion).

To better acknowledge the characteristics of dedicated knowledge, we can propose a combination of four hitherto rather fragmented but arguably central frameworks that may be built on to improve Bioeconomy policy agendas in terms of creating, diffusing, and using dedicated knowledge (note that the proposed list is non-exhaustive but may serve as a starting point for developing more adequate knowledge-based Bioeconomy policies):

- Consider the roles of policy makers and policy making from a co-evolutionary perspective (see also [138]), where the 'state' is conceived as one of several sub-systems (for example, next to the individuals, civil society, the market, and nature) shaping contemporary capitalist societies [106]. Through the special co-evolutionary mechanism of promotion, political entities are able to deliberately influence the propagation (or retention) of certain knowledge, skills, ideas, values, or habits within other sub-systems and, thereby, trigger change in the whole system [106].

- Take up insights from culture design (e.g. [133,160–163,200]) and findings on transmission and learning biases in cultural evolution (e.g. [201–203]) that may help to explain and eventually overcome the stickiness and locality of both systems and normative knowledge and thereby increase the absorptive capacities of DIS actors for dedicated knowledge.

- Use suggestions from the literature on adaptive governance such as the combination of indigenous knowledge with scientific knowledge (to overcome path dependencies), continuous adaptation of transformative knowledge to new systems knowledge (to avoid lock-ins), embracing uncertainty (accepting that the behaviour of systems can never be completely understood and anticipated), and the facilitation of self-organisation (e.g. [183,184]) by empowering citizens to participate in the responsible co-creation, diffusion, and use of dedicated knowledge.

- Apply reflexive governance instruments as guideposts for DIS, including principles of transdisciplinary knowledge production, experimentation, and anticipation (creating systems knowledge), participatory goal formulation (creating and diffusing normative knowledge), and interactive strategy development (using transformative knowledge) ([130,204]) for the Bioeconomy transformation.

In summary, we postulate that for more sustainable Bioeconomy policies, we need more adequate knowledge policies.

4.5 Conclusions

Bioeconomy policies have not effectively been linked to findings and approved methods of sustainability sciences. The transformation towards a Bioeconomy, thus, runs into the danger of becoming an unsustainable and purely techno-economic endeavour. Effective public policies that take due account of the knowledge dynamics underlying transformation processes are required. In the context of sustainability, it is not enough to just improve the capacity of an IS for creating, diffusing, and using economically relevant knowledge. Instead, the IS must become more goal-oriented and dedicated to tackling wicked problems [3,205]. Accordingly, for affording such systemic dedication to the transformation towards an SKBBE, it is central to consider dedicated knowledge (that is, a combination of the understanding of economically relevant knowledge with systems knowledge, normative knowledge, and transformative knowledge).

Drawing upon our insights into such dedicated knowledge, we can better understand why current policies have not been able to steer the Bioeconomy transformation onto a sustainable path. We admit that recent policy revision processes (e.g. [173,175,176,206–208]) - especially in terms of viewing the transition to a Bioeconomy as a societal transformation, a focus on participatory approaches, and a better coordination of policies and sectors - are headed in the right direction. However, we suggest that an even stronger focus on the characteristics of dedicated knowledge and its creation, diffusion, and use in DIS is necessary for the knowledge-based Bioeconomy to become truly sustainable. These characteristics include stickiness, locality, context specificity, dispersal, and path dependence. Taking dedicated knowledge more seriously entails that the currently most influential players in Bioeconomy governance (that is, the industry and academia) need to display a serious willingness to learn and acknowledge the value of opening up the agenda-setting discourse and allow true participation of all actors within the respective DIS. Although in this article, we focus on the role of knowledge, we are fully aware of the fact that in the context of an SKBBE, other points of systemic intervention exist and must also receive appropriate attention in future research and policy endeavours [127,209].

While many avenues for future inter- and transdisciplinary research exist, the next steps may include

- enhancing systems knowledge by analysing which actors and network dynamics are universally important for a successful transformation towards an SKBBE and which are contingent on the respective variety of a Bioeconomy,
- an inquiry into knowledge mobilisation and, especially the role(s) of knowledge brokers for the creation, diffusion, and use of dedicated knowledge (for example, installing regional Bioeconomy hubs),
- researching the implications of extending the theory of knowledge to other relevant disciplines,
- assessing the necessary content of academic and vocational Bioeconomy curricula for creating Bioeconomy literacy beyond techno-economic systems knowledge,
- applying and refining the RBA to study which subject rules and which object rules are most important for supporting sustainability transformations,
- and many more.

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Chapter 5

Knowledge Networks in the German Bioeconomy: Network Structure of Publicly Funded R&D Networks

Chapter 5

Knowledge Networks in the German Bioeconomy: Network Structure of Publicly Funded R&D Networks

Abstract

Aiming at fostering the transition towards a sustainable knowledge-based Bioeconomy (SKBBE), the German Federal Government funds joint and single research projects in predefined socially desirable fields as, for instance, in the Bioeconomy. To analyze whether this policy intervention actually fosters cooperation and knowledge transfer as intended, researchers have to evaluate the network structure of the resulting R&D network on a regular basis. Using both descriptive statistics and social network analysis, I investigate how the publicly funded R&D network in the German Bioeconomy has developed over the last 30 years and how this development can be assessed from a knowledge diffusion point of view. This study shows that the R&D network in the German Bioeconomy has grown tremendously over time and thereby completely changed its initial structure. When analysing the network characteristics in isolation, their development seems harmful to knowledge diffusion. Taking into account the reasons for these changes shows a different picture. However, this might only hold for the diffusion of mere techno-economic knowledge. It is questionable whether the network structure also is favourable for the diffusion of other types of knowledge, as e.g. dedicated knowledge necessary for the transformation towards an SKBBE.

Keywords

knowledge; dedicated knowledge; knowledge diffusion; social networks; R&D networks; Foerderkatalog; sustainable knowledge-based Bioeconomy (SKBBE)

Status of Publication

This paper has already been submitted at an academic journal. If the manuscript should be accepted, the published text is likely going to differ from the text that is presented here due to further adjustments that might result from the review process.

5.1 Introduction

"Only an innovative country can offer its people quality of life and prosperity. That's why (Germany) invest(s) more money in research and innovation than any other country in Europe. (...) We encourage innovation to improve the lives of people. (...) We want to open up new, creative ways of working together to faster turn ideas into innovations, to faster bring research insights into practice." (BMBF 2018a)

In the light of wicked problems and global challenges as increased population growth and urbanisation, high demand for energy, mobility, nutrition and raw materials and the depletion of natural resources and biodiversity, the German Federal Government aims at undergoing the transition towards a sustainable, knowledge-based Bioeconomy (SKBBE) (BMBF 2018a). One instrument used by the government to foster this transition and, at the same time, keep Germany's leading position, is the promotion of (joint) research efforts of firms, universities and research institutions by direct project funding (DPF) in socially desirable fields. In their Bundesbericht Forschung und Innovation 2018 (BMBF 2018a), the Government explicitly states that "the close cooperation between science, economy and society is one of the major strengths of our innovation system. The transfer of knowledge is one of the central pillars of our research and innovation system, which we want to strengthen sustainably and substantially." (BMBF 2018a, p. 25). To foster this close cooperation and knowledge transfer as well as to increase innovative performance in 'socially desirable fields' in the Bioeconomy, in the last 30 years the German Federal Government supported companies, research institutions and universities by spending more than 1 billion Euro on direct project funding (own calculation). To legitimise these public actions and help politicians creating a policy instrument that fosters cooperation and knowledge transfer in predefined socially desirable fields, policy action has to be evaluated (and possibly adjusted) on a regular basis.

Many studies which evaluate policy intervention concerning R&D subsidies analyse the effect of R&D subsidies and their ability to stimulate knowledge creation and innovation (Czarnitzki and Hussinger 2004; Ebersberger 2005; Czarnitzki et al. 2007; Görg and Strobl 2007). Most of these researchers agree that R&D subsidies are economically highly relevant by actually creating (direct or indirect) positive effects. In contrast to these studies, the focus of my paper is on the network structures created by such subsidies and if the resulting network structures foster knowledge transfer, as intended by the German Federal Government (BMBF 2018a). Different studies so far use social network analysis (SNA) to evaluate such artificially created R&D networks. While many researchers in this context focus on EU-funded research and the resulting networks (Cassi et al. 2008; Protogerou et al. 2010a, 2010b), other researchers analyse the network properties and actor characteristics of the publicly funded R&D networks in Germany (Broekel and Graf 2010, 2012; Buchmann and Pyka 2015; Bogner et al. 2018; Buchmann and Kaiser 2018). In line with the latter, I use both descriptive statistics as well as social network analysis to explore the following research questions:

- What is the structure of the publicly funded R&D network in the German Bioeconomy and how does the network evolve? How might the underlying structure and its evolution influence knowledge diffusion within the network?

- Are the results still valid in the context of *dedicated knowledge*, i.e. knowledge necessary for the transformation towards a sustainable knowledge-based Bioeconomy (SKBBE)?

To answer these questions, the structure of this paper is as follows: Section 5.2. gives an overview of the literature on knowledge diffusion in R&D networks in general, as well as an introduction into how different network characteristics and structures influence knowledge diffusion performance, in particular. This is followed by a brief introduction into the concept of different types of knowledge, especially so-called *dedicated knowledge*, and some information on the particularities of publicly funded R&D networks. In section 5.3., I will focus on the analysis of the R&D network in the German Bioeconomy. In this chapter, I shed light on the actors and projects funded in the German Bioeconomy to show and explain the most important characteristics of the resulting R&D network. In the fourth section, the results of my analysis are presented, and statements about the potential knowledge diffusion within the R&D network are given. The last section summarises this paper and gives a short conclusion as well as an outlook to future research avenues.

5.2 Knowledge and its Diffusion in R&D Networks

Within the last years, the analysis of knowledge and its role in generating technological progress, economic growth and prosperity gained impressive momentum. Knowledge is seen as a crucial economic resource (Lundvall and Johnson 1994; Foray and Lundvall 1998), both as an input and output of innovation processes. Some researchers even state that knowledge is “the most valuable resource of the future” (Fraunhofer IMW 2018) and the solution to problems (Potts 2001), both decisive for being innovative and staying competitive in a national as well as in an international context. Therefore, the term ’knowledge-based economy’ has become a catchphrase (OECD 1996). In the context of the Bioeconomy transformation, already in 2007, the European Commission used the notion of a *Knowledge-Based Bioeconomy* (KBBE), implying the importance of knowledge for this transformation endeavour (Pyka and Prettner 2017).

Knowledge and the role it potentially plays actively depends on different, interconnected actors and their ability to access, apply, recombine and generate new knowledge. A natural infrastructure for the generation and exchange of knowledge in this context are networks. “Networks contribute significantly to the innovative capabilities of firms by exposing them to novel sources of ideas, enabling fast access to resources, and enhancing the transfer of knowledge” (Powell and Grodal 2005, p. 79). Social networks are shaping the accumulation of knowledge (Grabher and Powell 2004), such that innovation processes nowadays take place in complex innovation networks in which actors with diverse capabilities create and exchange knowledge (Levén et al. 2014). As knowledge is exchanged and distributed within different networks, researchers, practitioners and policy makers alike are interested in network structures fostering knowledge diffusion.

In the literature, the effects or performance of diffusion have been identified to depend on a) what exactly diffuses throughout the network, b) how it diffuses throughout the network, and c) in which networks and structures it diffuses (Schlaile et al. 2018). In this paper the focus is on c), how network characteristics and structures influence knowledge diffusion. Therefore, section 5.2.1 gives an overview over studies on the effect of network characteristics and structures on knowledge diffusion. Moreover, as the understanding and definition of knowledge are extremely important for its diffusion, section 5.2.2 gives a brief introduction into the different kinds and characteristics of knowledge for the transformation towards a sustainable knowledge-based Bioeconomy (SKBBE). In section 5.2.3, particularities of publicly funded project networks are explained.

5.2.1 Knowledge Diffusion in Different Network Structures

Due to the omnipresence of networks in our daily lives, in the last 50 years, an increasing number of scholars focused on the analysis of social networks (Barabási 2016). While some studies analyse the structure and the origin of the structure or physical architecture of networks, the majority of network research aims at explaining the effect of the physical architecture on both actor and network performance (Ozman 2009). Interested in question c) how specific network characteristics or network structures affect knowledge or innovation diffusion within networks, scientists investigated the effects of both micro measures and macro measures, as well as the underlying network structures resulting from certain linking strategies or combinations of network characteristics. Micro-measures that have been found to influence knowledge diffusion performance can be both actors' positions within the network as well as other actors' characteristics. Micro measures, as actor-related centrality measures, are, e.g. investigated in Ibarra (1993), Ahuja (2000), Tsai (2001), Soh (2003), Bell (2005), Gilsing et al. (2008), or Björk and Magnusson (2009). Actor characteristics as, e.g. cognitive distance or absorptive capacities, are analysed in Cohen and Levinthal (1989, 1990), Nooteboom (1994, 1999, 2009), Morone and Taylor (2004), Boschma (2005), Nooteboom et al. (2007), or Savin and Egbetokun (2016). Concerning the effect of macro measures or network characteristics on (knowledge) diffusion, most scholars follow the tradition of focusing on networks' average path lengths and global or average clustering coefficients (Watts and Strogatz 1998; Cowan and Jonard 2004, 2007). Besides (i) networks' average path lengths and (ii) average clustering coefficients, further network characteristics as (iii) network density, (iv) degree distribution, and (v) network modularity have also been found to affect diffusion performance within networks somehow.

