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Incremental by Design? On the Role of Incumbents in Technology Niches -

An Evolutionary Network Analysis

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Abstract

The purpose of the present paper is to study the positioning strategies of incumbent actors within technological niches, and which effect their presence might have for the development of emerging technologies within these "protected" spaces. Public funded research, development and demonstration projects represent such a protected space, offering firms an environment to experiment in joint learning activities on emerging technologies shielded from the selection pressure on open markets. The engagement of large incumbent actors in the development of emerging technologies is generally positively perceived. However, the involvement of incumbents might alter niche dynamics, making technology outcomes more incremental and adapted to the current unsustainable socio-technical regime. The incumbents ability to direct the trajectory of technological development can to a large extend be explained by their position in the niche network. If path-dependent and cumulative characteristics such as reputation, age or size of actors are main drivers of change in these networks, evolutionary processes will enable them to inherit central and dominant positions and thus shape the niche's further development by their will. Deploying a stochastic-actor-based model, we analyse if network dynamics of public funded R&DD in technological niches favour incumbent actors in a way that they are able to occupy central and dominant positions. As empirical base the paper explores the evolution within the Danish electricity grid-infrastructure. We indeed find path-dependent and cumulative effects in the development of the research network which favour incumbent actors which over time appear as likely to lead to a structure dominated by them.

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Abstract: The purpose of the present paper is to study the positioning strategies of incumbent actors within technological niches, and which effect their presence might have for the development of emerging technologies within these "protected" spaces. Literature on sustainability transitions outlines the significance of niches for the protection and development of path-breaking technologies in early stages. Public funded research, development and demonstration projects represent such a protected space, offering firms an environment to experiment in joint learning activities on emerging technologies shielded from the selection pressure on open markets. The engagement of large incumbent actors in the development of emerging technologies, and especially joint research projects together with young SME's, is generally positively perceived. Apart from the direct effect of the engagement, it is likely to generate a positive signalling effect. However, the involvement of incumbents might alter niche dynamics, making technology outcomes more incremental and adapted to the current unsustainable socio-technical regime. The incumbents ability to direct the trajectory of technological development can to a large extend be explained by their position in the niche network. If path-dependent and cumulative characteristics such as reputation, age or size of actors are main drivers of change in these networks, evolutionary processes will enable them to inherit central and dominant positions and thus shape the niche's further development by their will. Deploying a stochastic-actor-based model, we analyse if network dynamics of public funded R&DD in technological niches favour incumbent actors in a way that they are able to occupy central and dominant positions. As empirical base the paper explores the evolution within the Danish electricity grid-infrastructure. We indeed find path-dependent and cumulative effects in the development of the research network which favour incumbent actors which the over time appear as likely to lead to a structure dominated by them.

1 Introduction

The multidisciplinary literature on system innovation, often empirically focused on sustainability transitions, outlines the significance of niches for the protection and development of path-breaking technologies in early stages (Geels, 2002, 2004; Hoogma et al., 2004; Kemp et al., 1998). Public funded research, development and demonstration (R&DD) protects represent such a protected space, offering firms an environment to experiment in joint learning activities on emerging technologies. Most likely, knowledge created and transmitted in the resulting innovator networks highly influence the establishment of technological trajectories.

Even though the niche is not an explicit concept within the innovation systems literature, the Technological Innovation Systems (TIS) approach highlights the importance of creating protected spaces to foster market formation and diffusion (Bergek et al., 2008; Hekkert et al., 2007b).

Both streams of literature share a systemic understanding of innovation and acknowledge evolutionary phenomena such as path-dependency, lock-in, nonlinearity and multiple interdependency. However, there is arguably one significant difference between the frameworks: The TIS approach has been criticized for being "inward looking" (Markard and Truffer, 2008), in a way that it underplays the potential tension between path-breaking innovations and established technologies, or more broadly the selection environment.

