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

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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 analyse 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. While from a traditional perspective the development of the network characteristics in isolation 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 artificially generated network structure also is favourable for the diffusion of other types of knowledge, e.g. dedicated knowledge necessary for the transformation towards an SKBBE.

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

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 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 3, I will focus on the analysis of the R&D network in the German Bioeconomy. In this section, 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.

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 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 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 2.3, particularities of publicly funded project networks are explained.

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

[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.

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 have been shown also to have quite ambiguous effects on knowledge diffusion and to depend on the knowledge exchange mechanism strongly. While some studies found that 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 for the positive effect of an asymmetric degree distribution is, that a network with a more asymmetric degree distribution is characterised by a few highly connected actors that collect knowledge and distribute it very fast and with little degradation throughout the network.

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

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

(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, "(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 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.

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 miti-

[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).

gation 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

[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.

market”. Therefore, e.g. Urmetzer et al. (2018) argue that “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, section 5 also entails some concluding remarks on the structure of the R&D network and its potential effect on the diffusion of dedicated knowledge.

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

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

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. 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.

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

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

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 (bi-directed) 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 Bioeconomy (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, (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 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 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 section 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.

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

The following section presents and discusses the major descriptive statistics of the actors and projects of the R&D network over time. The focus in this subsection 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 1 shows some general descriptive statistics of both joint and single research projects. By looking at the table, it can be seen that dur-

[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).

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

ing 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 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 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 over-embeddedness 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 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 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

[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=`.

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 1. Figure 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 in the Appendix). This is in line with the results of the network analysis in the next subsection, 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 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.

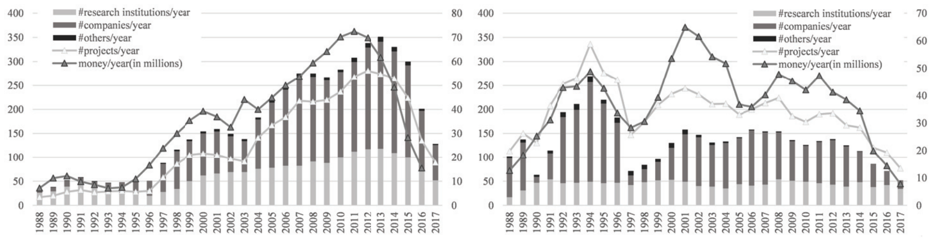

Figure 1: Type and number of actors/year, number of projects/year and money/year in joint (l.h.s.) and single projects (r.h.s.) over the last 30 years.

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. 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.

3.2 Network Structure of the R&D Network

In the following subsection, the structure of the knowledge network is analysed in detail by first looking at the graphical representation of the network (Figure 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 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, repeatedly 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 visualised network growth and the change of its structure also reflect themselves in the network characteristics and their development over time (see Table 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

