The Evolution of R&D Networks in Public funded Renewable Energy Research*

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July 5, 2013

Abstract: A major task for science and innovation policy is to facilitate the development of favourable R&D network structures leading to a rapid transformation of science into commercial technology. Yet, social networks are far from uniform across technology sectors and over time, and our understanding of the cooperation pattern in the science–technology nexus is limited. This paper therefore targets the structure and dynamics of networks based on cooperation between academia and industry in public funded R&D projects. I separately analyse Danish *hydrogen & fuel cells* and *wind energy* related research activities, thereby contrasting two technological fields in different development stages. Besides traditional comparative social network analysis, I utilize a stochastic actor-based approach, a state-of-the-art tool for dynamic network analysis allowing for endogenous network development. I demonstrate the co-evolutionary character of networks in and between academia and industry and derive implication how policy can influence their development with selective research grant awarding mechanisms. I find evidence for path dependencies in the development of public funded R&D networks, resulting in the establishment of reinforcing structures, which differ substantially between both industries under observation.

*I would like to thank Guido Bünsdorf, Per Dannemand Andersen, and all participants at the 2012 IKE seminar at AAU Aalborg, the 2012 EIS seminar at DTU Copenhagen and the 2013 DRUID winter academy Denmark for great and inspiring comments and suggestions. All opinions, and errors, remain my own.

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1 Introduction

Cooperation and interaction between various actors involved in processes of technology development such as universities, firms, intermediate and end users, are of high important for the smooth functioning of innovation systems [e.g. Hekkert et al., 2007; Lundvall, 1992; Malerba, 2002]. A major task for science and innovation policy is therefore to facilitate the development of favourable R&D network structures [Carlsson and Jacobsson, 1997]. Here, interaction between academia and industry is crucial for the transformation of science into commercial technology [Etzkowitz and Leydesdorff, 2000]. Acknowledging that, scholars from various strands of research have produced seminal contributions in enhancing our understanding of science–industry networks. Yet studies emphasizing cross-sectoral heterogeneity and longitudinal dynamics are scarce, even though network structures and development paths are far from uniform across technologies and industries, and over time [Pyka, 2000].

The major share of existing quantitative analyses utilizes co-authorship [e.g. Gittelman, 2007; Newman, 2004; Singh, 2005; Wagner and Leydesdorff, 2005] or co-patenting [e.g. Fleming and Frenken, 2007; Schilling and Phelps, 2007] information to map research networks, where the former resembles mainly an academic and the latter a more commercially oriented cooperation mechanism. Research networks resulting from cooperation in public funded R&D projects has received much less attention, though. Yet, studying this form of networks is important for at least two reasons. First, public funded R&D projects by design represent a direct intercept of science and applied technology, hence can be envisioned as an intermediate layer between academic publishing and commercial patenting networks, thus vital for the diffusion of scientific knowledge. A closer examination of public research grant cooperation network therefore may significantly contribute to enhance our understanding of the interaction between both spheres of the science–technology nexus. Indeed, there exists a common consensus that cooperation between industry and university differs in terms of underlying motives as well as performance [Kaufmann and Tödtling, 2001]. Second, studying patterns of networks formed trough cooperation in public funded research projects enables us to derive valuable implication for science and innovation policy. With defining selection criteria for the awarding of research grants, states are able to not only steer rate and direction of research [Pavitt, 1998] but also of cooperation and interaction [Mytelka and Delapierre, 1987; Sharp, 1991], given its proper understanding of the drivers of network change.

However, structures of innovation networks are by no mean static but constantly changing over time [Doreian and Stokman, 2005], when actors enter or leave the network, create or terminate existing ties. Furthermore, the micro characteristics and motives of actors in a network are likely to change during the life-cycle of industries and technologies [Pyka, 2000]. The driving forces of this co-evolution are likely to be at last to some extend endogenous. If the current network structure impacts its possible future development, the network evolution becomes an endogenous and path dependent process [Glückler, 2007; Kilduff, 2003]. Indeed, real-life knowledge and other social network structures tend to be highly dispersed, where current characteristics are of limited power in explaining the uneven distribution of network ties across actors. Instead, existing ties often tend to become more persistent over time [Burt, 2000], and preferential attachment makes the likelihood of creating new ties influenced by the actors stock [Barabási and Albert, 1999], leading to a process of structural reinforcement [Gulati, 1999].

This paper therefore targets the structural network dynamics of public funded projects in renewable energy research from an evolutionary perspective. I construct cooperation patterns based on joint consortium membership in projects that received public research grants in the period 1996 – 2011 in Denmark, a country with ambitious energy targets and a strong knowledge base and research community many relevant core technologies[Andersen et al., 2009]. I separately analyse *hydrogen & fuel cells* and *wind energy* related research activities, thereby contrast a technological field in an early phase with a mature one [Borup et al., 2008]. I emphasize the role of industry-university cooperation, and how its role differs between industries, an changes over time.

Besides traditional comparative social network analysis, I utilize a stochastic actor-oriented approach, which resembles a state-of-the-art concept of evolutionary network modelling [see Snijders et al., 2010] and enables me to identify endogenous drivers of network development. By doing so, I respond to manifold calls from the research community for more dynamic models of social network analysis [e.g. Ahuja et al., 2007].

The attempted contributions of this paper are threefold. First, with mapping cooperation networks in research across sectors and over time, I illustrate in how sectoral particularities manifest in different network pattern and evolution paths. Second, with enhancing our understanding of the network dynamics in public funded R&D projects and their underlying mechanisms, I provide insights how policy can shape their pattern by applying selective grant awarding mechanisms. Third, with applying a stochastic actor-based approach, I introduce a novel methodology to the context of research networks. I thereby demonstrate the richness of this approach to address open questions in the field and suggest fruitful avenues for future research.