Looking at the effects of these macro measures in more detail shows that general statements are difficult, as researchers found ambiguous effects of different characteristics.

When looking at the average path length, it has been shown that distance is decisive for knowledge diffusion (especially if knowledge is not understood as information). "(T)he closer we are to the location of the originator of knowledge, the sooner we learn it" (Cowan 2005, p. 3). This, however, does not only hold for geographical distances (Jaffe et al. 1993), but especially for social distances (Breschi and Lissoni 2003). In social networks, a short average path length, i.e. a short distance between the actors within the network, is assumed to increase the speed and efficiency of (knowledge) diffusion, as short paths allow for a fast and wide spreading of knowledge with little degradation (Cowan 2005). Hence, keeping all other network characteristics equal, a network with a short average path length is assumed to be favourable for knowledge diffusion.

Having a more in-depth look at the connection of the actors within the network, the average clustering coefficient (or cliquishness/local density) indicates if there are certain (relatively small) groups, which are densely interconnected and closely related. A relatively high average cliquishness or a high local density is assumed to be favourable for knowledge creation, as the actors within these clusters "become an epistemic community, in which a common language emerges, problem definitions become standardised, and problem-solving heuristics emerge and are developed." (Cowan 2005, p. 8). Often misunderstood, it is not the case that a high average clustering coefficient in general is harmful to knowledge diffusion just as it is favourable for knowledge creation. It is the case that theoretical network structures often either are characterised by both high normalized average path length and cliquishness (regular networks), or by low normalized average path length and cliquishness (random networks), which theoretically would imply a tension between the optimal structures for knowledge creation and diffusion (Cowan 2005). Some studies indicate a positive effect of a high clustering coefficient while other studies indeed indicate an adverse effect of a high clustering coefficient on knowledge diffusion performance (see also the discussion on structural holes (Burt 2004, 2017) and social capital (Coleman 1988)). Coleman's argument of social capital (Coleman et al. 1957) argues that strong clusters are good for knowledge creation and diffusion, whereas Burt's argument on structural holes (Burt 2004) contrasts this. Only looking at diffusion in isolation, as the average clustering coefficient is a local density indicator, a high average clustering coefficient (other things kept equal) seems to be favourable for knowledge diffusion, at least within the cluster itself. How the average clustering coefficient influences knowledge diffusion on a network level, however, depends on how the clusters are connected to each other or a core[1]. Assessing the effect of the overall network density (instead of the local density) is easier.

A high network density, as a measure of how many of all possible connections are realised in the network, per definition is fostering (at least) fast knowledge diffusion. As there are more channels, knowledge flows faster and can be transferred easier and with less degradation. This, however, only holds given the somewhat unrealistic assumption that more channels do not come at a cost and does not account for the complex relationship between knowledge creation and diffusion. It has to be taken into account, that there is no linear relationship between the number of links and the diffusion performance. On the one hand, new links seldom come at no costs, so there always has to be a cost-benefit analysis ("Is the new link worth the cost of creating and maintaining it?"). On the other hand, how a new link affects diffusion performance strongly depends on where the new link emerges (see also Cowan and Jonard (2007) and Burt (2017) on the value of clique spanning ties). Therefore, valid policy recommendation would never only indicate an increase in connections but rather also what kind of connections have to be created between which actors.

Networks' degree distributions can also have quite ambiguous effects on knowledge diffusion. The size and the direction of the effect of the degree distribution has been found to strongly depend on the knowledge exchange mechanism. While some studies found that the asymmetry of degree distributions may foster diffusion of knowledge (namely if knowledge diffuses freely, as in Cowan and Jonard (2007), and Lin and Li (2010)), others come to contrasting conclusions (namely if knowledge is not diffusing freely throughout the network, as in Cowan and Jonard (2004, 2007), Kim and Park (2009), and Mueller et al. (2017)). The reason is that very central actors are likely to collect much knowledge in a very short

[1] Looking at studies on network modularity, a concept closely related to the clustering coefficient, indicates that there seems to be an optimal modularity for diffusion (not too small and not to large) (Nematzadeh et al. 2014), which might also be the case for the clustering coefficient.

time. If knowledge diffuses freely, the small group of very well connected actors collects and re-distributes this knowledge very fast, which is favorable for overall diffusion. If knowledge diffuses limited by the diffusion mechanism, the group of very well connected actors collects knowledge very fast without re-distributing it. In this situation, there emerges a knowledge gap relatively early on. Actors with very different amounts of knowledge do not exchange this knowledge anymore (either because they don't want to or because they simply can't). In this situation, a skewed degree distribution is harmful for overall diffusion.

However, interpreting network characteristics in isolation and simply transferring their theoretical effect on empirical networks might be highly misleading. As already indicated above, diffusion performance does not only depend on the underlying structure, but also on a) what exactly diffuses and b) the diffusion mechanism. This explains why different studies found ambiguous effects of (i-v) on diffusion performance. Moreover, which network characteristics and structures are favourable for knowledge diffusion can also depend on other aspects, as, e.g. on the moment in the industry life cycle (see, for instance, Rowley et al. (2000) on this topic). In addition, network structures and characteristics do not only affect diffusion performance itself but also mutually influence each other. Therefore, researchers often also focus on the combination of these network characteristics by investigating certain network structures repeatedly found in reality. This facilitates making statements on the quality and the potential diffusion performance of a network.

Interested in the effects of the combination of specific characteristics on diffusion performance, scholars found that in real world (social) networks there exist some forms of (archetypical) network structures (resulting from the combination of certain network characteristics). Examples for such network structures exhibiting a specific combination of network characteristics in this context, are, e.g. random networks (Erdős and Renyi 1959, 1960), scale-free networks (Barabási and Albert 1999), small-world networks (Watts and Strogatz 1998), core-periphery networks (Borgatti and Everett 2000), or evolutionary network structures (Mueller et al. 2014).

In random networks, links are randomly distributed among actors in the network (Erdős and Renyi 1959). These networks are characterised by a small average path length, small clustering coefficient and a degree distribution following a Poisson distribution (i.e. all nodes exhibit a relatively similar number of links). Small-world network structures have both short average paths lengths, like in a random graph, and at the same time, a high tendency for clustering, like a regular network (Watts and Strogatz 1998; Cowan and Jonard 2004). Small-world networks exhibit a relatively symmetric degree distribution, i.e. links are relatively equally distributed among the actors. Scale-free networks have the advantage of explaining structures of real-world networks better than, e.g. random graphs. Scale-free networks structures emerge when new nodes connect to the network by preferential attachment. This process of growth and preferential attachment leads to networks which are characterised by small path length, medium cliquishness, highly dispersed degree distributions, which approximately follow a power law, and the emergence of highly connected hubs. In these networks, the majority of nodes only has a few links and a small number of nodes are characterised by a large number of links. Networks exhibiting a core-periphery structure entail a dense cohesive core and a sparse, unconnected periphery (Borgatti and Everett 2000). As there are many possible definition of the core or the periphery, the average path lengths, average clustering coefficients and degree distributions might differ between different core-periphery network structures. However, we often find hubs in such structures, leading to a rather skewed degree distribution.[2]

Same as for network characteristics in isolation, different studies found ambiguous effects of some network structures on knowledge diffusion. Many scholars state that small-world network structures are favourable (especially in comparison to regular and random network structures), as their combination of both relatively short average path length and relatively high clustering coefficient fosters both knowledge creation and diffusion (Cowan and Jonard 2004; Kim and Park 2009; Chen and Guan 2010). However, while many other studies identified small-world network structures as indeed being favourable for knowledge diffusion, this sometimes only holds in certain circumstances or at certain costs. Cowan and Jonard (2004) state that small-world networks lead to most efficient but also to most unequal knowledge diffusion. Morone and Taylor (2004) found that if agents are endowed with too heterogeneous knowledge levels even small-world structures cannot facilitate the equal distribution of knowledge. Bogner et al. (2018) found that small-world networks only provide best patterns for diffusion if the maximum cognitive distance at which agents still can learn from each other is sufficiently high. Cassi and Zirulia (2008) found that whether or not small-world network structures are best for knowledge diffusion depends on the opportunity costs of using the network. Morone et al. (2007) even found in their study that small-world networks do perform better than regular networks, but consistently underperform compared with random networks.

In contrast to this, Lin and Li found that not random or small-world but scale-free patterns provide an optimal structure for knowledge diffusion if knowledge is given away freely (as in the R&D network in the German Bioeconomy) (Lin and Li 2010). Cassi and colleagues even state: "Numerous empirical analyses have focused on the actual network structural properties, checking whether they resemble small-worlds or not. However, recent theoretical results have questioned the optimality of small worlds" (Cassi et al. 2008, p. 285). Hence, even though, e.g. small-world network structures have been assumed to foster knowledge diffusion for a long time, it is relatively difficult to make general statements on the effect of specific network structures. This might be the case as the interdependent, co-evolutionary relationships between micro and macro measures, as well as the underlying linking strategies, make it somewhat difficult to untangle the different effects on knowledge diffusion performance. Strategies as 'preferential attachment' or 'picking-the winner' behaviour of actors within the network will increase other actors' centralities and at the same time increase asymmetry of degree distribution (other thinks kept equal). Hence, despite the growing number of scholars analysing these effects, the question often remains what exactly determines diffusion performance in a particular situation.

Summing up, there is much interest in and much literature on how different network characteristics and network structures affect knowledge diffusion performance. Studies show that the precise effect of network characteristics on knowledge diffusion performance within networks is strongly influenced by many different aspects, e.g. (a) the object of diffusion (i.e. the understanding and definition of knowledge, e.g. knowledge as information), b) the diffusion mechanism (e.g. barter trade, knowledge exchange as a gift transaction, ...), or micro measures as certain network characteristics, the industry lifecycle, and many more. Hence,

[2]Algorithms and statistical tests for detecting core-periphery structures can, e.g. found in Borgatti and Everett 2000.

"(a)nalysing the structure of the network independently of the effective content of the relation could be therefore misleading" (Cassi et al. 2008, pp. 284-285). When analysing the overall system, we have to both quantitatively and qualitatively assess the knowledge carriers, the knowledge channels, as well as the knowledge itself. Especially the object of diffusion, i.e. the knowledge, needs further investigation. As will be explained in 5.2.2, especially in (mainstream) neo-classical economics, knowledge has been assumed to be equal to information, therefore many studies so far rather analyse information diffusion instead of knowledge diffusion, which makes it quite difficult to generalize findings (see also Schlaile et al. (2018), on a related note). Being fully aware of this, I start my research with rather traditional analyses of the network characteristics and structure of the R&D network in the German Bioeconomy to get a first impression of the structure and the potential diffusion performance. Moreover, as many politicians and researchers still have a traditional understanding of knowledge (or information) and its diffusion within networks, it is interesting to see how an empirical network will be evaluated from a theoretical point of view.

5.2.2 Knowledge for a Sustainable Knowledge-Based Bioeconomy

Network characteristics and structures as well as the way in which these have been identified to influence knowledge diffusion strongly depend on the understanding and definition of knowledge. Policy recommendations derived from an incomplete understanding and representation of knowledge will hardly be able to create R&D networks fostering knowledge diffusion. How inadequate policy recommendations derived from an incomplete understanding of knowledge actually are, can be seen by the understanding and definition of knowledge in mainstream neo-classical economics. Knowledge in mainstream neo-classical economics is understood as an intangible public good (non-excludable, non-rival in consumption), somewhat similar to information (Solow 1956; Arrow 1972). In this context, new knowledge theoretically flows freely from one actor to another (spillover) such that other actors can benefit from new knowledge without investing in its creation (free-riding leading to market failure) (Pyka et al. 2009). Therefore, there is no need for learning as knowledge instantly and freely flows throughout the network; the transfer itself comes at no costs. Policies resulting from a mainstream neo-classical understanding of knowledge, therefore, focused on knowledge protection and incentive creation (e.g. protecting new knowledge via patents to solve the trade-off between static and dynamic efficiency) (Chaminade and Esquist 2010). Hence, "policies of block funding for universities, R&D subsidies, tax credits for R&D etc. (were) the main instruments of post-war science and technology policy in the OECD area" (Smith 1994, p. 8).

While most researchers welcome subsidies for R&D projects, like, e.g. those in the German Bioeconomy, these subsidies have to be spent in the right way to prevent waste of time and money and do what they are intended. In contrast to the understanding and definition of knowledge in mainstream neo-classical economics, neo-Schumpeterian economists created a more elaborate definition of knowledge, e.g. by accounting for the fact that knowledge rather can be seen as a *latent public good* (Nelson 1989). Neo-Schumpeterian economists and other researchers identified many characteristics and types of knowledge, which necessarily have to be taken into account when analysing and managing knowledge exchange and diffusion within (and outside of) R&D networks. These are, for instance, the tacitness (Galunic and Rodan 1998; Antonelli 1999; Polanyi 2009), stickiness (von Hippel 1994; Szulanski 2002) and dispersion of knowledge (Galunic and Rodan 1998), the context-specific and local character of knowledge (Potts 2001) or the cumulative nature (Foray and Mairesse 2002; Boschma 2005), and path-dependence of knowledge (Dosi 1982; Rizzello 2004). As already explained above, (a) what flows throughout the network, strongly influences diffusion performance. Hence, the different kinds and characteristics of knowledge affect diffusion and have to be taken into account when creating and managing R&D networks and knowledge diffusion within these networks[3]. Therefore, when the understanding of knowledge changed, policies started to focus not only on market failures and mitigation of externalities but on systemic problems (Chaminade and Esquist 2010). Nonetheless, even though the understanding of knowledge as a latent public good has been a step in the right direction, many practitioners, researchers and policy makers still mostly focus on only one kind of knowledge, i.e. on mere techno-economic knowledge (and its characteristics) when analysing and managing knowledge creation and diffusion in innovation networks. Therefore, it comes as no surprise that nowadays, economically relevant or techno-economic knowledge and its characteristics most of the time are adequately considered in current Bioeconomy policy approaches, whereas other types of knowledge are not (Urmetzer et al. 2018). Especially in the context of a transformation towards a sustainable knowledge-based Bioeconomy (SKBBE), different types of knowledge besides mere techno-economic knowledge have to be considered (Urmetzer et al. 2018).