The engagement of large incumbent actors in the development of emerging technologies, and especially joint research projects together with young SME's, is generally positively perceived as they have the capabilities to fulfil necessary systemic functions in a better way than new start-up firms (Suurs and Hekkert, 2005). Apart from the direct effect of the engagement, it is likely to have a positive signalling effect. Thus, it might contribute positively to the status of the niche, improving financial credibility and triggering interest of other companies (Smith et al., 2005). Arguably, the involvement of incumbents might however alter niche dynamics, making technology outcomes more incremental and adapted to the current unsustainable socio-technical regime. This is particularly evident if the emerging technology is a potential substitution to the existing solutions (Tushman and Anderson, 1986). The incumbents' ability to influence the trajectory of technological development can to a large extend be explained by their position in the niche network. If path-dependent and cumulative characteristics such as reputation, age or size of actors are main drivers of change in these networks, evolutionary processes will enable them to obtain central and dominant positions and thus shape the niche's further development by their will.

To investigate the existence of such effects, social network analysis represents a promising and more formalized methodological approach for analysing how actors get connected to each other and how they jointly develop a more or less conducive environment for innovation. In these strands of literature is is well established that a firm's strategic positioning in interorganizational networks may affect its innovative performance (e.g. Baum et al., 2000; Powell et al., 1996), and the structure of the overall network affects the innovation output on the aggregated (Fleming et al., 2007) and firm level (Kudic, ming; Schilling and Phelps, 2007) alike. Research also shows that networks are by no mean static constructs in time and space, but rather constantly rear-

range in an evolutionary process (Doreian and Stokman, 2005; Powell et al., 2005) and call for more dynamic and evolutionary approaches in empirical innovation network research (e.g. Ahuja et al., 2007; Cantner and Graf, 2011). More recent studies provide sound reasoning an empirical evidence how cumulative and path dependent forces strongly influence the actor composition, structure and outcome of networks. If the current network structure impacts its possible future development, the network evolution becomes a path dependent and endogenous process (Kilduff and Tsai, 2003). 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, 2002), leading to a process of structural reinforcement (Gulati, 1999).

In the terminology of innovation and transition literature that relates to the development of a niche into a "proto-regime" (Geels and Raven, 2006) with increasingly established institutions and emerging stabilization mechanisms. Actors in central positions of such networks are likely to have a high influence on the rate and direction of future research through their higher social influence and their role as "knowledge hubs". In public funded R&DD networks, consortium leaders of such projects based on public grants additionally have the opportunity to determine the content of research as well as the inclusion of further organisations. However, an actors ability to successfully obtain research grants is also said to develop in a cumulative and path dependent manner (Viner et al., 2004). While this stabilisation mechanisms are well known features of social networks (e.g. Barabási and Albert, 1999), we know very little about how the characteristics and rationales of central actors affect the outcome of such networks. Incumbent actors who over time carried out fixed investments in infrastructure, developed technological competences and secured market shares have a high incentive to protect and replicate the old regime's logics and reinforce existing technological trajectories rather than develop new ones (Geels, 2011). This reflects a more critical and nuanced consideration of network structures in research collaborations, which may not necessarily be fully cooperative and consensus oriented, as mostly envisioned in innovation system and networks oriented approaches. Following that argumentation and first empirical evidence (c.f. Jurowetzki, 2013), actor driven network dynamics in technological niches can be assumed to lead to more incremental outcomes which reinforce old technological paths if (i.) the network evolution is driven by endogenous and cumulative effects, such as the actors size, age, reputation or network position; (ii.) incumbent actors embodying such characteristics are involved; and (iii.) there exist possible new niche trajectories which lead to an underutilization of their accumulated resources.

As empirical base the paper explores the evolution within the Danish electricity grid-infrastructure network of joint participation in public funded R&DD projects in the period 2009 until 2012. Companies and projects were identified by exploring the Danish research project database. The Danish case is of particular interest because of the explicit political aspiration to become a European technology hub for the development and testing of advanced energy grid technologies (KEMIN, 2013). A national smart grid strategy from May 2013 emphasizes the importance of interaction between research institutes, utilities and technology producers and the development of a various technologies. A number of research programs was established to support R&DD projects from basic research to large-scale demonstration and commercialization.

The purpose of the present paper is to study the positioning strategies of incumbent actors within technological niches, and which effect their presence might have for the development of emerging technologies within these "protected" spaces. In particular, deploying a stochastic-actor-based model (Snijders et al., 2010b), we analyse if network dynamics of public funded R&DD in technological niches favour incumbent actors in a way that they are able to occupy central and dominant positions. Against the empirical and theoretical background, we conceptualize the research network as consisting of directed ties between the actors, assuming the project-leader to project-partner link as a hierarchically ordered relationship. By doing so, we are able to analyse up to now unobserved cumulative and self-reinforcing effects of network dynamics.