I find evidence for path dependencies in the development of public funded R&D networks, resulting in the establishment of reinforcing structures, which differ substantially between both industries under observation. In public funded *wind energy* research projects, the initial central role of some leading Danish universities amplifies over time and makes them the dominant initiator of research projects with various participants on industry level, while inter-industry cooperation and transitivity appears to be poor. As a result, the network structure over time becomes more centralized around leading universities. In contrast, *hydrogen & fuel cells* research develops from a more heterogeneous initial set of actors in industry and university alike to a core-periphery structure, where initially active actors form a highly interconnected network, which is complemented by satellite networks in the outer periphery.

The remainder of the paper is structured as follows. Section two provides an overview of existing theories and empirical findings of relevant strands of research, focussing on the the role and impact of public R&D funding, rationales, dynamics and network structures in and between academia – industry. Section three discusses the co-evolution of science–technology networks and provides testable hypothesis for empirical analysis. It also introduces the concept of the stochastic agent-based approach and specifies the deployed model. The analysis of networks in renewable energy research follows in section four, where I apply traditional static social network analysis and mapping as well a dynamic stochastic actor-based approach. Section five discusses the relevance of the findings, concludes and provides implications for research, industry and policy.

2 Literature Review

The direct funding of R&D in selected technologies of interest represents an integral component of modern innovation policy. Given the proper institutional setup it offers a powerful tool to directly steer rate and direction of research activities [Pavitt, 1998]. Indeed, throughout history most technological revolutions fundamentally changing our society, such as rail roads, modern ITC and biotechnology initially where triggered by massive government funded research programs before spilling into the private sector [Mazzucato, 2011; Perez, 2011]. However, in general our understanding how governments interact with the system they try to affect is limited [Jaffe, 2008], and in particular the efficiency of public R&D funding is still under heavy discussion.[1]

Economic theory suggests the direct funding of R&D by the state as a mean to: (i.) Prevent market failure associated with the characteristics of knowledge production [Arrow, 1962] and uncertainty of innovation [Knight, 1921], which otherwise would lead to an underinvestment in innovative activities on a general level.(ii.) Promote a development in direction of technologies with large expected social but at the current state lacking economic returns [Klette et al., 2000]. (iii.) Securing the presence of a broad and diverse set of technological opportunities [Freeman, 1974]. (iv.) Correcting system failure by generating networks among firms, societal organizations and knowledge institutions [Carlsson and Stankiewicz, 1991].

While the former three functions represent represent a prominent topic in innovation and science policy research, literature how public funding of R&D activities creates relationships and networks in and between academia and industry is scarce. Research and innovation networks in general have received much attention and findings offers much insight of their rationales, pattern and rationales, their heterogeneity across sectors and dynamics over time. However, if these findings can be directly

[1]For an overview of the academic discourse regarding the impact of public R&D funding consider David et al. [2000]; Klette et al. [2000]

projected to the context of public funded R&D research networks remains questionable. Therefore the remainder of this section therefore provides an overview of contemporary research on research alliances and networks, which can be broadly divided in three major streams.

Sociological, bibliometric and scientometric research that has produced a vast bulk of literature analysing knowledge exchange among researchers, both within and across individual companies and academic research groups [e.g. Zucker et al., 1995], and investigating social networks of academic scientists [e.g. Melin and Persson, 1996; Newman, 2004]. Recent research on this field is especially interested in the emergence of small world structures among academic cooperation [e.g. Wagner and Leydesdorff, 2005]. These studies usually exploits information on co-authorship of scientific papers.

Scholars focussed on cooperation among firms mainly come from the strand of strategic management. They analyse research and product development alliances with particular interest in their general rationales, their social [Gulati, 1995] and governance structure [Rowley et al., 2000], resulting knowledges flow and technology transfer among participants [Giuliani, 2007; Powell et al., 1996]. Data hereto is mainly derived from large scale surveys among firms in a specific sector, or literature-based datasets.[2]

Another stream of scientific cooperation in industry an academia focusses on co-inventions by utilizing information contained in patent data. Singh [2005] reports especially social proximity as important driver of patent-cooperation networks and resulting knowledge flows. Fleming and Frenken [2007] and Fleming et al. [2007] investigate the evolution of inventor networks in the Boston and Silicon Valley area, where they illustrate in both cases the phase transformation of globally sparse structures with a high share of isolated networks to one gigantic main component with small world properties, where some key actors bridge formerly unconnected clusters. They also provide anecdotal evidence, how path-dependencies brought these actors in their key positions.

[2]Such as the MERIT CATI database on interorganizational strategic alliances [see Hagedoorn, 1990, and subsequent publications].