Inspired by sustainability literature, researchers coined the notion of so-called *dedicated knowledge* (Urmetzer et al. 2018), entailing besides techno-economic knowledge at least three other types of knowledge. These types of knowledge relevant for tackling problems related to a transition towards a sustainable Bioeconomy are: Systems knowledge, normative knowledge, and transformative knowledge (Abson et al. 2014; Wiek and Lang 2016; ProClim 2017; von Wehrden et al. 2017; Knierim et al. 2018). Systems knowledge is the understanding of the dynamics and interactions between biological, economic, and social systems. It is sticky and strongly dispersed between many different actors and disciplines. Normative knowledge is the knowledge of collectively developed goals for sustainable Bioeconomies. It is intrinsically local, path-dependent, and context-specific. Transformative knowledge is the kind of knowledge that can only result from adequate systems knowledge and normative knowledge, as it is the knowledge about strategies to govern the transformation towards an SKBBE. It is local and context-specific, strongly sticky, and path-dependent (Urmetzer et al. 2018). Loosely speaking, systems knowledge tries to answer the question "how is the system working?". Normative knowledge tries to answer the question "where do we want to get and at what costs?"[4]. Transformative knowledge answers the question "how can we get there?". In this context, economically relevant or techno-economic knowledge rather tries to answer, "what is possible from a technological and economic point of view and what inventions will be successful at the market". Therefore, e.g. Urmetzer et al. (2018) argue that

[3] In most studies and models so far, knowledge has been understood and represented as numbers or vectors (Cowan and Jonard 2004; Mueller et al. 2017; Bogner et al. 2018). However, "considering knowledge as a number (or a vector of numbers) ... restricts our understanding of the complex structure of knowledge generation and diffusion" (Morone and Taylor 2010, p. 37). Knowledge can only be modelled adequately, and these models can give valid results when incorporating the characteristics of knowledge, as, e.g. in Schlaile et al. (2018).

[4] Costs in this context do (not only) represent economic costs or prices but explicitly also take other costs, such as ecological or social costs, into account.

"knowledge which guided political decision-makers in developing and implementing current Bioeconomy policies so far has, in some respect, not been truly transformative." (Urmetzer et al. 2018, p. 9). While it is without doubt important to focus on techno-economic knowledge, there so far is no dedication (towards sustainability); most of the time new knowledge and innovation are assumed per se desirable (Soete 2013; Schlaile et al. 2017). The strong focus on techno-economic knowledge (even in the context of the desired transformation towards a sustainable knowledge-based Bioeconomy) for sure also results from the linear understanding of innovation processes. In this context, politicians might argue that economically relevant knowledge is transformative knowledge, as it brings the economy in the 'desired state'. This, however, only holds to a certain extent (it at all). Techno-economic knowledge and innovations might be a part of transformative knowledge, as they might be able to change the system and change technological trajectories (Urmetzer et al. 2018)[5]. However, as knowledge "is not just utilized by and introduced in economic systems, but it also shapes (and is shaped by) societal and ecological systems more generally (...) it is obvious that the knowledge base for an SKBBE cannot be a purely techno-economic one" (Urmetzer et al. 2018, p. 2). Without systems knowledge and normative knowledge, techno-economic knowledge will not be able to create truly transformative knowledge that enables the transition towards the target system of a sustainable knowledge-based Bioeconomy. Therefore, in contrast to innovation policies we have so far, assuring the creation and diffusion of dedicated knowledge is mandatory for truly transformative innovation in the German Bioeconomy. Besides the analysis and evaluation of the structure of the R&D network in the German Bioeconomy from a traditional point of view, chapter 5.5 also entails some concluding remarks on the structure of the R&D network and its potential effect on the diffusion of dedicated knowledge.

5.2.3 On Particularities of Publicly Funded Project Networks

The subsidised R&D network in the German Bioeconomy is a purposive project-based network with many heterogeneous participants of complementary skills. Such project networks are based on both interorganisational and interpersonal ties and display a high level of hierarchical coordination (Grabher and Powell 2004). Project networks, as the R&D network in the Bioeconomy, often are in some sense primordial, i.e. even though the German Federal Government acts as a coordinator, which regulates the selections of the network members or the allocation of resources, it steps in different kinds of pre-existing relationships. The aim of a project-based network is the accomplishment of specific project goals, i.e. in the case of the subsidised R&D network, the generation and transfer of (new) knowledge and innovations in and for the Bioeconomy. Collaboration in these networks is characterised by a project deadline and therefore is temporarily limited by definition (Grabher and Powell 2004) (e.g. average project duration in the R&D network is between two to three years). These limited project durations lead to a relatively volatile network structure in which actors and connections might change tremendously over time. Even though the overall goal of the network of publicly funded research projects is the creation and exchange of knowledge, the goal orientation and the temporal limitation of project networks might be problematic especially for knowledge exchange and learning, as they lead to a lack of trust.

[5]See, also Giovanni Dosi's discussion on technological trajectories (Dosi 1982).

This is to some extent solved by drawing on core members and successful prior cooperation. Hence, even temporarily limited project networks can entail some kind of stable long-term network components of enduring relationships (as can also be found in the core of the R&D network in the Bioeconomy). Even though the German Federal Government eventually coordinates the R&D network, the selection of actors as well as how these are linked is influenced by both the actors that are aiming at participating in a subsidised research project and looking for research partners as well as by politicians trying to foster research cooperation between, e.g. universities and industry. Thus, the R&D network is to some extent both 'artificially generated' by the government and its granting schemes as well as stepping in different kinds of pre-existing relationships. Even though there seems to be no empirical evidence for a 'designed by policy' structure (Broekel and Graf 2012), it is obvious that there is a top down decision on which topics and which projects are funded. Hence, the tie formation mechanism can be described as a two-stage mechanism. At the first stage, actors have to find partners with which they jointly and actively apply for funding. As research and knowledge exchange is highly related to trust, this implies that these actors either already know each other (e.g. from previous research) or that they at least have heard of each other (e.g. from a commonly shared research partner). This indicates that in the first stage, the policy influence in tie formation is lower (however, what kind of actors are allowed to participate is restricted by the granting schemes). At the second stage, by consulting experts, the government decides which possible research cooperations will be funded and so, the decision which ties actually will be created and between which actors knowledge will be exchanged is a highly political one. Regarding this two-stage tie formation mechanism, we can assume that some patterns, well known in network theory, are likely to emerge. First, actors willing to participate in a subsidised research project can only cooperate with a subset of an already limited set of other actors from which they can choose possible research partners. The set of possible partners is limited as, in contrast to theory, to receive funding, actors can only conduct research with other actors that are (i) allowed to participate in the respective project by fulfilling the preconditions of the government, (ii) actors they know or trust and (iii) actors that actually are willing to participate in such a joint research project. Furthermore, it is likely that actors chose other actors that already (either with this or another partner) successfully applied for funding, which might lead to a 'picking-the-winner' behaviour. Second, from all applications they receive, the German federal government will only choose a small amount of projects they will fund and of research partnerships they will support. Here, it is also quite likely that some kind of 'picking-the-winner' behaviour will emerge as the government might be more likely to fund actors that already have experience in projects and with the partner they are applying with (e.g. in form of joint publications). What is more, the fact that often at least one partner has to be a university or research organisation, and the fact that these heavily depend on public funds, will lead to the situation that universities and research institutions are chosen more often than, e.g. companies. This is quite in line with the findings of, e.g. Broekel and Graf (2012). They found that networks that primarily connect public research organisations, as the R&D network in the German Bioeconomy, are organized in a rather centralised manner. In these networks, the bulk of linkages is concentrated on a few actors while the majority of actors only has a few links (resulting in an asymmetric degree distribution). All these particularities of project networks have to be taken into account when analysing knowledge diffusion performance within these networks.

5.3 The R&D Network in the German Bioeconomy

In order to analyse both the actors participating in subsidised R&D projects in the Bioeconomy in the last 30 years as well as the structure of the resulting R&D network, I exploit a database on R&D projects subsidised by the German Federal Government (Förderkatalog[6]). The database entails rich information on actors funded in more than 110.000 joint or single research projects over the last 60 years and has so far only been used by a few researchers (as, e.g. by Broekel and Graf (2010, 2012); Bogner et al. (2018); Buchmann and Kaiser (2018)). The database entails information on the actors as well as the projects in which these actors participate(d). Concerning the actors, the Förderkatalog gives detailed information on, e.g. the name and the location of the money receiving and the research conducting actors. Concerning the projects, the Förderkatalog, e.g. gives detailed information on the topics of the projects, their duration, the grant money, the overall topic of the projects and their cooperative or non-cooperative nature. Actors in the Förderkatalog network mostly are public or private research institutions, companies, and some few actors from civil society.

The database only entails information on projects and actors participating in these projects, network data cannot be extracted directly but has to be created out of the information on project participation. Using the information entailed in the Förderkatalog, I created a network out of actors that are cooperating in joint research projects. The actors in the resulting network are those institutions receiving the grant money, no matter if a certain subsidiary conducted the project (i.e. the actor in the network is the University of Hohenheim, no matter which institute or chair applied for funding and conducted the project). The relationships or links between the agents in the R&D network represent (bidirected) flows of mutual knowledge exchange. My analysis focuses on R&D in the German Bioeconomy, hence the database includes all actors that participate(d) in projects listed in the granting category 'B', i.e. Bioeconomy. For the interpretation and external validity of the results, it is quite important to understand how research projects are classified. The government created an own classification according to which they classify the funded projects and corporations, i.e. 'B' lists all projects which are identified as projects in the Bioeeconomy (BMBF 2018a). However, a project can only be listed in one category, leading to the situation that 'B' does not reflect the overall activities in the German Bioeconomy. The government states that especially cross-cutting subjects as digitalisation (or Bioeconomy) are challenging to be classified properly within the classification (BMBF 2018b), leading to a situation in which, e.g. many bioeconomy projects are listed in the Energy classification. Hence, 'B' potentially underestimates the real amount of activities in the Bioeconomy in Germany. Besides, the government changed the classification and only from 2014 on (BMBF 2014) the new classification has been used (BMBF 2016). Until 2012, 'B' classified Biotechnology instead of Bioeconomy (BMBF 2012), explaining the large number of projects in Biotechnology[7].

Taking full amount of the dynamic character of the R&D network, I analysed both the actors and the projects as well as the network and its evolution over the last 30 years, from 1988 to 2017. For my analysis, I chose six different observation periods during the previous 30 years, (1) 1988-1992, (2) 1993-1997, (3) 1998-2002,

[6]The Förderkatalog can be found online via: https://foerderportal.bund.de/.

[7]In their 2010 "Bundesbericht Bildung und Forschung", the government didn't even mention Bioeconomy except for one sentence in which they define Bioeconomy as the diffusion process of biotechnology (BMBF 2010).

(4) 2003-2007, (5) 2008-2012, (6) 2013-2017, as well as (7) an overview over all 30 years from 1988-2017. In each observation period, I included all actors that participated in a project in this period, no matter if the project just started in this period or ended at the beginning of this period. I decided to take five years, as the average project duration of joint research projects is 38 months. I assumed one-year cooperation before project start as well as after project ending, just as there always has to be time for creating consortia, preparing the proposal, etc. As the focus of my work is on determinants of knowledge diffusion, I structured my analysis in two parts. First, in 5.3.1, I analyse the descriptive statistics of both the actors and the projects that might influence knowledge creation and diffusion. Hence, I shed some light on the number of actors and the kind of actors, as well as on the average project duration, average number of participants in a project or the average grant money per project. Second, in 5.3.2, I analyse the network structure of the network of actors participating and cooperating in subsidised research projects. In this context, I shed some light on how the actors and the network structure evolved and try to explain the rationales behind this. In chapter 5.4, this is followed by an explanation of how the network structure and its evolution over time might potentially influence knowledge diffusion performance within the network.

5.3.1 Subsidised R&D Projects in the German Bioeconomy in the Past 30 Years

The following chapter presents and discusses the major descriptive statistics of the actors and projects of the R&D network over time. The focus in this sub-chapter is on descriptive statistics that might influence knowledge diffusion and learning. In my analysis, I assume that knowledge exchange and diffusion are influenced by the kind of actors, the kind of partnerships, the frequency of corporation, project duration and the amount of subsidies.