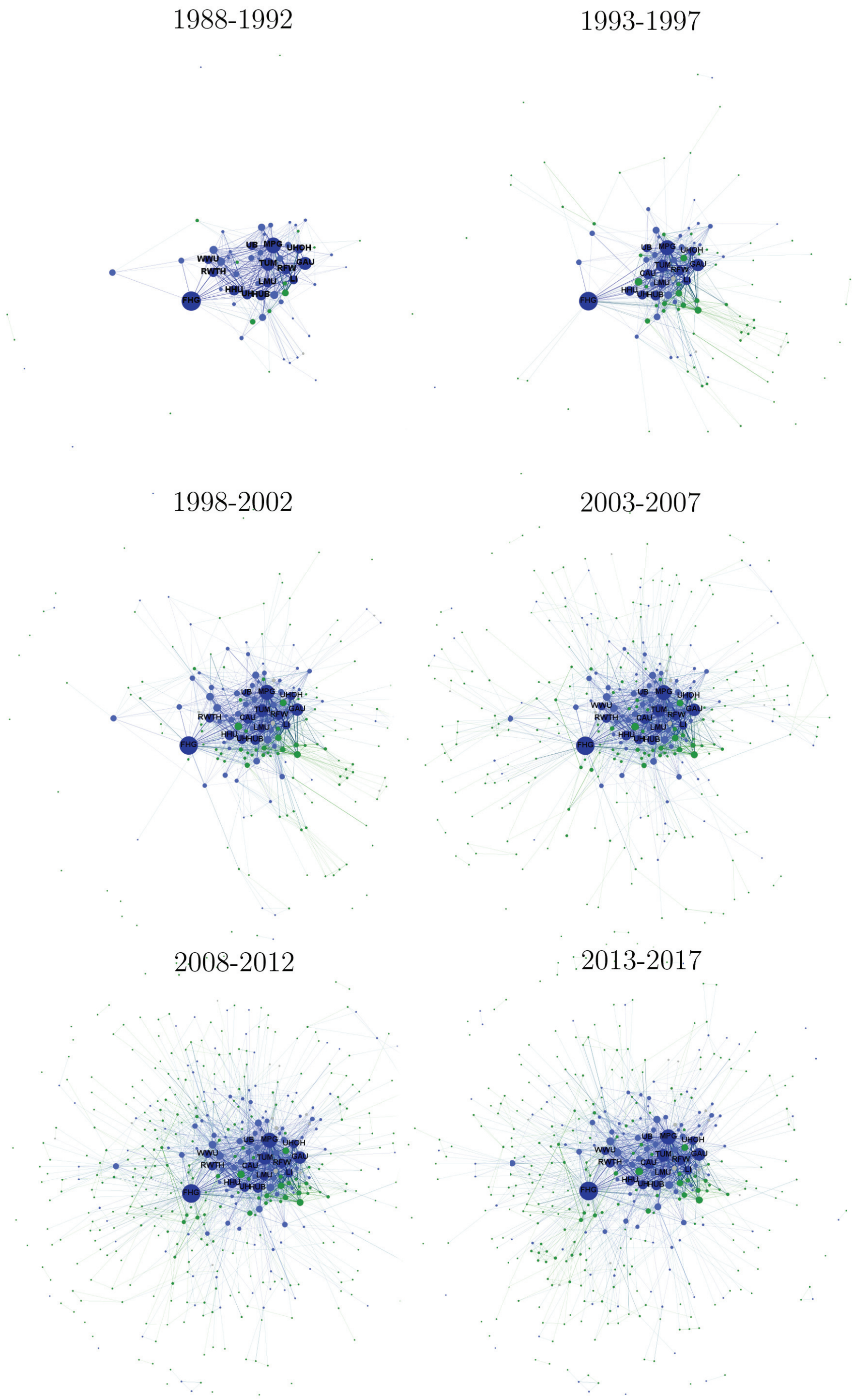

Figure 2: Visualisation of the knowledge network in the six different observation periods. Blue nodes represent research institutions, green nodes represent companies and grey nodes represent others. Dark blue indicates research institutions, which already participated in the observation period before.

periods in time (see Table 2 and Figure 3).

Table 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 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 2 and Figure 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 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. 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

[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

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.

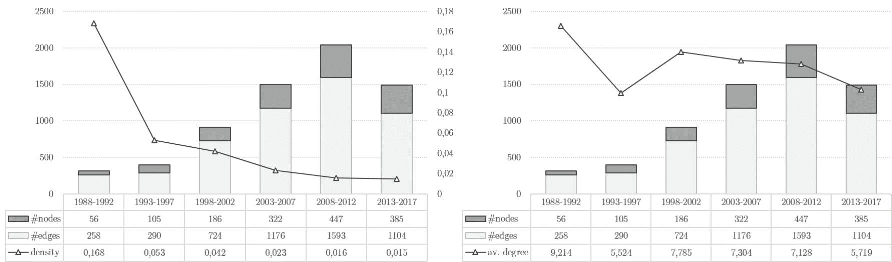

Figure 3: Number of nodes/edges and network density for all six periods (l.h.s) and number of nodes/edges and average degree for all six periods (r.h.s.).

Looking at Figure 4 first gives the same impression. Figure 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

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.

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

Summing up, Figure 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 (Figure 6 in the Appendix). 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 have many links. Table 5 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

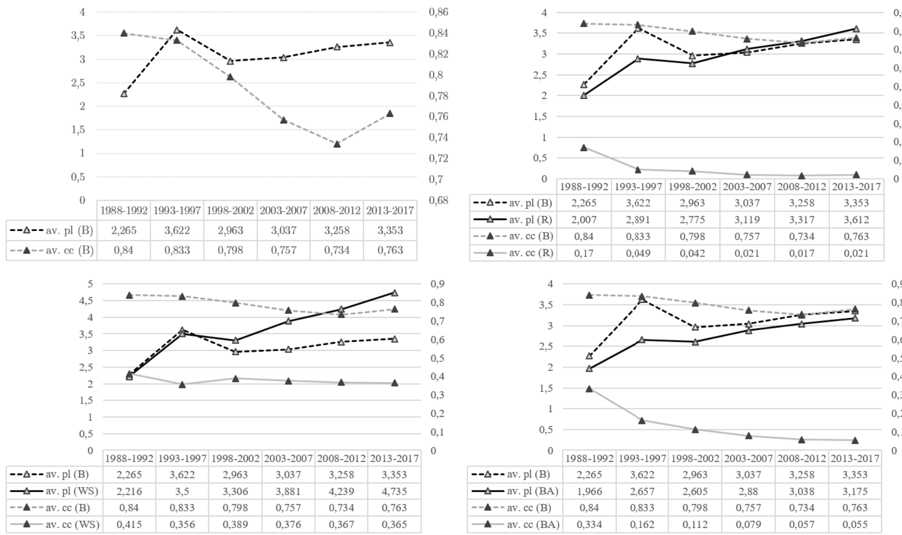

Figure 4: Average path length (av. pl) and average clustering coefficient (av. cc) of the R&D network (B) in the six different observation periods (upper l.h.s), as well as average path length and average clustering coefficient of the R&D network (B) in comparison to the those of the random network (R) (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.).