However, it is also recognized that on it's own, all of these data sources are likely to underestimate knowledge transfer and research cooperation in reality, which takes places in various formal as well as informal dimensions [Fleming et al., 2007; Murray, 2002]. Furthermore, cooperation between academia and industry appear to underlie a very distinct logic and incentive structure, which cannot be fully captured with one indicator. Recently, with combining co-authorship and co-invention data, scholars started to investigate how the two realms of academic science and industrial research are connected. Indeed, even though the social structure and incentives of *academic science* and *commercial technology* appear as rather distinct, this stream reveals first evidence of co-evolutionary processes to be at work. Murray [2002] opens this field with proposing a novel methodology to analyse these developments by using patent–publication pairs in the field of biomedicine. Even though not able to establish a predictable relationship, she provides plenty of anecdotal evidence regarding the importance of key-scientists to connect both realms. Bonaccorsi and Thoma [2007] investigate the performance of co-inventions explained by additional cooperation in scientific publication in the emerging field of nano science and technology. They report that patents filed by inventors which also co-author together tend to outperform others in terms of patent quality. They attribute this act to human capital and institutional complementaries at the intersection of science and business. Recently, Breschi and Catalini [2010] conducted a large scale analysis of European and U.S. American academia–corporate networks in three science intensive fields, i.e. lasers, semiconductors and biotechnology, to assess the extent of overlap between the two communities. Their findings are that on the individual researcher level the connectedness among scientists and inventors is rather large, and highlight again the importance of certain persons which are prominent in both worlds and act as gatekeepers. They furthermore demonstrate that the connectedness of both spheres may be highly underestimated by only considering either co-author or co-patent networks.

Again, studies network pattern based on the joint cooperation in public funded research projects is rather scarce. Very early, Sharp [1991] and Mytelka and Delapierre [1987] demonstrate the important role of research funding in establishing research alliances and networks in the European electric industries. van Rijnsoever et al. investigate the network structure emerged in the recent

Dutch electric vehicle subsidy program, raising the question how the actors network position influences their probability of a successful grant application. To the best of my knowledge,Salerno et al. firstly suggest the analysis of public funded R&D networks as valuable method for policy evaluation and technology forecast. Following this emerging idea, Mogoutov et al. [2008] combine the analysis of patent, publication and public funded R&D projects, where they demonstrate the important role of the latter in linking the former two.

Most work presented up to now is of static nature and analyses social networks in research at a given point of time, while few [e.g. Fleming et al., 2007] choose a longitudinal approach. However, there exists a growing awareness of co-evolutionary mechanisms driving the development of multilevel networks such as research cooperation [e.g. Ahuja et al., 2007; Breschi and Catalini, 2010; Murray, 2002]. However, analysing evolutionary developments also call for new methods able to capture them. Just recently, researchers responded to this challenge with applying more dynamic and endogenously driven models to the context economic cooperation in general, and research cooperation in particular. To the best of my knowledge, Van de Bunt and Groenewegen [2007] firstly introduce dynamic actor-oriented to analyse endogenous effects in cooperation pattern of the genomics industry, where they report strong preference to form alliance with high-status partners. At the context of the project based film industry Ebbers and Wijnberg [2010] try to disentangle reputation and network position effects, where they report weak evidence that actors tend to team up with partners of equal reputation. Recently, Fischer et al. [2012] provide first evidence in the Swiss telecommunication sector how regulatory changes – here the liberalization of the sector – lead to a endogenous reconfiguration of cooperation pattern. Finally, Kronegger et al. [2012] apply dynamic agent based models to scientific networks in the Slovenian research community. Combining a graph-theoretical perspective with with the sociological concept of accumulated advantage, they attempt to explain which mechanisms drive the observed emergence of small worlds, but are ultimately not able to provide an unambiguous answer. To the best of my knowledge, cooperation in public funded R&D projects was up to now not utilized in dynamic network models. Even though able to enhance our understanding of endogenous dynamics of network evolution, this emerging stream of research has – partially due to current methodological limitations – up to now made no attempt to explain the co-evolution of complex multi-level networks in research cooperation.

3 Modelling Network Evolution in Public Funded R&D

This section introduces an evolutionary model of network dynamics to the context of public funded R&D research. It discusses it's merits and drawbacks and explains the considered exogenous and endogenous effects. Instead of stating concrete hypotheses, I instead test some of the most effects in literature, which are mostly related with the actors network structure. Thereby my attempt is to enhance our understanding of the networks internal dynamics. By contrasting networks in two technological fields with a different degree of maturity, I expect to also reveal differences in structure and dynamics.

3.1 Data

As source for public funded research projects I utilize the database provided by Energiforskning.dk and maintained by the Risø National Laboratory for Sustainable Energy of Denmark's Technical University (DTU). By combining data from several energy technology research and development programs, it up to now represents the most comprehensive source for public funded energy research in Denmark. It covers projects funded by the Strategic Research Council, ForskEL, ForskNG, ForskVE, ELFORSK, Green Labs DK, the High Technology Foundation and the European Union, overall 1,807 projects with 1,292 organizations involved. It has to be mentioned that these criteria are rather heterogeneous, for example in their focus on basic versus applied research, specific sectors or specific actor constellations. It is distinguished between eight technological fields of research, namely (i.) wind energy, (ii.) sun energy, (iii.) wave energy, (iv.) biomass and waste, (v.) hydrogen and fuel cells, (vi.) energy efficiency, (vii.) smart-grid and systems, and (viii.) others, a residual category containing technological research in experimental forms of energy creation as well as research in social science. In my dataset I include projects started from beginning 1996 to the end of 2011, which represents the longest time frame where qualitatively rich full year data is available up to now.

After preliminary analyses of the different network structures and actor characteristics, the technological fields *hydrogen & fuel cells* and *wind energy* where selected for a further in-depth investigation. Their comparison allows to contrast between the former as an emerging technology still in the phase of market formation and the latter as a mature counterpart with well developed industry and market structures [Borup et al., 2008]. *Wave energy* and *smart-grid & systems* represent further interesting candidates for emerging technologies with even higher internal dynamics. Unfortunately the small number of actors prevents a deeper analysis; the model would be highly over-specified for the given population.