Table 5.1 shows some general descriptive statistics of both joint and single research projects. By looking at the table, it can be seen that during the last 30 years, 759 actors participated in 892 joint research projects while 867 actors participated in 1.875 single research projects. On average, the German Federal Government subsidised 169 actors per year in joint research projects (on average 44% research institutions and 52% companies) and around 134 actors per year in single research projects (on average 36% research institutions and 59% companies). Looking at the research projects, Table 5.1 shows that joint research projects on average have a duration of 38,30 months, while single research projects are on average one year shorter, i.e. 26,99 months. Depending on the respective goals, projects lasted between 2 and 75 months (joint projects) and between 1 and 95 months (single projects), showing an extreme variation. During the last 30 years, government spent more than one billion Euros on both joint and single project funding, i.e. between 190 (single) and 290 (joint) thousand Euros per project per year, with joint projects getting between 74 and 440 thousand Euros per year and single projects getting between 101 and 266 thousand Euros per year. Joint projects have been rather small with 2,6 actors on average. The projects did not only vary tremendously regarding duration, money and number of actors, but also in topics. The government subsidised projects in fields as plant research, biotechnology, stockbreeding, genome research, biorefineries, social and ethical questions in the Bioeconomy and many other Bioeconomy-related fields. Most subsidies have been spent on biotechnology projects while there was only little spending

TABLE 5.1: Descriptive statistics of both joint and single research projects.

	joint projects	**single projects**
#actors 1988-2017	759	867
#projects 1988-2017	892	1875
average project duration in months	38,30 (mean) 38 (median) 2 (min) 75 (max)	26,99 (mean) 24 (median) 1 (min) 95 (max)
grant money in euros	1.017.866.506,00	1.135.437.546,00
#actors/year	169 (mean) 151,5 (median) 32 (min) 351 (max)	134,53 (mean) 133,5 (median) 53 (min) 269 (max)
%research institutions/year	44 (mean) 37 (median) 29 (min) 81 (max)	36 (mean) 31 (median) 16 (min) 74 (max)
%companies/year	52 (mean) 60 (median) 18 (min) 68 (max)	59 (mean) 65 (median) 19 (min) 79 (max)
money/year in euros	33.928.883,53 (mean) 33.940.646,98 (median) 5.451.267,85 (min) 72.446.764,16 (max)	37.847.918,20 (mean) 39.816.568,36 (median) 7.799.703,97 (min) 64.940.289,27 (max)
money/project/year in euro	290.176,49 (mean) 273.952,87 (median) 174.246,48 (min) 404.032,09 (max)	191.025,14 (mean) 190.975,58 (median) 101.294,86 (min) 266.661,90 (max)
#projects/year	127 (mean) 105 (median) 17 (min) 281 (max)	195,23 (mean) 196 (median) 77 (min) 336 (max)
#projects/year	2,63 (mean) 2,64 (median) 1,91 (min) 3,54 (max)	1 (mean) 1 (median) 1 (min) 1 (max)

on sustainability or bioenergy[8]. This variation in funding might also influence the amount and kind of knowledge shared within these projects. It can be assumed that more knowledge and also more sensitive and even tacit knowledge might be exchanged in projects with a longer duration and more subsidies. The reason is that actors that cooperate over a more extended period are more likely to create trust and share more sensitive knowledge (Grabher and Powell 2004). Besides, projects which receive more money need for stronger cooperation, potentially fostering knowledge exchange. The number of project partners, on the other hand, might at some point have an adverse effect on knowledge exchange. In larger projects with more partners, it is likely that not all actors are cooperating with every other actor, but rather with a small subset of the project partners. Of course, all project partners have to participate in project meetings, so it might be the case that more information is exchanged among all partners, but less other knowledge (especially sensitive knowledge) is shared among all partners and problems of overembeddedness emerge (Uzzi 1996). Knowledge exchange might also depend on the topics and the groups funded. If too heterogeneous actors are funded in too heterogeneous projects, too little knowledge between the partners is exchanged as the cognitive distance in such situations simply is too large (Nooteboom et al. 2007; Nooteboom 2009; Bogner et al. 2018). Hence, it is quite likely that the amount and type of knowledge exchanged differs tremendously from project to project. In contrast to what might have been expected, Table 5.1 shows that the Government does not put particular emphasis on research funding of joint research in comparison to single research. Within the last 30 years, both single and

[8]For more detailed information on all fields, have a look at: `https://foerderportal.bund.de/foekat/jsp/LovAction.do?actionMode=searchlist&lov.sqlIdent=lpsys&lov.header=LPSYS,%20Leistungsplan&lov.openerField=suche_lpsysSuche_0_&lov.ZeSt=`.

joint research projects are subsidised more or less to the same amount concerning money and the number of actors. From a diffusion point of view, this is surprising, as funding isolated research efforts seems less favourable for knowledge exchange and diffusion than funding joint research projects, at least if these actors are not to some extent connected to other actors of the network. Looking at the actors in more detail, however, shows that 29% of all actors participating in single projects also participated in joint research projects. This at least theoretically allows for some knowledge diffusion from single to joint research projects, et *vice versa*.

Besides the accumulated information on the last 30 years, the evolution of funding efforts in the German Bioeconomy over time is depicted in Figure 5.1. Figure 5.1 shows how the number of actors (research institutions, companies and others), the number of projects, and the amount of money (in million Euros) developed over time. The left axis indicates the number of actors and projects and the right axis indicates the amount of money in million euros. Looking at joint projects (l.h.s.) shows that the number of actors and projects, as well as the amount of money per year, increased tremendously until around 2013. This is a clear indicator of the growing importance of Bioeconomy-related topics and joint research effort in this direction. Spending this enormous amount of money on Bioeconomy research projects shows clearly government's keen interest in promoting the transformation towards a knowledge-based Bioeconomy. Looking at the actors in more detail shows that even though the number of companies participating in projects strongly increased until 2013, the Top-15 actors participating in most joint research projects (with one exception) still only are research institutions (see also Figure 5.5 in Appendix). This is in line with the results of the network analysis in the next sub-chapter, showing that there are a few actors (i.e. research institutions) which repeatedly and consistently participate in subsidised research projects, whereas the majority of actors (many companies and a few research institutions) only participate once. From 2013 on, however, government's funding efforts on joint research projects decreased tremendously, leading to spendings in 2017 as around 15 years before.

Comparing this evolution with the funding of single research projects shows that the government does not support single research projects to the same amount as joint research projects (anymore). The right-hand side of Figure 5.1 shows that after a peak in the 1990s, the number of actors and projects only increased to some extent (however, there was massive government spending in 2000/2001). As in joint research projects, the percentage of companies increased over time. We know from the literature, that public research often is substantial in technology exploration phases in early stages of technological development, while firms' involvement is higher in exploitation phases (Balland et al. 2010). Therefore, the increase in the number of firms participating in subsidised projects might reflect the stage of technological development in the German Bioeconomy (or at least the understanding of the government of this phase). Common to both joint and single research projects is the somewhat surprising decrease in the number of actors, projects and the amount of money from 2012 on. This result, however, is not in line with the importance and prominent role of the German Bioeconomy in policy programs (BMBF 2016, 2018a, 2018b). Whether this is because of a shifting interest of the government or because of issues regarding the classification needs further investigation.

Summing up, the German Federal Government increased its spending in the German Bioeconomy over the last 30 years with a growing focus on joint research efforts. However, there is a quite remarkable decrease in funding from 2013 on.

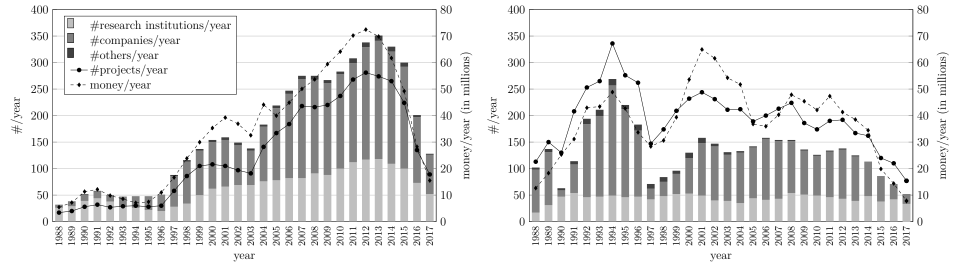

FIGURE 5.1: Type and number of actors/year, number of projects/year and money/year in joint (l.h.s.) and single projects (r.h.s.) over the last 30 years.

While a decrease in (joint) research indeed is harmful to knowledge creation in the Bioeconomy, the question is how government decreased funding, i.e. how this decrease changed the underlying network structure and how this structure finally affects knowledge diffusion.

5.3.2 Network Structure of the R&D Network

In the following sub-chapter, the structure of the knowledge network is analysed in detail by first looking at the graphical representation of the network (Figure 5.2) and later investigating the evolution of the network characteristics over time and comparing it with the structure of three benchmark networks known from the literature.

Figure 5.2 shows the evolution of the knowledge network of actors subsidised in joint research projects. The blue nodes represent research institutions, the green nodes represent companies, and the grey nodes represent actors neither belonging to one of these categories. In dark blue are those nodes (research institutions) which persistently participate in research projects, i.e. which have already participated before the visualised observation period.

In the first observation period, we see a very dense, small network consisting of well-connected research institutions. From the first to the second observation period, the network has grown, mainly due to an increase in companies connecting to the dense network of the beginning. This network growth went on in the next period, such that in (3) (1998-2002), we already see a larger network with more companies. The original network from the first observation period has become the strongly connected core of the network, surrounded by a growing number of small clusters, consisting of firms and a few research institutions. This development lasts until 2008-2012. In the last observation period the network has shrunken, the structure, however, stays relatively constant.

The visualisation of the network not only shows that the network has grown over time. It especially shows how it has grown and changed its structure during this process. The knowledge network changed from a relatively small, dense network of research institutions to a larger, sparser but still relatively well-connected network with a core of persistent research institutions and a periphery of highly clustered but less connected actors that are changing a lot over time. This is in line with the findings of the descriptive statistics, namely that a few actors (research institutions) participate in many different projects and persistently stay in the network while other actors only participate in a few projects and afterwards are not part of the network anymore.

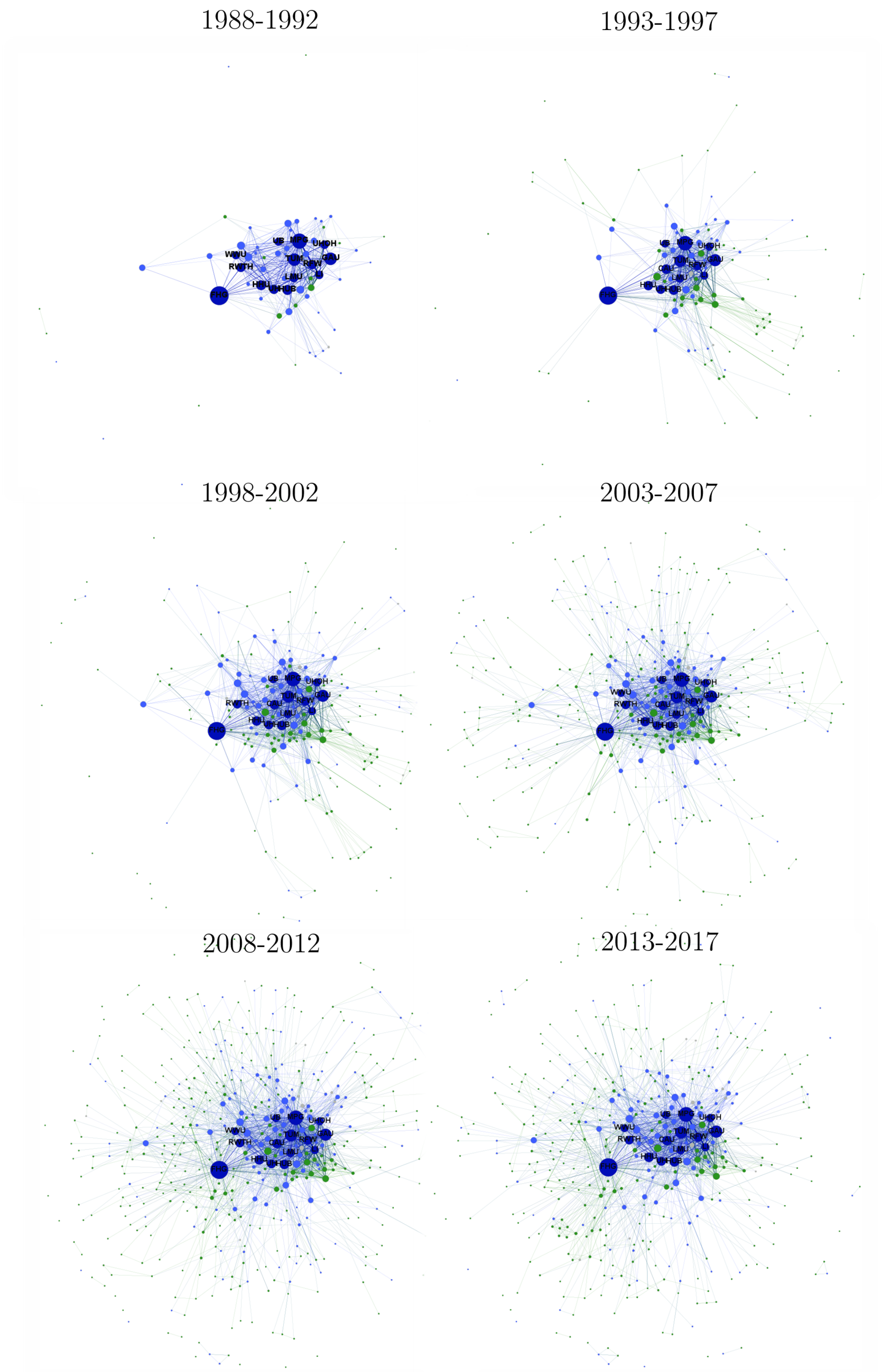

FIGURE 5.2: Visualisation of the knowledge network in the six different observation periods. Blue nodes represent research institutions, green nodes represent companies and grey nodes represent others. Dark blue indicates research institutions, which already participated in the observation period before.