As a result, we indeed find such path-dependent and cumulative effects in the development of the research network that favour incumbent actors, in the long run leading to a a reinforcing process of structural stabilization with central and influential positions.

The remainder of this paper is composed as follows: The following section 2 aims at linking different streams of literature that advocate for the creation and protection of technological niches with network theory. This connection is made to understand strategies of different niche actors and possible macro outcomes of their behaviour. Section 3 provides an overview over the technological and policy context of the smart grid development in Denmark. In section 4 we introduce the stochastic actor-based model deployed to identify the evolution in the niche-network, and describe the research networks data used for the analysis as well as our empirical strategy. Section 5 presents the results, and the final section 6 concludes.

2 Theoretical Background

2.1 Incumbent strategies

Incumbent firms with substantial shares of their resources bound in an established technological regime are said to struggle in maintaining a certain level of innovation activity, particularly when facing radical, discontinuous technological change (e.g. Bower and Christensen, 1995; Wagner, 2010). One can broadly distinguish between *competence-enhancing* innovation building upon existing technological and organizational structures, and *competance-destroying* innovation turning them obsolete (Tushman and Anderson, 1986). In case of *competence-enhancing* technological innovation, established firms have incentives to actively engage in and support the development of the technology updating the existing (Gilbert and Newbery, 1982) regime.*Competence-destroying* innovation in turn appear as more likely to be pioneered by newcomers (Anderson and Tushman, 1990; Tushman and Anderson, 1986).

Over time Incumbents might also develop adoptive capabilities, enabling them to absorb knowledge on more radical novelties and combine it with their stock of knowledge to develop superior products and processes (Bergek et al., 2013). This can be done i.a. by engaging in joint R&D projects with entrant firms or the acquisition of their technology (e.g. Wagner, 2010). However, once internalized, the absorbed novelty is likely to be aligned with existing resources in a complementary way. Therefore, when engaging in joint R&D projects, we assume that established firms - given the power - will influence technological trajectories in a way that makes the outcomes more compatible with their established assets and therefore potentially less radical.

2.2 Large technical systems transition and lock-in

The achievement of the sustainability goals in highly dependent on the determination and ability to transform a number of large technical systems (LTS's) worldwide. LTS's, such as the energy grid, the transportation or the agri-food sector build complex, extremely interwoven technical, economic, institutional and administrative structures (Hughes, 1987). As these systems gain momentum, they also develop effective resistance mechanisms against change (e.g. Van der Vleuten and Raven, 2006; Walker, 2000). Such sector heavily build and rely on existing tangible and institutional infrastructures (e.g. development and trial systems, supplier and distribution networks, energy transmission grids and other complementary assets). This dependence leads to high entry barriers in aforementioned industries and explains, why key players are likely to be large companies (e.g. electric utilities, car manufacturers, railway operators).

The resulting set-up creates a power and capability imbalance between usually small enterprises that are pioneering the development of sustainable solutions and incumbent actors (Hockerts and Wüstenhagen, 2010). As long as production and distribution processes within existing trajectories are economically favourable, incumbents will not see urgent reasons to make large investments and reorganize existing production structures. On the contrary, they are most likely to defend the system against change (Walker, 2000). In the most extreme case this leads to inertia and lock-in (Arthur, 1989), as one might observe in our current fossil fuel dependent energy system (Unruh, 2000).

2.3 System innovation thinking

Technological change embedded in large systemic context has been conceptualized and analyzed throughout the past three decades. Early theoretical approaches include i.a. overall evolutionary economic theory (Dosi, 1982; Nelson and Winter, 1982), the notion of large technical systems (Hughes, 1987), social construction of technology (Bijker, 1997), long-wave theory on techno-economic paradigm shifts (Freeman and Louçã, 2001; Freeman and Perez, 1988) and technological revolutions (Perez, 2002).