The first instigation of the data shows a high turnover in only once appearing actors in the project consortia, often representing very small craftsmen, consultants, accountants or other actors equally distant from the technology under research. To reduce random noise in the network pattern, these one-shots as well as actors only participated in stand-alone projects where excluded. The Rersearch Center Risø where until 2005 among the most active organizations in Danish energy research, and became afterwards associated with Denmark's Technical University. To avoid the high disturbance this change causes for the resulting network patter, both where for the whole period merged together. The final dataset consists of 167 projectswith 48 actors in *hydrogen & fuel-cell*, and 193 projects with 51 actors in *wind energy*.

3.2 The Stochastic Actor-Based Approach – Introduction an Assumptions

To model the temporal dynamics of networks in the different technological fields, I apply an stochastic actor-based approach. Here, the evolution of social networks – in terms of tie establishment and termination between the different actors – is driven by exogenous as well as endogenous forces. In detail that means the probabilities of tie changes is modelled as as a function of individual actor characteristics as well as their network position. The latter presents the main merit of this recent approach. It enables to capture endogenous effects, which are of high importance when explaining the evolution of social networks [Gulati, 1995]. Fundamental underlying assumptions are the following [see also Snijders et al., 2010]:

First, the network under analysis evolves as a stochastic process driven by the actors, which have control over their outgoing ties. This fundamentally implies that ties are directed, hence send by one actor and received by another,[3] where the former controls the tie establishment. I therefore assume the leading actor in the project as responsible for the constellation of the project consortium. In the context of public research projects, this assumption appears legit; an invitation to join such a project is unlikely to be turned down, since it represents a source of revenue and reputation. However, a caveat here is that the composition of a research consortium only to some extend lies in the hand of the project leader; the final decision is made by the grant awarding public authority. However, when the authorities selection criteria are known and anticipated by the actors, it can be assumed that project leader choose their cooperation partners partially to optimize their probability of a successful grant application. However, when interpreting the results one have to be aware that the resulting network structure is subject to *ex-ante* as well as *ex-post* selection biasses.

Second, tie changes are assumed to be a gradual process. This is usually valid for persistent relationships such as friendship, trust, strategic alliances *et cetera*. In contrast, relationships based on event data, such as phone calls, e-mails or research projects have a predetermined start and end point, hence in general cannot be interpreted as enduring ties. Nevertheless, if aggregated over a sufficiently large amount of time, these events can be threaten as persistent states. However, with a to high level of temporal aggregation, the cumulation of gradual structural change can lad to very dissimilar network pattern between two periods. As a reasonable compromise I assume a tie between alter and ego as persistent as long as latest two years after the official end of the last one, another joint project starts. This leads to a segmentation of the observation period in eight waves á two years.

[3] In this section and elsewhere I refer with *ego* to the focal actor, thus the sender of the tie. *Alter* refers to the ties counterpart, the receiver of the tie.

Objective function and dependent variable

Stochastic actor-based networks basically consist of some objective function $f(.)$ consisting of a set of individual parameters β_k which determine how likely it is for an actor i to change own the ego-network in a particular way. In the decision process, i has the opportunity to chose between some set C, containing all possible ties with other network actors to remain either unchanged or change from being absent (o, χ_a) to present (o, χ_b), and *vice versa*. The likelihood of actor i to create a particular tie is captured by the log odd ration $f_i(\chi_b, \beta_k) - f_i(\chi_a, \beta_k)$. As a result, the probability of a tie being present or absent is $\exp(f_i(\chi_b, \beta)) - \exp(f_i(\chi_a, \beta))$. Consequently, the probability of the overall network to change to some new state χ is given by the formula:

$$\chi = \frac{\exp(f_i(\beta, \chi))}{\sum\limits_{\chi' \in C} \exp(f_i(\beta, \chi'))} \tag{1}$$

It basically resembles a multinomial logistic regression, modelling the probability that an actor chooses a specific (categorical) new network configuration χ as proportional to the exponential transformation of the resulting networks objective function.

3.3 Model Setup and Variables

Independent Variables

The individual parameters β_k can be divided into three categories: (i.) *Network base effect*, referring to the actors general tendencies to form ties in a particular way, independent of alter and ego's network position and other characteristics. (ii.) *Degree related effects* capture the endogenous influence of several effects associated with alter and ego's in- and out-degree[4] of ties, which represent an important driving force in many models of social network dynamics. (iii.) *Covariates* are exogenous characteristics of the actor. In the following I discuss in detail the main effects included.

[4] With *out-degree* I refer to ties send in direction $i \rightarrow j$, hence invitations to join a research project send by the project leader i and received by a project partner j

Base effects

The baseline effect is given with the *outdegree* of actor i, representing the general tendency to form ties at all. It can be interpreted as the benefits and costs between an arbitrary tie. Arbitrary means in this context an tie with an actor embodying no characteristics making him/her particularly attractive [Snijders et al., 2010].[5] However, applying this measure to the context of networks based on research consortium ties brings some caveats, since a high *outdegree* can be reached either with a high number of projects or a high number of members per project. Therefore I also control for the average number consortium members per actor.

Another basic feature of most social networks is *reciprocity*, the tendency of an actor to respond to an $i \Rightarrow j$ with the establishment of an $j \Rightarrow i$ tie [Wasserman, 1979], or in our context to be invited to join a research project by an organization formerly participated in a project lead by the current organization.

Transitivity is a measure for the tendency towards transitive closure, sometimes also called the clustering coefficient. Formally, it determines the likelihood a connection between $i \Rightarrow j$ and $i \Rightarrow h$ is closed by a connection between $j \Rightarrow h$ and/or $h \Rightarrow j$, or in other words that partners of partners become partners [e.g. Davis, 1970].