The visualised network growth and the change of its structure also reflect themselves in the network characteristics and their development over time (see Table 5.2). When analysing the evolution of networks and comparing different network structures either between different networks or in the same network over time, it has to be accounted for the fact that network characteristics mutually influence each other (Broekel and Graf 2012). A decreasing density over time could result from an increase in actors (holding the number of links constant) as well as a decrease in links (keeping the number of actors constant) (Scott 2000). While there are many interesting and relevant network and actor characteristics, to get an overall picture of the evolution of the R&D network over time, I stay in line with the work of Broekel and Graf (2012). As the main goal of this paper is to analyse how the network structure might affect diffusion performance, I explicitly focus on the density, fragmentation, isolation, and centralisation of the network. This is done by analysing the evolution of the number of nodes and links, the network density, the average degree, the average path length and the average clustering coefficient, as well as the degree distribution in different periods in time (see Table 5.2 and Figures 5.3, 5.4, and 5.5).

TABLE 5.2: Network characteristics of the R&D network in different observation periods. In brackets () network characteristics including also unconnected nodes, in double-brackets (()) network characteristics of the biggest component.

	1988-1992	**1993-1997**	**1998-2002**	**2003-2007**	**2008-2012**	**2013-2017**	**1988-2017**
#nodes	56	105	186	322	447	385	704
(incl. unconnected)	(69)	(120)	(215)	(342)	(473)	(404)	(759)
((big. component))	((52))	((79))	((165))	((252))	((395))	((336))	((653))
%of the network	0,92	0,75	88,71	78,26	0,88	87,27	92,76%
%change of nodes		0,88	0,77	0,73	0,39	-0,14	
#edges	258	290	724	1176	1593	1104	2852
((big. component))	((256))	((255))	((702))	((1128))	((1551))	((1058))	((2820))
%of the network	0,99	0,87	0,96	0,95	0,97	96,09	0,98
%change of edges		0,12	1,5	0,62	0,35	-0,31	
av. degree	9,21	5,52	7,78	7,30	7,12	5,71	8,10
(incl. unconnected)	(7,47)	(4,83)	(6,73)	(6,87)	(6,73)	(5,45)	(7,51)
((big. component))	((9,84))	((6,45))	((8,50))	((8,95))	((7,85))	((6,29))	((8,63))
density	0,168	0,053	0,042	0,023	0,016	0,015	0,012
(incl. unconnected)	(0,11)	(0,041)	(0,031)	(0,02)	(0,014)	(0,014)	(0,01)
((big. component))	((0,19))	((0,08))	((0,05))	((0,03))	((0,02))	((0,01))	((0,01))
components	3	9	9	31	21	19	24
(incl. unconnected)	(16)	(24)	(38)	(51)	(47)	(38)	(79)
((big. component))	((1))	((1))	((1))	((1))	((1))	((1))	((1))
av. clustering coeff.	0,84	0,833	0,798	0,757	0,734	0,763	0,748
((big. component))	((0,84))	((0,81))	((0,78))	((0,74))	((0,72))	((0,75))	((0,74))
av.clust.coeff.(R)	0,17	0,049	0,042	0,021	0,017	0,021	0,011
av.clust.coeff.(WS)	0,415	0,356	0,389	0,376	0,367	0,365	0,335
av.clust.coeff.(BA)	0,334	0,162	0,112	0,079	0,057	0,055	0,044
path length	2,265	3,622	2,963	3,037	3,258	3,353	3,252
((big. component))	((2,26))	((3,66))	((2,96))	((3,04))	((3,26))	((3,35))	((3,25))
path length (R)	2,007	2,891	2,775	3,119	3,317	3,612	3,368
path length (WS)	2,216	3,5	3,306	3,881	4,239	4,735	4,191
path length (BA)	1,966	2,657	2,605	2,88	3,038	3,175	3,065

Table 5.2 gives the network characteristics for all actors in the network that have at least one partner, in brackets for all actors of the whole network and in double brackets only for the biggest component of the network. Table 5.2 and Figure 5.3 show the growth of the R&D network in the German Bioeconomy in more detail. By looking at these two graphs, it can be seen that in observation period (5) (2008-2012), the network consists of almost eight times the number of nodes and more than six times the number of links than in the first observation period. Resulting from the change in the number of actors and connections, the network density, as well as the actors' average number of connections (degree), decreased over time. Even though the network has first grown and then shrunken, as the number of nodes increases without an equivalent increase in the number of

links (or decreased with a decrease in the number of links), the overall network density decreased as well. The network density indicates the ratio of existing links over the number of all possible links in a network. We see that with the increase in nodes, the number of all possible links in the network increased as well, however, the number of realised links did not increase to the same amount (the network did not grow 'balanced'). The overall coherence decreases over time, the actors in the network are less well-connected than before. This could result from the fact that the German federal government increased the number of funded actors as well as the number of projects. However, the number of participants in a project stayed more or less constant (on average between two and four actors per project). Besides, it is often the case that actors participate in many different projects, but with actors, they already worked with before. Exclusively looking at the evolution of the density over time, given the fact that the network exhibits more actors but not 'enough' links to outweigh the increase in nodes, the sinking density would be interpreted as being harmful to knowledge diffusion speed and efficiency.

Looking at the average degree of nodes (Figure 5.3, r.h.s) (which is closely related to the network density, but less sensitive to a change in the number of links), a relatively similar picture emerges.

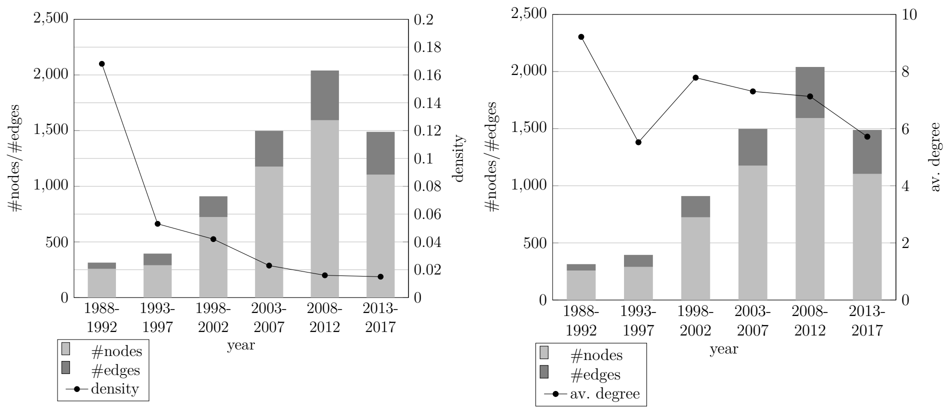

FIGURE 5.3: Number of nodes/edges and network density for all six periods (l.h.s) and number of nodes/edges and average degree for all six periods (r.h.s.).

As the density, the average degree of the nodes decreased over time (with a small increase in the average degree from the second to the third observation period). The average degree of nodes within a network indicates how well-connected actors within the network are and how many links they on average have to other actors. In the R&D network (which became sparser over time), the connection between the actors decreased as well as the number of links the actors on average have. The explanation is the same as for the decrease in the network density. With a lower average degree, agents on average have more constraints and fewer opportunities or choices for getting access to resources. In the first observation period (1988-1992), actors on average were connected to nine other actors in the network. Nowadays, actors are on average only connected to five other actors, i.e. they have access to less sources of (new) knowledge. This can again be explained by the fact that the number of subsidised actors, as well as the number of projects, increased, but the number of actors participating in many different projects did not increase to the same amount. This is in line with the finding explained before. The persistent core of repeatedly participating research institutions in later periods is surrounded by a periphery of companies and a few other research intuitions, which only participate in a few projects[9]. As in the case of the shrinking network density, looking at the shrinking average degree in isolation would be interpreted as being harmful to knowledge diffusion.

Looking at Figure 5.4 first gives the same impression. Figure 5.4 shows the evolution of the average path length as well as the average clustering coefficient of the R&D network (upper left side). For reasons of comparison, the average path length and the average clustering coefficient of the R&D network are compared to the potential average path length and average clustering coefficient the network would have had if it had been created according to one of the benchmark network algorithms. These benchmark algorithms are the random network algorithm (R) (top right), the small-world network algorithm (WS) (bottom left), and the scale-free network algorithm (BA) (bottom right), creating a network with the same number of nodes and links as the R&D network in the German Bioeconomy but exhibiting the respective network structures. This can be seen as a kind of policy experiment, allowing for a comparison of the real world network structures and the benchmark network structures. Such policy experiments enhance the assessment of potential diffusion performance, as there already is much literature on the performance of these three network structures. Therefore, the comparison of the R&D network with these networks gives a much more elaborate picture of the potential diffusion performance.

First looking at the average path length and the average clustering coefficient of the empirical network (B) shows, that the average path length increases over time, while the average clustering coefficient decreases (with a small increase in the last observation period). The reason for the increase in path length and the decrease in the clustering coefficient can be found in the increase of nodes (with a lower increase in links), and in the way, new nodes and links connect to the core. Comparing this development with those of the benchmark networks shows, that also in the benchmark networks, the average path length increases while the average clustering coefficient decreases. The difference, however, can be explained by how the different network structures grew over time. The increase in the average path length of the small-world and the random network is higher, as new nodes are connected either randomly, or randomly with a few nodes being brokers. So the over-proportional increase of nodes in comparison to links has a stronger effect here. In the empirical as well as in the scale-free networks, however, new nodes are connected to the core of the network. This, however, does not increase the average path length as substantial as in the other network algorithms. In general, the empirical network in the German Bioeconomy has a much higher average clustering coefficient, as at the beginning, it only consisted of a very dense, highly connected core. In later stages, the network exhibits a kind of core-periphery structure such that nodes are highly connected within their cliques. Still, looking at the development of those two network characteristics in isolation rather can be seen as a negative development for knowledge diffusion. However, from the comparison with the benchmark networks, we see that the characteristics would have even

[9]This, however, comes as no surprise in a field as the Bioeconomy, including projects in such heterogeneous fields as plant research, biotechnology, stockbreeding, genome research, biorefineries, social and ethical questions in the Bioeconomy, and many more. Having such heterogeneous projects does not allow all actors to be connected to each other or all actors to work in many different projects. Rather one would expect to have a few well-connected cliques working on the various topics, but little gatekeepers or brokers between these cliques. When interpreting the average degree, it has to be kept in mind that the interpretation of the mere number in isolation can be misleading.

been worse if the R&D network had another structure, even if it was a structure commonly assumed positive for diffusion performance.

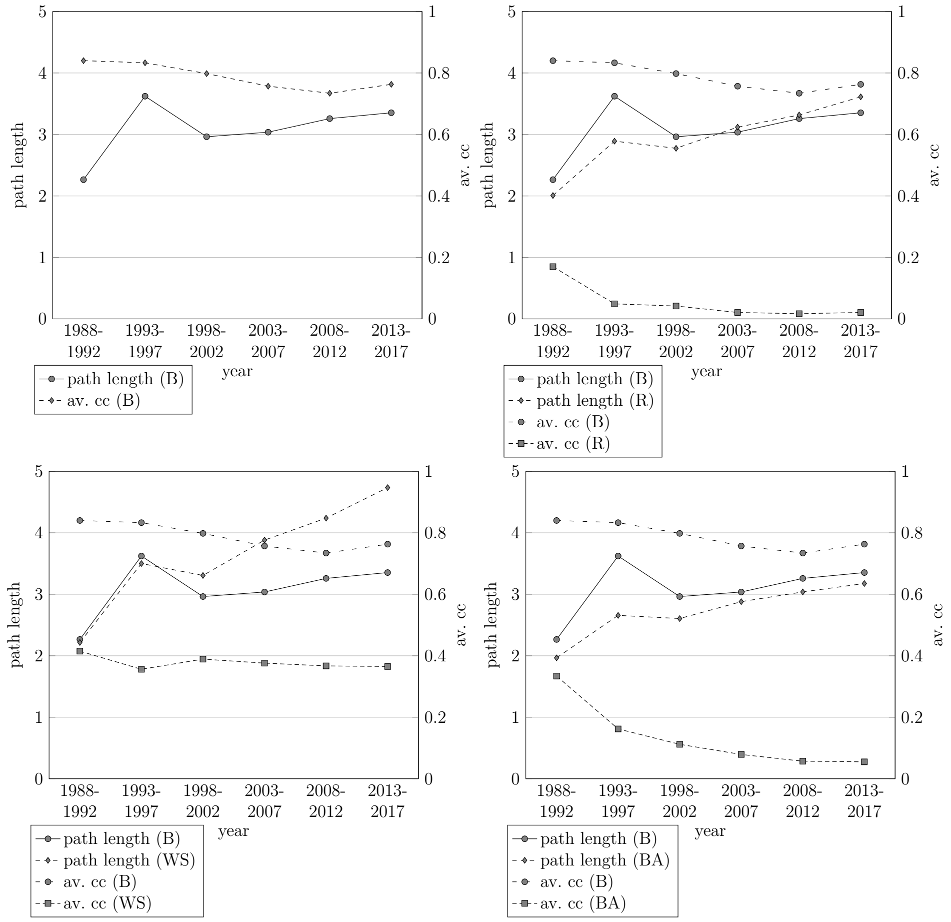

FIGURE 5.4: Average path length (av. pl) and average clustering coefficient (av. cc) of the R&D network (B) in the six different observation periods (upper l.h.s), as well as average path length and average clustering coefficient of the R&D network (B) in comparison to the those of the random network (R) (upper r.h.s.), of the small-world network (WS) (lower l.h.s.), and of the scale-free network (BA) (lower r.h.s.).