The technological innovation system TIS sub-orientation (Bergek et al., 2008; Carlsson and Stankiewicz, 1991) within the innovation system (IS) literature is seen as conductive for the analysis of emergent industries on the basis of radically innovative technologies and the institutional and organizational changes that accompany the technological development (Truffer et al., 2012). While system delineation, particularly the set-up of the TIS in relation to geographical and sectoral embededness, still remains under dispute, the concept did experience a major conceptual refinement, shifting the analytic emphasis from system composition towards a key functions assessment for the determination of system performance (Bergek et al., 2008). System functions are seen as intermediate variables between the structure of the system and its performance, emerging out of the interplay between actors and institutions (Jacobsson and Bergek, 2011). This perspective was developed to facilitate the junction between technology-specific and more general industrial dynamics. Thus, the TIS is by definition tied to higher system levels (e.g. SSI or NIS) (Jacobsson and Johnson, 2000).

Core contributions within the TIS literature identify key system functions: (i) Market formation, (ii) Entrepreneurial experimentation, (iii) Influence of the direction of search, (iv) Resource mobilization, (v) Knowledge development and (vi) Legitimation. In this context niches are perceived as highly important structural elements, which support these core functions and and the creation of protected spaces for new technologies is essential for their development (Hekkert et al., 2007b) and is situated at the heart of this formation process of the TIS (Jacobsson and Bergek, 2004). While it is acknowledged that incumbent players may employ strategies to prevent disruptive innovation (Hekkert et al., 2007b), participation of established players in the TIS is generally seen as fruitful, highlighting their resources, knowledge integration capabilities (e.g. Bulathsinhala and Knudsen, 2013) and the positive signalling.

In the recent decade, a second stream of literature situated closer to the science, technology and society (STS) tradition gained considerable attention. The multi level perspective (MLP) at the center of the transition literature explains socio-technical transitions by the interplay of three systemic concepts. The landscape on the macro-, the socio-technical regime on the meso- and niches on the micro level respectively (Geels, 2002, 2005). The character and intensity of the interplay between the three levels define the paths, which a socio-technical transition might take. The key concept of the MLP is the regime, which represents a coherent, stable structure at the meso-level, combining established products, technologies and institutions (routines, norms, practices). Refering to work by Arie Rip and René Kemp, Hoogma (2002) defines the regime as: "the whole complex of scientific knowledge, engineering practices, production process technologies, product characteristics, skills and procedures, established user needs, institutions and infrastruc-

tures". The regime is characterized by a high level of "structuration" (Coenen and Díaz López, 2010), well articulated rules, and hence path-dependency and mechanisms for self-stabilization. It corresponds in many respects to the selection environment in terms of evolutionary economic theory and generates entry barriers for innovative technologies.

2.4 Niches & protected spaces

Niches are conceptualized as spaces that shield path-breaking innovations in early stages of development from selection pressure on mainstream markets (Hoogma et al., 2004; Kemp et al., 2001; Schot, 1992). Due to alternative selection criteria, population and interaction dynamics, niches can develop own technological trajectories substantially differing from the established regime.

Raven (2007) described possible evolution pathways on niche-level, focusing particularly on technological outcomes. He suggests the distinction between *niche hybridization* when moderate technological novelties merge together with the existing regime and *niche accumulation* what describes the incubated development of radical innovation that eventually penetrates the regime level. To understand, how niche dynamics evolve and eventually transform established regimes, it is essential to have a conceptual insight into the processes within niches. Smith and Raven (2012) suggest to assess niche dynamics, using three essential niche functions: (i.) shielding, (ii.) nurturing and (iii.) empowerment. Selecting the appropriate level of protection and upholding a continuous assessment might be crucial, in order to prevent protection of poor innovations (Hommels et al., 2007) or on the other hand a too low level of protection.

The direct funding of R&DD in selected technologies of interest represents an integral component of modern innovation policy. Shielded from the selection pressure of open markets, these research projects present an ideal platform for a broad, experimental and long term oriented search for new technologies. Nurtured with public investments, new entrants and incumbents alike are able to stem projects which would due to their high technological uncertainty and long payoff periods not be carried out otherwise. Given the proper institutional set-up public R&DD financing offers a powerful tool to directly influence rate and direction of research activities (Pavitt, 1998) and to create technology niches. With selective grant allocation policies, public authorities are able to directly influence the characteristics of technologies, actors and interaction structures of these niches, thereby they can lay the foundation for the establishment of alternative technological trajectories.