Degree related effects

Additionally to this structural basic control variables, another set of degree related measures are of particular interest against the background of this study. *In-degree popularity* represents the tendency of actors to form ties alters already receiving a high amount of in-degrees, hence popular ones. A positive *in-degree popularity* implies a self-reinforcing mechanism that over time leads to increasing dispersion of the in-degree distribution of the networks. It can be interpreted as the impersonation of the "Matthew Effect" [c.f. Merton, 1968, 1988; Price, 2007] in network structuralism.

[5] Most social network structures observed in reality tend to be sparse, which means a high share of all possible ties is absent, thus this effect in most cases shows a negative coefficient. Hence, the costs of maintaining a relationship *per se* usually outweighs its benefits.

Respectively, *out-degree popularity* captures the recognition effect of the network on the activities of actor i, thus if actors establishing a high amount of ties are also considers more attractive to establish a tie with.

Furthermore, a higher in-degree may also enable an actor to establish more outgoing ties in herself. This effect is captured by the *in-degree activity* effect. It basically represents an interaction between in-degree and out-degree. In the same way as degree related popularity, activity effects lead to an self-reinforcing differentiation of degrees and increasing skewness of their distribution [Barabási and Albert, 1999].

Degree assortativity refers to the preference of actors to form ties with alters based on their own as well as the alters degree [Morris and Kretzschmar, 1995]. The combination of in- and out-degrees gives four possibilities. The two in- and out-degree combinations can be interpreted as tie supply and demand driven, or as a specialization of actors, in our context as project leader or project partner. Here, I will consider the *out- to in-degree assortativity*, stating that actors with a high out-degree prefer to establish ties with alters with a high in-degree. The in–in and out–out combination represent a measurement for homophily and social stratification in the network patter, since it captures the tendency of actors to form ties with alters of a similar degree. Here, I use the *in-to in-degree assortativity*, as an indicator for a equal level of popularity. When testing for assortative effects, Snijders et al. [2010] recommend include controls for degree related popularity and activity, what is given in the presented model. To test if these effects differ between universities and other organizations, I also include an interaction term between the university dummy and popularity effects.

Other effects and controls

To depict the different network pattern between universities and other organizations, I include a dummy indicating if the actor represents an university. Since some actors may be more capable in acquiring and managing large long term projects, which may make them an more attractive cooperation partner, I also control for the average budget of projects the actor participated in this period. To capture unobserved changes over time in industry, research and policy,[6] I also include time dummies for every period.

4 Results and Discussion

For the calculation of the model, I utilized *SIENA*, a package for the statistic software environment R,which is particularly designed for evolutionary network modelling by combining a panel data and an actor-driven approach [see Ripley and Snijders, 2010]. The complementary graphical presentation and static analysis of structural network properties where conducted with the R packages *SNA*, *Network* and *Igraph*.

4.1 Descriptives and Preliminary Inspection

Static Properties

Table 1 depicts a network structure analysis of the *hydrogen & fuel cell* and the *wind energy* network, for the sake of brevity here only separated in two periods. For the following actor-based model, I utilize a directed network structure, which leads to the results that project participants are only connected with the project leader but not among each other. To check for major differences in the resulting network structure, I also consider the descriptives of the undirected network, where all project members are equally connected.

[6] Such as for instance the abandonment of the *professors privilege* in Denmark in 2000 [see Lissoni et al., 2009]

Table 1: Static Network Comparison

	Undirected network				Directed network			
	Hydrogen and fuel cell		Wind energy		Hydrogen and fuel cell		Wind energy	
	1996–2003	2004–2011	1996–2003	2004–2011	1996–2003	2004–2011	1996–2003	2004–2011
Nodes	19,00	44,00	30,00	43,00	19,00	44,00	30,00	43,00
Edges	24,00	195,00	83,00	128,00	94,00	276,00	182,00	246,00
Density	0,46	0,38	0,36	0,36	0,27	0,15	0,21	0,14
Components (weak)	5,00	3,00	2,00	9,00	5,00	3,00	2,00	9,00
Main component (size)	15,00	42,00	29,00	35,00	3,00	11,00	7,00	7,00
Main component (share)	0,79	0,95	0,97	0,81	0,16	0,25	0,23	0,16
Isolates	4,00	2,00	1,00	8,00	4,00	2,00	1,00	8,00
Connectedness	0,61	0,91	0,93	0,66	0,61	0,91	0,93	0,66
Centralization (degree)	2,15	2,13	2,83	3,57	0,42	0,55	0,32	0,45
Centralization (between)	0,38	0,25	0,57	0,39	0,08	0,12	0,22	0,15
Centralization (evcent)	0,78	0,66	0,82	0,79	1,02	0,62	1,05	1,07
Mean degree (degree)	8,32	16,45	10,47	15,21	8,32	16,45	10,47	15,21
Diameter (MC)	4,00	4,00	3,00	3,00	2,00	5,00	2,00	3,00
Average distance (MC)	2,08	1,87	1,81	1,76	0,89	2,05	1,45	1,39
Transitivity (MC)	0,43	0,51	0,41	0,49	0,00	0,27	0,05	0,53

Note:: Calculation for the undirected network on basis of weighted edges, for the directed network with unweighed edges

As expected, the initial structural network properties in both fields substantially differ among each other and in their development over time. However, many network properties in the two fields seems to converge over time. While the initial *wind energy* network network consists of more actors as well as activity between them, in the second observation period both networks are of comparably equal size, reflecting the different maturity of both fields and their associated growth rate. As a emerging field of research in Denmark, *hydrogen & fuel-cell* also shows network dynamics as the more established *wind energy*, which ultimately leads a catching up. Even though tending to converge, the direction of change between both networks is quite distinct and reveals interesting pattern. While the *hydrogen & fuel cell* network develops in direction of one large main component (MC – largest component of actors all with connection paths among each others), the main component's share in *wind energy* decreases and new isolated components (research "niches") appear.