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).

This again shows how the network structure has changed towards a kind of core-periphery structure having a scale-free degree distribution. As knowledge is shared freely between the participants in R&D projects, the highly asymmetric degree distribution of the network can instead be interpreted as being favourable for knowledge diffusion.

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

In the third section 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 section, I'm going to summarise and critically discuss the main results of section 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 sees 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 integrate all relevant stakeholders into policy making only superficially (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

[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.

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 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. 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). On the one hand, 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). On the other hand, 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 want 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 Bioeconomy 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 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 by politicians. 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

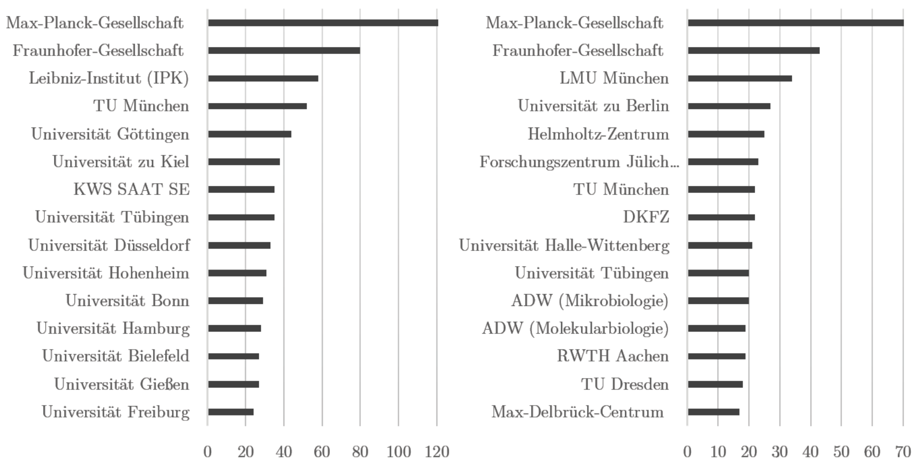

Figure 5: Top-15 actors with most joint projects (l.h.s.) and most single projects (r.h.s.).

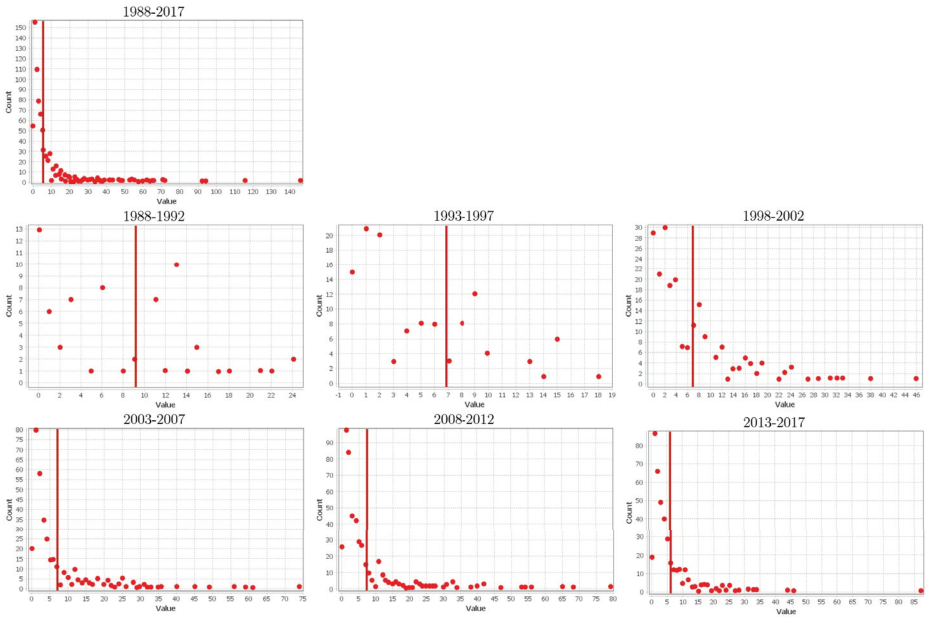

Figure 6: Degree distribution of the R&D network in the different observation periods.

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