Summing up, Figure 5.4 shows what had already been indicated by looking at the visualisation of the network over time. The R&D network in the German Bioeconomy changed its structure over time, from a very dense, small network towards a larger, sparser network exhibiting a kind of core-periphery structure with a persistent core of research institutions and a periphery of many (unconnected) cliques with changing actors. This can also be seen by looking at the degree distribution of the actors over time in Figure 5.5.

While at the earlier observation periods, the actors within the network had a rather equal number of links (symmetric degree distribution), in later periods the distribution of links among the actors is highly unequal, resembling in a skewed or asymmetric degree distribution. In these cases, the great majority of actors only has a few links while some few actors are over-proortionally well embedded and have many links. As the direction and the size of the effect of the (a)symmetry of degree distribution has been found to depend on the diffusion mechanism

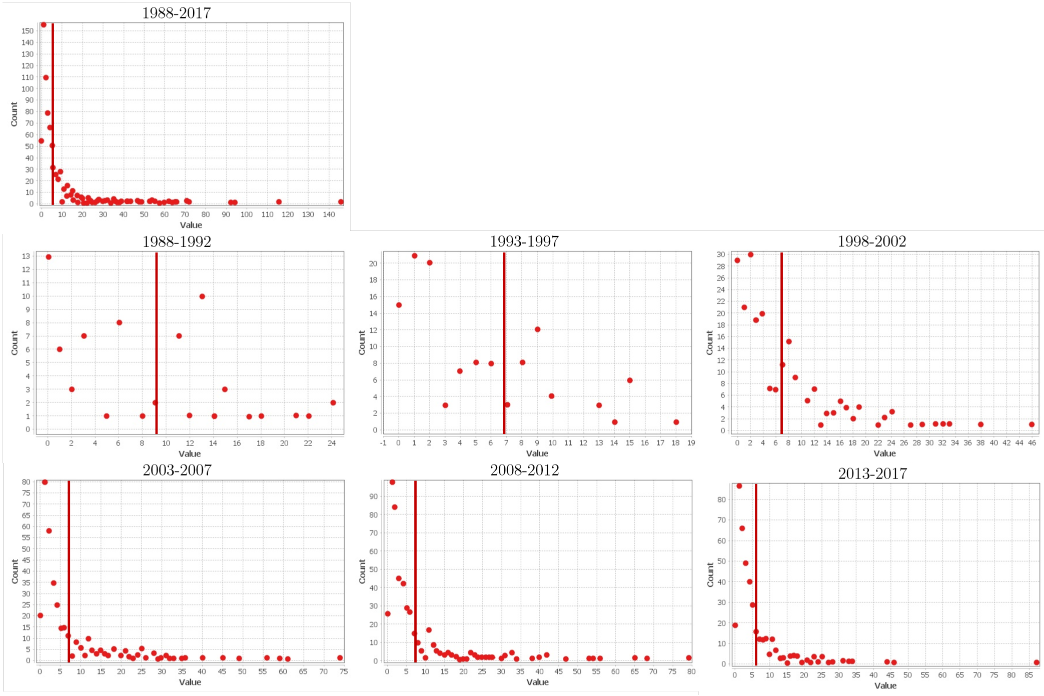

FIGURE 5.5: Degree distribution of the R&D network in the different observation periods.

(Mueller et al. 2017, Bogner et al. 2018), the underlying mechanism in the empirical network has to be investigated thoroughly. In the artificially created network in the German Bioeconomy knowledge can be assumed to be shared freely and willingly among the actors. As knowledge exchange is a precondition for funding, knowledge exchange happens as a gift transaction. However, especially in such a heterogeneous field as the Bioeconomy, it is quite likely that there exist a rather small maximum cognitive distance at which actors can still learn from each other. It is rather unrealistic, that actors conducting research in, e.g. plant research, can fully understand and internalise project results from medicine or genome research. Therefore, we can assume a diffusion mechanism according to which knowledge diffuses freely, however limited by a rather small maximum cognitive distance at which actors can still learn from each other (as, e.g. in Bogner et al. 2018). If this actually is the case, the rather skewed degree distribution over time can be rather harmful for knowledge diffusion performance. The small group of strongly connected actors will collect large amounts of knowledge quite rapidly while the large majority of nodes with only a few links will fall behind. Therefore, same as the traditional network characteristics, the analysis of the degree distribution and its evolution over time seems to become more and more harmful over time.

Table 5.6 in the Appendix shows those 15 actors with most connections in the networks (these are also the persistent actors of the network core). While the average degree over all years ranges between 5 and 10, the top 15 actors in the networks have between 55 (Universität Bielefeld) and 146 (Fraunhofer-Gesellschaft) links. In general, over the last 30 years, the 15 most central actors are the two public research institutions Fraunhofer-Gesellschaft and Max-Planck-Gesellschaft. Followed by 10 Universities (GAU Göttingen, TU München, HU Berlin, HHU Düsseldorf, CAU Kiel, RFWU Bonn, U Hamburg, RWTH Aachen, LMU München, U Hohenheim), another public research institution (Leibnitz-Institut), and again, two universities (WWU Münster, U Bielefeld). There hasn't been a single period with a company being the most central actor and from all top 15 most central actors in all six observation periods, only six companies were included (only 6,6% of all top 15 actors).

Summing up, over time the network structure has changed tremendously towards a core-periphery structure. Due to the network growth, the network characteristics changed quite naturally. Only interpreting the network characteristics in isolation and without comparing them to, e.g. benchmark network structures, results in interpreting the development of these characteristics as being rather harmful for knowledge diffusion.

5.4 The R&D Network in the German Bioeconomy and its Potential Performance

In the third chapter of this paper, both the descriptive statistics as well as the network characteristics of the development of the publicly funded R&D network in the German Bioeconomy have been described. From the first look at the network characteristics in isolation, the development of the R&D network over time seems to be harmful to knowledge diffusion; the structure has seemingly worsened over time. In this chapter, I'm going to summarise and critically discuss the main results of chapter 5.3, also in the context of dedicated knowledge. The three main results of this paper are:

(1) Over the last 30 years, the R&D network of publicly funded R&D projects in the German Bioeconomy has grown impressively. This growth resulted from an increase in subsidies, funded projects and actors. Both in joint and single research projects, there had been a stronger increase in companies in comparison to research institutions. However, within the last five years, the government reduced subsidies tremendously, leading to a decrease in the number of actors and projects funded and a de-growth of the overall R&D network. From a knowledge creation and diffusion point of view, the growth in the R&D network is a very positive sign, while the shrinking in government spending is somewhat negative (and surprising). This positive effect of network size has also been found in the literature. "(T)he bigger the network size, the faster the diffusion is. Interestingly enough this result was shown to be independent from the particular network architecture." (Morone et al. 2007, p. 26). In line with this, Zhuang and colleagues also found that the higher the population of a network, the faster the knowledge accumulation (Zhuang et al. 2011). Despite this network growth, to make statements about diffusion, it is always important to assess how a network has grown over time. In general, the growth of the network (i.e. of the number of actors and projects) is per se desirable as it implies a growth in created and diffused techno-economic knowledge (at least this is intended by direct project funding). Besides, government funded more (heterogeneous) projects and more actors, which is positive for the creation and diffusion of (new) knowledge. Following this kind of reasoning, the decrease of funding actives within the last five years, is negative for knowledge creation and diffusion, as fewer actors are actively participating and (re-)distributing the knowledge within (and outside of) the network. The question, however, is whether the government decreased funding activities in the Bioeconomy, or whether this just results from the special kind of data classification and collection. Keeping the strategies of the German Federal

Government in mind (BMBF 2018a, 2018b), it is more likely, that the development we see in the data actually results from peculiarities of the classification scheme. As a project can only be classified in one field, many projects, which deal with Bioeconomy topics are listed in other categories (e.g. Energy, Medicine, Biology ...). Still, one could argue that if this actually is true, the government interprets Bioeconomy rather as a complement to other technologies, as it is listed within another field. On the other hand, as Bioeconomy is, without doubt, cross-cutting (as, for instance, digitalisation), this does not necessarily have to be a negative sign. Nonetheless, this special result needs further investigation, e.g. by sorting the data according to project titles instead of the official classification scheme[10].

Looking at the funded topics and project teams itself shows that the government still has a very traditional (linear) understanding of subsidising R&D efforts, i.e. creating techno-economic knowledge in pre-defined technological fields. This is in line with the fact that many Bioeconomy policies have been identified to have a rather narrow techno-economic emphasis, a strong bias towards economic goals and to insufficiently integrate all relevant stakeholders into policy making (Schmidt et al. 2012; Pfau et al. 2014; Schütte 2017). While dedicated knowledge or knowledge that has a dedication towards sustainability transformation, necessarily entails besides mere techno-economic knowledge also systems knowledge, normative knowledge and transformative knowledge, these types of knowledge are neither (explicitly) represented in the project titles nor in the type and combination of actors funded.[11] While growing funding activities are desirable for the German Bioeconomy, it has to be questioned, whether the chosen actors and projects actually could produce and diffuse systems knowledge and normative knowledge (which is a prerequisite for the creation of truly transformative knowledge).

(2) The government almost equally supports both single and joint research projects. From a knowledge diffusion point of view, this is somewhat negative, as single research projects at least do not intentionally and explicitly foster cooperation and knowledge diffusion. Still, almost 30% of all actors participating in single research projects are also participating in joint research projects, which at least theoretically allows for knowledge exchange. Also, looking at the funding activities in more detail shows that there has been more funding for single projects at the beginning and an increase in joint research projects in later observation periods. Hence, even though this funding strategy could be worse from a traditional understanding of knowledge, such a large amount of funding for single research projects could be harmful to the creation and diffusion of systems and normative knowledge, as only a small group of unconnected actors independently perform R&D. While this might not always be the case for (single parts of) transformative knowledge, both systems knowledge and normative knowledge have to be created and diffused by and between many different actors in joint efforts. It is therefore questionable whether this funding strategy allows for proper creation and diffusion of dedicated knowledge.

(3) With its growth over time, the network completely changed its initial structure. The knowledge network changed from a relatively small, dense network

[10] A first analysis, sorting the data according to keywords entailed in project titles surprisingly did not change these results. Future research, therefore, should conduct an in-depth keyword analysis, not only in project titles but also in the detailed project description.

[11] To fully assess whether these types of dedicated knowledge are represented in the funded projects, an in-depth analysis of all projects and call for proposals would be necessary.

of research institutions to a larger, sparser but still relatively well-connected network with a persistent core of research institutions and a periphery of highly clustered but less connected actors. This results in a structure with a persistent core of strongly connected research institutions and a periphery of many different small clusters, changing over time. This is in line with the findings of the descriptive statistics, namely that a few actors (research institutions) participate in many different projects and persistently stay in the network, while other actors only participate in a few projects and afterwards are not part of the network anymore. The way the network has grown over time resulted in a decrease of the density, the average degree, as well as the average clustering coefficient, while the average path length increased over time. In line with this development, the degree distribution of the network has become more skewed, showing that the majority of actors only have a few links while some few persistent actors are over-proportionally well embedded in the network. From the traditional understanding and definition of knowledge and its diffusion throughout the network, the network characteristics in isolation became rather harmful to knowledge diffusion. Decreasing density, average degree as well as average clustering coefficient harm diffusion performance, as actors have fewer connections to other actors and need more time to reach other actors. An increasingly skewed degree distribution has also been found harmful to knowledge diffusion in this context. However, comparing the development of the network characteristics with those of three benchmark networks, the characteristics and their development could have been worse. Besides, interpreting network characteristics in isolation can be highly misleading. Even though the network characteristics have seemingly worsened, this is created and outweighed by the overall growth of the network itself. It comes as no surprise, that a network, which has grown that much cannot exhibit, e.g. the same density as before. In addition, as the topics and projects in the German Bioeconomy have become more and more heterogeneous (which indeed is good), it comes as no surprise that the network characteristics changed as they did. What is more, especially when comparing the structure with those of the benchmark networks shows that the core-periphery structure government created seemingly is a rather good structure for knowledge diffusion (given a fixed amount of money they can spend as subsidies). The persistent core (of research institutions) consistently collects and stores the knowledge. These over-proportionally embedded actors can serve as important centres of knowledge, and the resulting skewed network structure can so be favourable for a fast knowledge diffusion (Cowan and Jonard 2007). In addition to this, the rapidly changing periphery of companies and research institutions connected to the core bring new knowledge to the network while getting access to knowledge stored within the network. This is especially favourable for knowledge creation and diffusion, as new knowledge flows in the network and can be connected to the old knowledge stored in the persistent core.