Table 5 and 4 to be found in the appendix provides a graphical representation of the network evolution in both technological fields over the full eight periods, which provides further insights. Table 4 depicts the development of the *wind energy* network as strongly centred around one main actor, Denmark's Technical University, who over time establishes the role of the dominant player in terms of initiation and participation of research projects. Besides that, only Vestas and Aalborg University develop in later periods to further high connected actors, even though still small in comparison. Aside of the main component, in the later periods isolated small research networks emerge. In contrast, the *hydrogen & fuel-cell* network develops to a network resembling a core–periphery structure. Here, a core of highly connected main player, equally distributed between universities and other organizations, develops. Over time some of these actors become gatekeepers and connect formerly isolated actors in the outer perimeter to the main core.

Dynamic Properties

Besides the already discussed assumptions, stochastic actor-based models have further requirements regarding the analysed data to be able to provide valid and meaningful results.

The networks under observation have to show some variation between its' periods. However, too rapid changes indicate that the assumption of gradual change – compared to the observation frequency – is violated. To ensure the validity of the gradual change assumption, I consult the Jaccard index, a common measure of similarity between two networks.[7] Snijders [2002] suggest this index to be higher than 0.3 and never drop beyond 0.2. As shown in table 5, this is given in both networks under study here. Again we see that both networks show positive net tie-creation values, hence are continuously growing over time, with accelerated rate in the last two periods.

Stochastic actor based models of network dynamics are still under development, and up to now there exists no equivalent to the R^2 indicator to make statements regarding the overall explanatory power of the model. However, as first goodness-of-fit measure one can consider the t-convergence values of the parameters, indicating whether the simulated values deviate from the observed values. For a good model convergence, Snijders et al. [2010] suggests to only include parameters with t-values smaller than 0.1, what is given for both models. Overall, a first inspection suggests a data structure suitable for utilizing stochastic actor-based models.

[7] The Jaccard index as a measure of similarity between two network waves is computed by $\frac{N_{11}}{N_{11}+N_{01}+N_{10}}$, where N_{11} represents the number of ties stable over both waves, N_{01} the newly created and N_{10} newly terminated ties in wave 2 [see Batagelj and Bren, 1995].

4.2 Results and Discussion

Table 2 reports the results of the stochastic actor-based model for both technological fields, which suggest the following. The influence of the structural base effects appears as rather limited. Even though showing rather high coefficients, they mostly remain statistically insignificant. The *outdegree* density shows as expected a negative coefficient and is in most models significant at least at the ten percent level. *Reciprocity* even though showing a high coefficient remains insignificant. *Transitivity* is only of significance at ten percent level in the first *hydrogen & fuel-cell* model, indicating the higher tendency of this research field to cluster over time, as already observed in the static analysis.

Table 2: Network Evolution Models

	Hydrogen and fuel cells						**Wind energy**					
	Model I			Model II			Model I			Model II		
	Estim.	S.E.	Sig.	Estim.	S.E.	Sig.	Estim.	S.E.	Sig.	Estim.	S.E.	Sig.
Rate parameters												
Rate period 1	0.21	(0.07)		0.21	(0.07)		2.50	(0.82)		2.17	(0.67)	
Rate period 2	0.22	(0.11)		0.20	(0.10)		1.92	(0.66)		1.74	(0.60)	
Rate period 3	1.41	(0.52)		1.43	(0.52)		1.76	(0.62)		2.31	(0.81)	
Rate period 4	1.00	(0.35)		0.94	(0.34)		3.09	(1.35)		3.10	(1.22)	
Rate period 5	0.57	(0.17)		0.56	(0.16)		3.04	(1.06)		2.99	(1.02)	
Rate period 6	1.79	(0.43)		1.80	(0.42)		7.64	(11.09)		6.88	(6.57)	
Rate period 7	1.22	(0.22)		1.27	(0.23)		0.32	(0.08)		0.32	(0.08)	
Base effects												
outdegree	-4.15	(0.40)	*	-3.96	(0.37)	*	-7.29	(0.65)	*	-6.63	(1.19)	
reciprocity	5.23	(2.26)		5.24	(2.82)		10.59	(5.99)		8.79	(4.27)	
transitivity	3.32	(0.26)	*	3.43	(1.68)		3.70	(2.07)		3.07	(1.23)	
Degree related effects												
in pop.	0.76	(0.05)	*	0.79	(0.04)	*	0.93	(0.08)	*	0.63	(0.06)	*
in act.	1.51	(0.01)	***	1.49	(0.01)	***	4.00	(0.01)	***	2.61	(0.01)	***
in-out ass.	-3.22	(1.58)		-3.28	(1.97)		-4.52	(2.79)		-4.11	(2.65)	
in-in ass.	1.13	(0.85)		0.97	(0.85)		-0.38	(1.65)		0.60	(1.79)	
Covariates and controls												
ego members	-0.06	(0.18)		-0.02	(0.16)		-0.44	(0.52)		-0.33	(0.38)	
budget sim.	0.88	(1.07)		1.17	(1.44)		1.26	(2.95)		0.21	(2.10)	
alter uni				0.74	(0.03)	**				3.13	(1.07)	
ego uni				0.54	(1.43)					2.65	(0.09)	**
ego uni x in pop.				-1.09	(1.07)					-0.56	(1.86)	
ego uni x out pop.				0.77	(0.71)					0.84	(0.86)	
time dummies	Yes			Yes			Yes			Yes		
N (actors)	48			48			51			51		

*, **, *** indicates significance at 10, 5, 1 percent level.