2.5 A network perspective on technological niches

Cooperation and interaction between various actors involved in processes of technology development such as universities, firms, intermediate and end users, are said to be of high importance for the smooth functioning of innovation systems (e.g. Hekkert et al., 2007a; 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), triggering interaction between heterogeneous actors and the generation of technological variety.

Organizations form collaborative alliances in order to get access to their partners' technological assets and capabilities. Potentially fruitful interaction with other corporations come at the risk of opportunistic technology appropriation by the counterpart, making careful selection of partners crucial (Li et al., 2008).

One can broadly distinguish between two categories of information that actors can use in cooperation decisions. First, reputation, mostly stemming from past performance in similar settings (Shapiro, 1983). Second, information about an actor's position in relevant networks (Benjamin and Podolny, 1999; Burt, 1992; Granovetter, 1973).

Both appear to be highly interdependent, since an actor's reputation can be influenced by the reputations of past and current exchange partners (Benjamin and Podolny, 1999; Podolny, 1993) and collective reputations can be transferred to the a groups individual actors (Schweizer and Wijnberg, 1999). In addition, in our case we assume that it is the leaders of the particular projects that higher influence on the composition of the collaborations. They are usually the ones applying for and holding the largest share of the corresponding grant and since determining most of it's content, and selecting partners.

2.6 Summary

Overall, the above presented streams of literature draw a similar picture from their respective point of view: Innovation is particularly complex and costly in systemic set-ups. Path dependencies are especially pronounced in sectors with a high share of infrastructure. Frameworks that inform policy measures to spur change in these areas agree on the need to actively create technological and market niches in order to foster alternative technologies and in general solutions. Yet, the role of incumbent player within these niches needs more inquiry.

Innovation paths that are compatible with regime technologies are attractive for established firms. Resulting innovations can address some of the existing problems on the MLP-regime level without compromising existing socio-technical structures. Established firms are therefore likely to initiate or engage in niche activities, such as R&DD projects, which investigate such applications.
Facing radical or architectural technological change they will probably not directly support the early development of path-breaking innovations, but rather aim at gaining control, acquiring and integrating novel and existing technologies (Bergek et al., 2013; Pavitt, 1986). Here, we assume that this may alter the particular innovative technology towards a less radical solution. In the case of sustainable technologies that would mean that generally more desirable superior solutions are possibly devaluated as they become compatible with the existing unsustainable system.

3 Sociotechnical context of the smart grid development in Denmark

3.1 Paradigm shift in energy grids

The traditional architecture of the electricity grid assumes a unidirectional energy flow from centralized energy plants via the transmission and distribution grids to consumers, where energy production levels are constantly adjusted to match the over time fluctuating energy demand (Farhangi, 2010; Fox-Penner, 2010). Embracing the renewable energy paradigm, centralized energy production is gradually replaced by decentralized energy farming. The harmonization between production and consumption has to move from the traditional generation side into the transmission and consumption areas. ICT technologies will play a central role, supporting this process (Mattern et al., 2010).

In the Northeuropean set-up two options are possible and currently discussed. Firstly, the construction of a European transmission super-grid, to allow for instance energy exports from Denmark to Germany in wind-peak times. Secondly, the development of a national *smart grid*, that is able to transmit energy and information in both ways, thus allowing for harmonization by the means of flexible consumption. This requires the upgrade of the existing grid by adding a *layer of intelligence* - advanced measurement, communication and control technology - thus making the grid able to handle a higher share of decentralized renewable energy generation and the recently evolving consumption patterns (Elzinga, 2011). If flexible consumption can be activated by the introduction of smart functionality, costly investments in the reinforcement of the distribution system can be moved into the future or avoided (Forskningsnetværket, Smart Grid, 2013).

3.2 Danish smart grid research and aspirations

Denmark is already today counting the largest amount of R&DD projects within the smart energy area in Europe (Giordano et al., 2011, 2013). The extremely high ambition of the national energy agreement, passed by the government in 2012 targets a wind-power share of 50 percent by 2020 and the more recently announced Smart Grid Strategy sees the country as a European laboratory for innovative energy solutions (KEMIN, 2013). In their latest inventory report Giordano et al. (2013) outline that compared with other European countries Denmark manages to develop a large amount of smaller projects what spurs technological diversity. Figure 1 shows the various technology areas that can be summarized from an analysis of 99 research project descriptions[1].