However, it also has to be kept in mind that this seemingly positive structure might come at the risk of technological lock-in, systemic inertia and an extremely high influence of a small group of persistent (and probably resistant) actors (incumbents). As a small group of actors dominates the network, these actors quite naturally also influence the direction of R&D in the German Bioeconomy, probably concealing useful knowledge, possibilities and technologies besides their technological paths. Long-term networks (as the core of our network) benefit from well-established channels of collaboration (Grabher and Powell 2004). However, as this long-term stability increases cohesion and sure tightens patterns of exchange, this might lead to the risks of obsolescence or lock-in (Grabher and

Powell 2004). In addition, those actors building the core of the R&D network often are the actors evaluating research proposals and giving policy recommendations for future research avenues in this field (eight of the 17 members of the Bioeconomy Council are affiliated in research institutions and companies of the persistent core, 12 out of 17 members are affiliated at a university or research institution, and 15 out of 17 members hold a position as a professor (Bioökonomierat 2018)). This, again, quite impressively shows that general statements are difficult, even for mere techno-economic knowledge. The argument becomes even more pronounced for dedicated knowledge. It has to be questioned if and how systems knowledge and normative knowledge can be created and diffused in such a network structure. As the publicly funded R&D network in the German Bioeconomy is strongly dominated by a small group of public research institutions (which of course wants to keep their leading position), the question arises whether this group of actors actively supports or either even prevents the (bottom-up) creation and diffusion of some types of dedicated knowledge.

Summing up the main findings of my paper, the R&D network in the German Bioeconomy has undergone change. The analysis showed that there might be a trade-off between structures fostering the efficient creation and diffusion of techno-economic knowledge and structures fostering the creation and diffusion of other types of dedicated knowledge. While the growing number of actors and projects and the persistent core of the R&D network seems to be quite favourable for the diffusion of techno-economic knowledge, the resistance of incumbents in the network might lead to systemic inertia and strongly dominate knowledge creation and diffusion in the system. As systems knowledge is strongly dispersed among different disciplines and knowledge bases (which are characterised by different cognitive distances), subsidised projects in the German Bioeconomy must entail not only different, cooperating actors from, e.g. economics, agricultural sciences, complexity science, and other (social and natural) sciences, but also NGOs, civil society, and governmental organisations. As there is no general consensus about normative knowledge, but normative knowledge is local, path-dependent and context-specific, it is essential that many different actors jointly negotiate the direction of the German Bioeconomy. As "[i]nquiries into values are largely absent from the mainstream sustainability science agenda" (Miller et al. 2014, p. 241), it comes as no surprise that the network structure of the R&D network in the German Bioconomy might not account for this necessity of creating and diffusing normative knowledge. By funding certain projects and actors (mainly research institutions and companies) in predefined fields, the government already includes normativity, which, however, has not been negotiated jointly. As transformative knowledge demands for both systems knowledge and normative knowledge, actors within the R&D network creating and diffusing transformative knowledge, need to be in close contact with other actors within and outside of the network. For the creation and diffusion of dedicated knowledge, knowledge diffusion must be encouraged by inter- and transdisciplinary research. Therefore, politicians have to create network structures, which do not only connect researchers across different disciplines but also with practitioners, key stakeholders as NGOs, and society. The artificially generated structures have to allow for "transdisciplinary knowledge production, experimentation, and anticipation (creating systems knowledge), participatory goal formulation (creating and diffusing normative knowledge), and interactive strategy development (using transformative knowledge)" (Urmetzer et al. 2018, p. 13). To reach this goal, the government has to create a network including all relevant actors and to explicitly support and foster the diffusion of knowledge besides mere techno-economic knowledge. Without such network structures, the creation and diffusion of systems knowledge, normative knowledge, and transformative knowledge, as a complement to techno-economic knowledge, is hardly possible.

5.5 Conclusion and Future Research Avenues

In the light of wicked problems and current challenges, researchers and policy makers alike demand for the transformation towards a (sustainable) knowledge-based Bioeconomy (SKBBE). The transformation towards an SKBBE is seen as one possibility of keeping Germany's leading economic position without further creating the same negative environmental (and social) impacts our system creates so far. To foster this transition, the German Federal Government subsidises (joint) R&D projects in socially desirable fields in the Bioeconomy, leading to the creation of an artificially generated knowledge network. As "(t)he transfer of knowledge is one of the central pillars of our research and innovation system (...)" (BMBF 2018a), which strongly depends on the underlying network structure, researchers have to evaluate whether the knowledge transfer and diffusion within this network is as intended. Therefore, in this paper, I analysed the structure and the evolution of the publicly funded R&D network in the German Bioeconomy within the last 30 years using data on subsidised R&D projects. Doing this, I wanted to investigate whether the artificially generated structure of the network is favourable for knowledge diffusion. In this paper, I analysed both descriptive statistics as well as the specific network characteristics (such as density, average degree, average path length, average clustering coefficient and the degree distribution) and their evolution over time and compared these with network characteristics and structures which have been identified as being favourable for knowledge diffusion. From this analysis, I got three mayor results: (1) The publicly funded R&D network in the German Bioeconomy recorded significant growth over the previous 30 years, however, within the last five years government reduced subsidies tremendously. (2) While the first look on the network characteristics (in isolation) would imply that the network structure became somewhat harmful to knowledge diffusion over time, an in-depth look and the comparison of the network with benchmark networks indicates a slightly positive development of the network structure (at least from a traditional understanding of knowledge diffusion). (3) Whether the funding efforts and the created structure of the R&D network are positive for knowledge creation and diffusion besides those of mere techno-economic knowledge, i.e. dedicated knowledge, is not *a priori* clear and needs further investigation.

The transferability of my result, however, is subject to certain restrictions. First, as the potential knowledge diffusion performance within the network only is deducted from theory, this has to be taken into account when assessing the external validity of these results. Second, as the concept of dedicated knowledge and the understanding for a need for different types of knowledge still is developing, no elaborate statements about the diffusion of dedicated knowledge in knowledge networks can be made. Therefore, tremendous further research efforts in this direction are needed. Concerning the first limitation, applying simulation techniques such as simulating knowledge diffusion within the publicly funded

R&D network to assess diffusion performance might shed some further light on the knowledge diffusion properties of the empirical network. Concerning the second limitations, it is of utmost importance to further conceptualise the (so far) fuzzy concept of dedicated knowledge and to identify preconditions and network structures favourable for the creation and diffusion of dedicated knowledge. Only by doing so, researchers will be in a position that allows supporting policy makers in creating funding schemes which actually do what they are intended for, i.e. foster the creation and diffusion of knowledge necessary for a transformation towards a sustainable knowledge-based Bioeconomy.

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Appendix

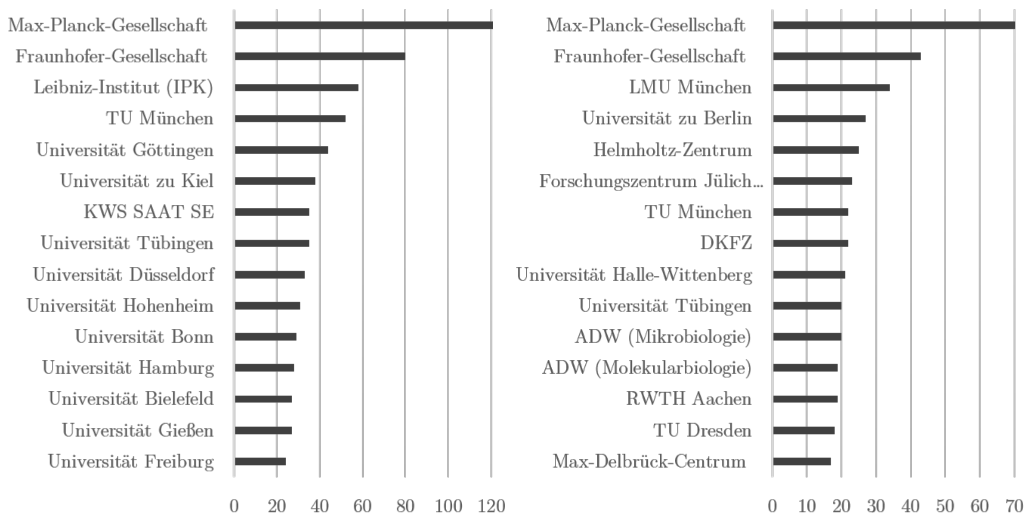

FIGURE 5.6: Top-15 actors in most joint projects (l.h.s.) and most single projects (r.h.s.).

Chapter 6

Discussion and Conclusion

Chapter 6

Discussion and Conclusion

"Knowledge is the most valuable resource of the future" (Fraunhofer IMW 2018). It is not only the input and output of innovation processes but the solution to problems (Potts 2001). This crucial economic resource is allowing firms to innovate and keep pace with national and international competitors. It is helping to generate technological progress, economic growth and prosperity. Understanding and managing the creation and diffusion of knowledge within and outside of firms and innovation networks is of utmost importance to make full use of this precious resource. As the knowledge base in today's economies has become more and more complex, nowadays it is almost impossible to create innovations without exchanging and generating (new) knowledge with other actors. This knowledge exchange uses to happen in different kinds of networks. Networks play a central role in the exchange and diffusion of knowledge and innovations as they provide a natural infrastructure for knowledge creation, exchange and diffusion.

Researchers found that knowledge diffusion within (and outside of) R&D networks strongly depends on the underlying structures of these networks. While in the literature, some structural characteristics of networks, such as the properties of small-world networks, often are assumed to foster fast and efficient knowledge diffusion, other network structures are assumed to rather harm diffusion performance. However, researchers so far have not been able to make general statements on the diffusion performance of knowledge in different network structures, but instead identified many different isolated, partly even ambiguous, effects of network characteristics and structures on knowledge diffusion performance. Due to this lack of a comprehensive overall understanding of knowledge diffusion within different networks and the relationship between the different effects, this doctoral thesis tries to contribute to creating a more comprehensive understanding. This contribution is presented in the four studies in chapter 2, 3, 4, and 5.

6.1 Summary and Discussion of Results

The results of the studies presented in this thesis mostly are in line with the literature and confirm the often identified ambiguity of effects.

Study 1 analyses the effect of different structural disparities on knowledge diffusion by using an agent-based simulation model. In this model, agents repeatedly exchange knowledge with their direct partners if it is mutually beneficial (a double coincident of wants), leading to knowledge diffusion throughout the network. As agents are connected via different linking strategies, knowledge diffuses through different networks exhibiting different network properties. These properties influence knowledge diffusion performance. This study especially emphasises the effect of an asymmetric degree distribution on knowledge diffusion performance and the roles of different groups of actors, thereby complements research, which so far mostly focused on properties as average path length or average clustering coefficient.

In line with many other studies, the network structures most favourable for knowledge diffusion are the small-world network structures (followed by random, scale-free and evolutionary network structures). This, however, seems not to be the case because of the often cited favourable combination of a relatively low average path length and a relatively high average clustering coefficient of small-world networks. These network characteristics, which so far often have been used to explain diffusion performance, fail to coherently explain the results we got in our experiments. Completely in contrast to theory, the higher the path length the better the diffusion performance. We also could not find the expected (linear) relationship between knowledge diffusion performance and the average clustering coefficient. In addition, our simulation found almost no effect of different absorptive capacities on knowledge diffusion performance. This can be explained by the fact that in this setting the named network and actor characteristics are less important for diffusion as diffusion mostly depends on whether agents actually are willing to exchange knowledge, i.e. the successful creation of double coincidences of wants.

In line with, e.g. Cowan and Jonard (2007) and Lin and Li (2010), our simulation confirmed that, instead of the average path length and the average clustering coefficient of the networks, the degree distribution rather explains the differences in diffusion performance. Networks with a rather symmetric degree distribution outperform networks with a rather asymmetric degree distribution. The similarity of agents concerning their number of links seems to be positive for knowledge diffusion performance. The explanation is that in networks with rather asymmetric degree distribution, there exist many ‚small', inadequately embedded agents. These agents stop trading knowledge quite early as they have too little knowledge to offer as a barter object to their partners (this also is in line with the theory that there is a positive relationship between degree and knowledge). By doing so, the many small agents rapidly fall behind and stop trading, which disrupts and disconnects the knowledge flow, leading to a lower knowledge diffusion performance as in networks with less inadequately embedded actors (i.e. more symmetric degree distributions).

Trying to give possible policy recommendations, we conducted a policy experiment to analyse which policy interventions might improve diffusion performance in the given network structures. In line with our previous findings, policies leading to a more symmetric degree distribution increase overall knowledge diffusion performance, while policies leading to a rather asymmetric degree distribution decrease overall knowledge diffusion performance. Connecting inadequately connected actors to better embedded actors increases overall diffusion performance. This becomes even more pronounced at the individual level, where structural homophily of small actors seems to be most favourable for them. Interestingly, creating new links between over-proportionally embedded actors (structural homophily between stars) harms diffusion performance as it increases the asymmetry of degree distribution (contradicting the idea of benefits resulting from ‚picking-the-winner' strategies for those actors).

Summing up, our analysis complements previous research not only by (i) confirming that the asymmetry of degree distribution indeed negatively affects knowledge diffusion performance but also by (ii) an in-depth explanation why it does so. Study 1 shows that exactly those structures which hinder knowledge diffusion in the network, actually are caused by the individual and myopic pursuit of knowledge by small nodes. Besides, individual optimal linking strategies of actors are not fully compatible with policy interventions that aim to enhance the diffusion performance at the systemic level. Therefore, we suggest, policy makers need to implement incentive structures that enable small firms to overcome their myopic, and at first glance, superior linking strategies.