Out of the set of degree related effects, the indegree popularity effect *in pop* shows in all models a positive coefficient, even though small always significant at ten percent level, providing first support that indeed an *Mattew effect* is at work in the observed research networks. While the outdegree popularity *out pop.* remains negative and insignificant, the indegree activity effect *in act.*, the interaction between *indegree* and *outdegree*, is positive and shows as only coefficient significance at one percent level in the whole model. This reveals indeed a strong connection between in- and outdegrees, which shows to be a major driving force of network developments in both technological fields. Actors that initiate and lead more projects are also more likely to be chosen as partner by others (or *vice versa*, since the direction of causality cannot be identified here), what leads to a higher correlation between in- and outdegree over time.

Out of the set of controls and covariate effects, only the university dummies *ego uni* and *alter uni* show significance at fiver percent level. Interesting here is that in the *hydrogen and fuel-cell* network, *alter uni* shows significance, while in *wind energy* it is *ego uni.* Since the effects capture the probability of tie creation between ego and alter, this means that in *hydrogen & fuel-cells*, universities over time develop to an more attractive and therefore often invited project-partner, while in *wind energy* they develop to an dominant leader of projects. *Budget sim*, measuring the similarity of average project budget between ego and alter, even though positive, stays insignificant. Hompphily theories would suggest that actors tend to select partners usually participating in projects of comparable size. Finally, the interaction effects *ego uni x in pop.* and *ego uni x out pop* remain insignificant in all models, indicating popularity effects to work similar for universities and firms.

Overall, the results are not surprising of nature but rather confirming former research. Weak evidence for populatrity effects, leading to a self-reinforcing dispersion of degrees over time. However, contrasting two research communities shows against initial expectations that both, even though structurally appearing as quite distinct, are from a dynamic perspective driven by the rather similar mechanisms.

5 Conclusion

This paper focussed on the evolution of research networks in and between universities and firms on basis of joint participation in projects funded by public research grants. Acknowledging the evolutionary character of research networks, it firstly introduce dynamic network models to this context. Utilizing a stochastic actor-based model, I compare the evolution of the *hydrogen & fuel-cell*with the *wind energy* network over 16 years, where I in this first model consciously focus on internal structural effects.

The presented first findings are limited in their explanatory power. One reason already mentioned is the very nature of research networks depicted by public R&D funding, since they are highly dependent on public authorities decisions which project receives funding and which not. Besides the criteria defined to evaluate the merit of the project and member-constellation, other influences unrelated to the specific chase, such as general policy trends, budgets and patronage of certain popular technologies undeniably also influence grant allocation and therefore network pattern across sectors and over time. Furthermore, the presented model does not utilize many determinants assumed to factor in grant allocation as well as general research cooperation pattern in general, such as age, size, innovation output, performance and reputation of actors. Besides structural effects determined endogenously in the network it only distinguishes between universities and other organizations, including firms as well as private research organizations.

Nevertheless, the current model represents a first attempt to introduce evolutionary social network models to the context of networks in public funded R&D projects. By observing this evolution of an up to now barely considered type of cooperation, it provides an additional layer to existing multilevel approaches of research network analysis. Augmented with more nuanced data on individual, firm and project level, analysing the co-evolution of co-authorship, research grant cooperation and co-patenting can be suggested as promising avenue for further research, to be addressed in the near future.

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Appendix

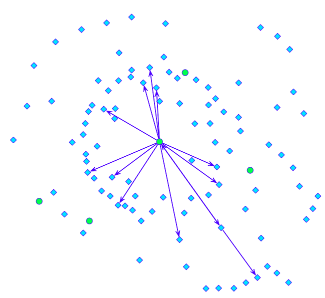
Table 3: Network turnover frequency – Hydrogen and fuel cells

	Hydrogen and fuel cells				Wind energy			
Periods	$0 \Rightarrow 1$	$1 \Rightarrow 0$	$1 \Rightarrow 1$	Jaccard	$0 \Rightarrow 1$	$1 \Rightarrow 0$	$1 \Rightarrow 1$	Jaccard
$1 \Rightarrow 2$	10	0	4	0.286	11	8	13	0.406
$2 \Rightarrow 3$	4	0	14	0.778	7	7	17	0.548
$3 \Rightarrow 4$	0	8	10	0.556	5	11	13	0.448
$4 \Rightarrow 5$	9	4	6	0.316	8	7	11	0.423
$5 \Rightarrow 6$	12	0	15	0.556	8	6	13	0.481
$6 \Rightarrow 7$	29	4	23	0.411	17	9	12	0.316
$7 \Rightarrow 8$	37	4	48	0.539	16	0	29	0.644

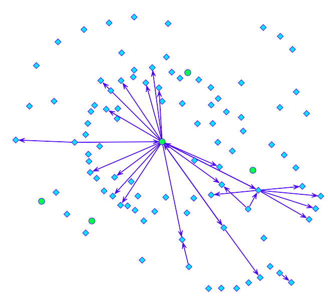
Network turnover frequency corresponding to the period indicated by rows and the tie outcomes indicated by columns, based on the directed and unweighed network.