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[1]Projects range from 1996 until 2013, what exceeds the later used data by approximately a third. The underlying analysis combines natural language analysis, vector space modelling and community detection within networks. A detailed methodology description and analysis can be found in (Jurowetzki, 2014)

Figure 1: Overview: Research project graph and cluster level TFIDF-Keywords

The tagclouds, indicating particularly important keywords for the respective clusters, suggest that R&D projects can be broadly gathered in 10 groups. Projects in communities 8 and 9 are less technical but rather focused on the interaction with the energy users and their ability to flexibilize consumption. Communities 5 and 7 examine different problems on a energy-sytem macro-level. Many of these projects develop models and simulations related to problems that stem from large scale renewable energy integration. The smaller communities 0 and 1 summarize projects on data-transfer and advanced battery technology respectively. The communities 6 and 2 gather different projects related to electric mobility and its compatibility with the energy grid. Finally the clusters 4 and 11 examine the role of the heating sector within the evolving grid infrastructure. Space and water heating is responsible for great share of energy consumption and due to its nature heating can be used as a source of flexible energy consumption and potentially also for energy storage. Research projects in this area mainly focus on the integration of mature heating technologies such as district heating and heat pumps into the emerging smart grid infrastructure.

While the obvious technological diversity can be interpreted as a sign of successful niche development, it also offers entry and influence opportunities for different types of established actors. This study aims at exploring this issue, employing an evolutionary network study approach. At the core of this research is the question of whether publically funded R&DD activities are able to provide necessary shielding in order to develop and introduce the needed amount of technological variety in the changing energy grid sector.

4 Modelling Network Evolution

In this paper, we will focus on directed interorganisational networks between an ego, representing the leading organisation in a public funded R&DD project, and an alter, representing a further partner in the same project. During the 1980^s, the emerging paradigm of inter-firm network forms of organization also started to receive growing attention in organizational and management science (see Podolny and Page, 1998). Reflecting ongoing socio-economic changes and contrasting the predominant transaction-cost based approach, it has been argued that in increasingly global, inter-connected and uncertain economy changing with accelerating pace, both markets and formal hierarchies display inefficiencies as modes of organizing production (Miles and Creed, 1995). In the early 1990^s the transaction-cost oriented explanations of hybrid organizational structures (Williamson, 1990) has been superseded to a large extend by new developments in evolutionary economics. Here, the Neo-Schumpeterian approach to economics explicitly acknowledges the collective nature of innovation process (Hanusch and Pyka, 2007). This is reflected most clearly in the innovation system concept which emphasize the creation, diffusion and use of knowledge and describe them by a set of components, relationships among these components and their attributes. Systems are characterized by built-in feed-back mechanisms and time plays a dominant role in a sense that the configuration of components, attributes, and relation-ships is constantly changing in these systems. It is plain that the systemic concept in evolutionary economics provides a solid theoretical foundation for an in-depth analysis of how and why innovation networks change over time.

4.1 Principles of stochastic actor-oriented models of network dynamics

The analysis of dynamic actor networks represents an empirical challenge which calls for distinct statistical models and methods. Drivers of tie formation processes in social settings, such as transitivity, reciprocity and popularity effects, by their very nature lead to multiple endogeneity and dependencies of observations (Rivera et al., 2010), thus violate most standard statistical model types (Steglich et al., 2010).

The class of stochastic actor-oriented models (SAOM) originally developed by Snijders (1996) represent an attractive solution, which scholars just recently started to deploy in the context of inter-organizational innovation networks (e.g. Balland, 2012; Hain et al., 2013). In contrast to the quite restrictive loglinear approach for modelling network dynamics (e.g. Holland and Leinhardt, 1977), SAOM are able to jointly analyse multiple endogenous structural effects, such as tendencies toward transitivity or structural balance and also allows for continuous variable scales. In its core, SAOM combine a random utility model, continuous time Markov process, and Monte Carlo simulation. Given the context of the study, we consider SAOM as the most suitable class of dynamic network models, and deploy it for the empirical analysis to follow.