In chapter 3, study 2 uses an agent-based simulation model to analyse the effect of different network properties on knowledge diffusion performance. As study 1, study 2 also focuses on the diffusion of knowledge. In contrast to study 1, study 2 analyses this relationship in a setting in which knowledge is diffusing freely throughout an empirical formal R&D network as well as through the four benchmark networks already investigated in study 1. The idea behind this approach is to investigate whether the identified negative effects of asymmetric degree distributions (created by the explained problems in the creation of double coincident of wants), can also be found if agents freely share their knowledge. In addition, the concept of cognitive distance and differences in learning between agents in the network are taken into account. In contrast to the majority of studies in this field or study 1 in this thesis, the best performing network structures are not always the small-world structures. In line with, e.g. Morone et al. (2007), random networks seem to provide a better pattern for diffusion performance in this setting. In contrast to, e.g. Cowan and Jonard (2004), but in line with Morone and Taylor (2004), the better performing network structures also lead to an equal distribution of knowledge. The model in study 2 indicates that the skewness of degree distribution to a large extent still explains the differences in diffusion performances. However, the maximum cognitive distances at which agents still can learn from each other as well as the point in time at which we observe diffusion performance might dominate the effect of degree distribution on diffusion performance. In this simulation, the effect of degree distribution on knowledge diffusion performance is sensitive to the agents' cognitive distances. Neither is there always a linear relationship between degree distribution and diffusion performance, nor does the degree distribution always dominate other network characteristics. For different maximum cognitive distances, different network structures seem to be favourable. Especially for small maximum cognitive distances between agents, the networks' average path lengths are more important for diffusion performance, leading to the situation known from the literature, i.e. that networks with smaller average path length foster knowledge diffusion performance.

In this setting, networks characterised by an asymmetric degree distribution most of the time perform worse than networks characterised by a rather symmetric degree distribution. This is not because of the lack of double coincidences of wants, but because of the knowledge race between actors. In line with previous studies and study 1, we found that agents with more links acquire more knowledge as they have more possibilities. Due to this, there quite early emerges a knowledge gap between actors with a high number of links and actors with a lower number of links, as actors with many links rapidly acquire much knowledge. In networks with a rather skewed degree distribution, the difference in actors' links is much higher, more nodes are cut off from the learning race and the structural imbalance discriminates less embedded actors. The resulting knowledge gap disrupts the knowledge flow quite early at the diffusion process, explaining why network structures with a skewed degree distribution might be harmful to diffusion performance. Networks with a skewed distribution of links perform worse, as they foster a knowledge gap between nodes relatively early on. Hence, this study also confirms that an asymmetric degree distribution might be harmful to diffusion performance, even for another exchange mechanism as the barter trade (presented in study 1). In line with the literature, we conclude that an asymmetric degree distribution harms diffusion as soon as there is a stopping condition in the knowledge exchange (e.g. a fail in the creation of a double coincidence of wants, as in the barter trade, or the inability to learn from partners due to a too high cognitive distance). However, as long as knowledge is exchanged freely without any restrictions, scale-free structures exhibiting asymmetric degree distributions, seem to be favourable for diffusion performance.

Study 2 complements study 1 and previous research on knowledge diffusion by showing that (i) the (asymmetry of) degree distribution and the distribution of links between actors in the network indeed influence knowledge diffusion performance to a large extent. However, (ii) inasmuch degree distribution dominates the effect of other network characteristics on diffusion performance depends on, e.g. the agents' maximum cognitive distances at which they still can learn from each other. Hence, while we could confirm that the effect of degree distribution on diffusion performance also holds for other diffusion mechanisms, study 2 could not find any linear relationship.

While study 1 and study 2 quite technically analyse knowledge diffusion performance by means of agent-based simulation models, in chapter 4 study 3 focuses on theoretically exploring different kinds of knowledge that are created and diffused throughout innovation systems dedicated to the transformation towards a sustainable knowledge-based Bioeconomy (SKBBE) (see, e.g. Pyka 2017, on so-called *dedicated innovation systems* (DIS)). In this context, we are proposing a concept of (different types of) knowledge called *dedicated knowledge*. This dedicated knowledge entails besides techno-economic knowledge also systems knowledge, normative knowledge and transformative knowledge. Based on the critique that current policy approaches are neither entirely transformative nor fostering the transformation towards sustainability, we tried to investigate which kinds of knowledge are necessary for such an endeavour and whether these kinds of knowledge are considered in current Bioeconomy policy approaches. To answer these questions, we analysed the understanding of knowledge and its characteristics which has informed policy makers so far. We then extended this concept of knowledge by three other types of knowledge and their characteristics to analyse if and how this so-called dedicated knowledge is considered in current Bioeconomy policy approaches.

As expected and in line with research, study 3 shows that there exist knowledge gaps in current Bioeconomy policies concerning different types of knowledge necessary for the transformation towards sustainability. Due to the tradition of solely focusing on mere techno-economic knowledge, Bioeconomy innovation policies so far mainly concentrate on fostering the creation and diffusion of knowledge known from a somewhat traditional understanding. This is why Bioeconomy policies brought forward by the European Union (EU) and several other nations show a rather narrow techno-economic emphasis. When looking at the different types of dedicated knowledge and their characteristics in more detail, this becomes even more pronounced. In our study, we found that economically relevant knowledge so far seems to be adequately considered in current Bioeconomy policy approaches. While normative and transformative knowledge at least have been partially considered, systems knowledge has only found insufficient consideration. We found that while the creation of dedicated knowledge might be possible in our current innovation system, the diffusion, especially of systems knowledge, rather is not. The given structures simply do not support the diffusion of all types of dedicated knowledge. By looking at the characteristics of these types of knowledge, we argue that especially the stickiness and dispersal of systems knowledge hinder its diffusion.

To give policy recommendations for the improvement of these structures, we analysed how policy makers can deal with characteristics of knowledge and actors transmitting knowledge (e.g. absorptive capacities or cognitive distances, as also analysed in study 1 and 2 in this thesis). Only by taking these characteristics into account, policy makers will be able to foster the diffusion of dedicated knowledge. In our study, we suggest that policies have to not only encourage both trans- and interdisciplinary research, but also to facilitate knowledge diffusion across disciplinary and mental borders. Only by doing so, policies will allow actors to overcome the wide dispersals of bioeconomically relevant knowledge. Strategies in this context have to both create connections between researchers of different disciplines as well as between researchers and practitioners. More sustainable Bioeconomy policies need for more adequate knowledge policies. The knowledge-based Bioeconomy will only become truly sustainable if all actors agree to focus on the characteristics of dedicated knowledge and its creation, diffusion, and use in DIS. These characteristics influencing the diffusion of dedicated knowledge are stickiness, locality, context-specificity, dispersal, and path dependence.

This study complements previous research on knowledge and its diffusion by taking a strong focus on the different types and characteristics of knowledge besides techno-economic knowledge (often overemphasised in policy approaches). It shows, that (i) different types of knowledge necessarily need to be taken into account when creating policies for the transformation towards a sustainable knowledge-based Bioeconomy, and that (ii) especially systems knowledge so far has been insufficiently considered by current Bioeconomy policy approaches.

The last study of this doctoral thesis combines insights from study 1 and 2 with those of study 3, by applying the concept of dedicated knowledge in a more traditional analysis of an empirical R&D network.

In chapter 5, study 4 analyses the effect of different structural disparities on knowledge diffusion by deducing from theoretical considerations on network structures and diffusion performance. This study focuses on the analysis of an empirical R&D network in the German Bioeconomy over the last 30 years utilizing descriptive statistics and social network analysis. The first part of the study presents the descriptive statistics of publicly funded R&D projects and the research-conducting actors in the German Bioeconomy within the last 30 years. The second part of the study presents the network characteristics and structures of the network in six different observation periods. These network statistics and structures are evaluated according to their role for knowledge diffusion performance.

In line with what would have been expected, the study shows that the publicly funded R&D network in the German Bioeconomy recorded significant growth over the last 30 years. Within this period, the number of actors and projects funded increased by factor eight and six, respectively. Surprisingly, over the last five years, government reduced subsidies in the German Bioeconomy tremendously, resulting in a decrease of both actors and projects funded. As this is in sharp contrast to Germany's political agenda on promoting the transformation towards a knowledge-based Bioeconomy, whether this development found in the data actually reflects Germany's overall efforts needs further investigation.

The analysis of the network in more detail shows that the growth of the R&D network in the German Bioeconomy led to a complete change in its initial structure. The R&D network changed from a relatively small, dense network of research institutions to a larger, sparser but still relatively well-connected network with a persistent core of research institutions and a periphery of highly clustered but less connected actors, whose participation is relatively volatile over time. While the first look on the network characteristics (in isolation) would imply that the network structure became somewhat harmful to knowledge diffusion over time, a more in-depth look and the comparison of the network with benchmark networks indicates a rather positive development of the network structure (at least from a traditional understanding of knowledge and its diffusion). Notwithstanding, it is not a priori clear whether the funding efforts and the created structures of the knowledge network are positive for the creation and diffusion of knowledge besides those of mere techno-economic knowledge, i.e. for dedicated knowledge. As the publicly funded R&D network in the German Bioeconomy is strongly dominated by a small group of public research institutions (which of course want to keep their leading position), the question arises whether this group of actors actively supports (or even unconsciously prevents) the (bottom-up) creation and diffusion of dedicated knowledge. This needs further investigation.

Summing up, study 4 especially complements previous research on knowledge diffusion by (i) analysing an empirical R&D network and its potential diffusion performance over such a long period of time, and by (ii) showing that even though a network and its structure might be favourable for the diffusion of information or mere techno-economic knowledge, this does not imply it also fosters the creation and diffusion of other types of knowledge (i.e. dedicated knowledge) necessary for the transformation towards a sustainable knowledge-based Bioeconomy (SKBBE).

6.2 Conclusions, Limitations and Avenues for Future Research

Understanding and managing knowledge and its exchange within and outside of innovation networks became a major task for companies, researchers and policy makers alike. In the four studies presented in this doctoral thesis, I investigated how networks and their structures affect knowledge diffusion, as well as which types of knowledge are needed for the transformation towards a sustainable knowledge-based Bioeconomy. From the results of my research, it can be concluded: Things aren't quite as simple as expected and general statements are hardly possible.

Policy makers are very keen on creating structures and networks that foster knowledge diffusion performance. However, in line with the literature, the studies within this thesis show that policy makers must be aware of the complex relationship between knowledge, networks, network structures and network performance. Diffusion performance strongly depends on what is diffusing (i.e. the kind of knowledge), how it is diffusing (how this respective knowledge is exchanged within the network), as well as where it is diffusing (the underlying network structure and the actors, which exchange the knowledge). Therefore, without analysing and understanding these three aspects and their (co-)evolutionary relationship in detail, it is almost impossible for policy intervention to (positively) affect knowledge creation and diffusion performance. The studies within this thesis show that strategies which have always been assumed to be favourable for knowledge diffusion (as, e.g. creating small-world structures on the network level or picking-the-winner behaviour on the actor level) can be rather harmful in certain circumstances. This becomes especially pronounced in innovation systems, in which the transformation and its direction have a particular dedication. The creation and diffusion of knowledge for a transformation towards a sustainable knowledge-based Bioeconomy, for instance, need for structures, which especially allow for and support the creation of dedicated knowledge instead of solely focusing on mere techno-economic knowledge. Germany lacks such structures, so far.

The results of my work, however, are subject to certain limitations. First, models do not represent reality but implicitly abstract some aspects from reality. Therefore, the results of the models used in this thesis strongly depend on how knowledge and its diffusion are modelled. Especially the somewhat oversimplified representation of knowledge as well as the analysis of static network structures without any feedback effects have to be taken into account and potentially expanded by future research. Besides, it is always possible (but not always enhancing explanatory power) to increase the heterogeneity of, e.g. agents, in an agent-based model. While many extensions to our models are possible, future research has to evaluate which also are necessary. No matter how adequately the model is calibrated, validated or verified, it still is a model that explicitly abstracts from reality. Therefore, results and policy recommendations should never be used without adequate knowledge of the underlying model and situation. Second, the concept of dedicated knowledge and the classification of its characteristics are still very fuzzy, so far. Therefore, the analysis of the potential diffusion of dedicated knowledge in the R&D network in the German Bioeconomy is rather superficial and no valid policy recommendations can be given. Without a further conceptualisation of dedicated knowledge and its characteristics, it is hardly possible to conduct future research in this context, e.g. by applying agent-based models for investigating the diffusion performance of dedicated knowledge or by analysing policy documents and their ability to foster the creation and diffusion of dedicated knowledge.

Concerning the first limitation, future research should focus on expanding existing research and models by modelling more adequate representations of knowledge and feedback effects between knowledge diffusion and network structures. Moreover, future research should also link results from simulation models with empirical evidence and other studies. Concerning the second limitation, as this concept (to my knowledge) has not been used before, future research has to further conceptualise dedicated knowledge by also investigating concepts and characteristics of knowledge known from other disciplines, hopefully creating a whole new definition and understanding of knowledge in economics and other disciplines.

Summing up, the studies within this doctoral thesis show that there still is a long way to go. Especially if we call for knowledge enabling transformations as the transformation towards a sustainable knowledge-based Bioeconomy, creating structures for the creation and diffusion of this knowledge is quite challenging and needs for the inclusion and close cooperation of many different actors on multiple levels and changing network structures adapted to different phases of the transformations process. Nonetheless, the understanding of the complexity of the problem and the need for such structures is a step in the right direction, allowing researchers and policy makers to identify and create structures that actually are able to do what they are intended for - fostering the creation and diffusion of different types of knowledge.

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Knowledge is an unending adventure at the edge of uncertainty.

It is important that students bring a certain ragamuffin, barefoot irreverence to their studies;
they are not here to worship what is known, but to question it.

- Jacob Bronowski (1908-1974)