Table 4: Network Development in Public Funded R&D in Wind Energy

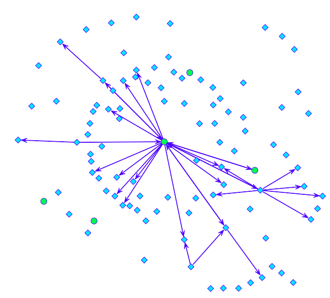
NW wind 1996-1997



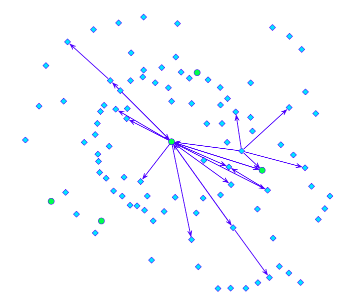
NW wind 1998-1999



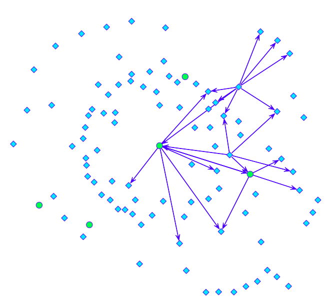
NW wind 2000-2001



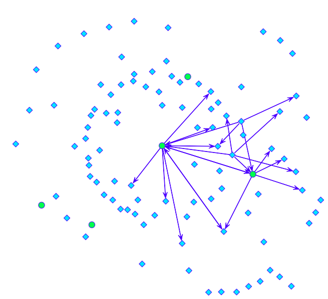
NW wind 2002-2003



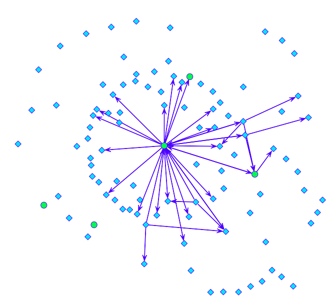
NW wind 2004-2005



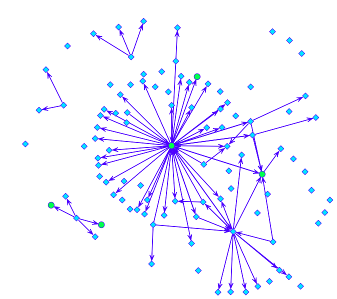
NW wind 2006-2007



NW wind 2008-2009



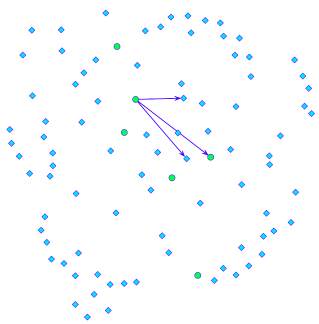
NW wind 2010-2011



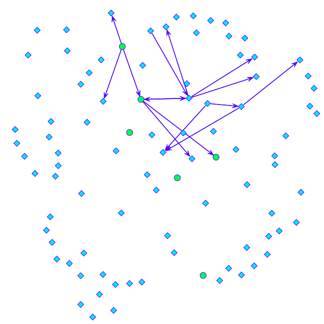
Note: Research network on basis of joint public funded research projects. Ties are directed from project-leader ⇒ project partner. Circles represent universities, squares all remaining types of organisations.

Table 5: Network Development in Public Funded R&D in hydrogen and fuel cells

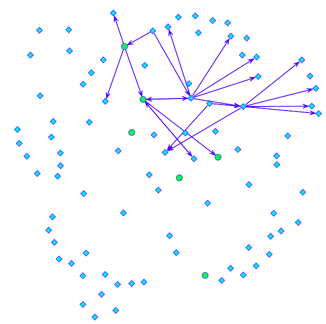
NW hydro 1996-1997



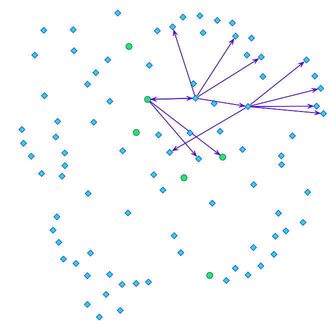
NW hydro 1998-1999



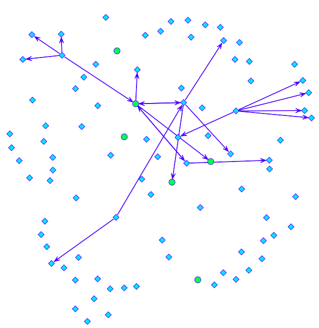
NW hydro 2000-2001



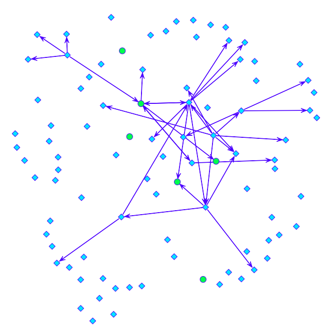
NW hydro 2002-2003



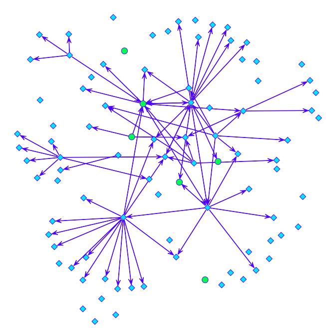
NW hydro 2004-2005



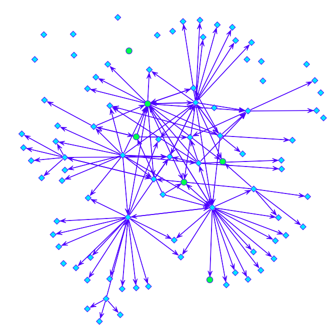
NW hydro 2006-2007



NW hydro 2008-2009



NW hydro 2010-2011



Note: Research network on basis of joint public funded research projects. Ties are directed from project-leader ⇒ project partner. Circles represent universities, squares all remaining types of organisations.