Originally, SAOM was developed in a sociological context and designed to model group dynamics in interpersonal networks (e.g. Van De Bunt et al., 1999). However, actor oriented modelling is also particularly suitable to depict the interaction between macro outcomes and firms' micro choices (Macy and Willer, 2002) in inter-organizational alliance formation process. Here, the

network structure is based on individual firms' choices, which are assumed to be driven by the expected amount of utility derived from the selection of collaboration partners with respect to individual, dyadic, structural and environmental determinants.

Snijders (1996) firstly proposed to address the problem of multiple endogeneity in the evolution of social network with transforming discrete datasets of panel waves into a continuous set of changes to be estimated as a Markov-chain.[2] Unobserved changes between the waves are simulated as continuous actor choices at stochastically determined points of time. Formally, following a Poisson function of rate λ_i, the actors are allowed to create, maintain, or dissolve ties until the network is transformed to the new structure χ. The decision of actor i to change the state of one tie to another actor j, this leads to a new overall state of the network χ, where the probability P_i for choosing this structure is given by:

$$P_i(\chi^0, \chi, \beta_k) = \frac{\exp(f_i(\chi^0, \chi', \beta_k))}{\sum\limits_{\chi' \in C(\chi^0)} \exp(f_i(\chi^0, \chi', \beta_k))} \tag{1}$$

It technically resembles a multinomial logistic regression, modelling the probability that an actor chooses a specific (categorical) new network configuration P_i as proportional to the exponential transformation of the resulting networks objective function $f_i(.)$, with respect to all other possible configurations. The parameters coefficients are stepwise adjusted by Monte Carlo simulation techniques in order to obtain convergence between the estimated and observed model, and finally held fixed to allow their comparison and post-estimation analyses. The objective function contains actor i's perceived costs and benefits of a particular network reconfiguration leading to a network state χ, χ, which are represented by the random utility model:

$$f_i(\chi^0, \chi', \beta_k) = \sum_k \beta_k s_i(\chi^0, \chi, \nu_i, \nu_j, c_{i,j}, \epsilon, r) \tag{2}$$

It depends on the current state of the network χ^0, the potential new one χ, the ego i's and alter j's individual covariates ν_i and ν_j, their dyadic covariates c_{ij}, exogenous environmental effects ϵ, and a random component r capturing omitted effects. Underlying assumption is that the actors observe current structure o the network χ^0 and the relevant characteristics of it's actor set and make their collaboration decisions in order to optimise their perceived current utility (Jackson and Rogers, 2007).

4.2 Data

Network Data

As source for public funded research projects we utilize the database provided by *Energiforskning.dk*. Combining data from several energy technology research and development programs, it represents the most comprehensive source for public funded energy research in Denmark, covering projects funded by the *Strategic Research Council, ForskEL, ForskNG, ForskVE, ELFORSK,*

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[2]Besides all its merits, the usage of estimations based on continuous-time Markov processes also has its drawbacks. It by definition does not allow for path dependencies. Yet, it is still possible to include variables aggregated over time to the current state.

Green Labs DK, the High Technology Foundation and the *European Union.* For the current analysis records from the *smart grid and systems* category were exported containing information on projects from 2009 to 2012 on yearly basis, overall 75 projects with 277 participants, and 132 single firms. Among those actors we identify 27 incumbent firms, 21 research institutions with the rest being either established diversifier companies or new entrants[3]. A graphical presentation of the network under observation and its change over time is provided in Table 3 in the appendix. On first glance it a formation of structural clusters around some incumbent actors can already be seen over time.

In order to utilise stochastic actor-oriented models, the dataset under observation has to fulfil certain properties in line with the underlying assumptions of this model class. First, the network has 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, we consult the Jaccard index to be found in table 6, a common measure of similarity between two networks.[4] Snijders (2002) suggest this index to be higher than 0.3 and never drop beyond 0.2, which is given in our data. Overall, after a first preliminary inspection, the network data appears to have suitable properties in line with the assumptions of stochastic actor oriented models. Some further descriptive statistics on structural network measures and their development over time are provided in table 6 in the appendix.

Actor Data

Data on firm characteristics, such as their age, size, legal form *et cetra* was extracted from the Danish firm database Navne & Numre Erherv (NNE). For additional information about firms' technological capabilities and their range of activity where gathered by studying annual reports, press articles, corporate websites *et cetra.*

4.3 Empirical Strategy

Model Setup and Specification

We model ties between ego i (project leader) and alter j (project partner) as unidirectional from $i \Rightarrow j$. To do so, the content of the network has to be hierarchical and not necessarily reciprocal, e.g. friendships or producer-consumer relationships. In our case this appears as fairly reasonable, since the leaders of such public funded projects are usually the ones applying for the corresponding grant, determining most of it's content, and selecting further partners. We furthermore choose a unilateral confirmation setup, where tie creating is only conditional to the ego's but not the alter's choice. By doing so, we assume potential partners to automatically join research projects when invited to. This appears as a strong but realistic assumption, since such a participation represents a save source of income (and potentially knowledge), where the main

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[3]A detailed description of the applied classification methodology is described below

[4]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).

upfront work such as the grant application and determination of the content is mostly carried out by the project leader.

As a 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. (2010b) suggests to only include parameters with t-values of convergence between estimated and observed parameters below 0.1, what is given for all parameters in all corresponding models. The values in general show better convergence in later models, which confirms the effectiveness of our applied forward-selection strategy of model choice.

To analyse the influence of actor characteristics and endogenous structural effects, we run a set of three models. All of them contain a set of standard structural dyadic and triadic ego-network control variables. Model I traditionally tests for ego (project leader) covariates, which are assumed to affect the capabilities of creating new outgoing ties. Model II instead tests for degree related structural effects. In comparison to the set of dyadic and triadic structural effects, degree related effects are related to the overall number of in- and outdegrees of alter and ego, independent of their position in the other's network. Thus, while the first set of controls refers to the local hierarchy of the actors ego network, degree related effects refer to a global hierarchy in the overall network. Finally, in model III we test for the joint effects of actor covariates and degree related effects simultaneously.

To account for changing dynamics over time, i.e. due to different policy focus and overall funding available, we carry out the test for time heterogeneity proposed by Lospinoso et al. (2011), which indeed shows a significant effect. As a result, we include year dummies in all models.

All parameters are estimated under full maximum likelihood according to the algorithm proposed by Snijders et al. (2010a), which has proven to be more efficient for small datasets.

Technically, we make use of the SAOM application of SIENA (Ripley and Snijders, 2013), a package for the statistical environment of R.

Dependent Variable

As outline above, collaboration choices driving the evolution of the network are the outcome of the actors mutual attempts to optimize their expected utility with respect to their own and their potential alters' covariates, and the current network structure. Thus, our model's the dependent variable represents the probability P_i that the focal actor i chooses a reconfiguration of the own network that leads to a tie with a corresponding alter j to change its state from non-existing to existing.

Independent Variables

Actor Level Characteristics: This set of variables represents the effect of individual actor characteristics on their likelihood to establish new ties with other organizations.

In order to examine the strategies of different actors in the combined network, we applied a classification strategy similar to the one used by Erlinghagen and Markard (2012). In many cases the actor-classification corresponds to certain combinations of NACE codes, size and age

of an actor. However, a classification exclusively based on these objective measures would often fail to identify actor roles. We therefore decided to use an industry expert for incumbent detection, asking the person to select "firms with a strong background/track-record and stakes in the traditional energy sector" from the list of all actors in the network. [5] The list below presents the description of the three classes of actors. Particularly interesting is for our analysis the incumbent-class and the strategic deviations of these actors as compared to other actors involved in smart grid research projects.

`Role incumbent`: This category aims at grouping actors with an origin in the energy sector and that have an interest in protecting the established infrastructure from significant change. It includes utilities, producers of transmission and distribution infrastructure, and producers of measuring devises. Apart from the utilities that went through a Europe wide policy induced organizational restructuring process, companies were founded before 2000. `New Entrant`: This group summarizes companies which were (apart from 2) founded after 2000 and have their main activity in the energy sector. The firms provide a broad range products and services. Many of the firms develop ICT related solutions for the envisioned communication structure of the smart grid. Another large share are technology consultancies that are often responsible for analysis and system integration. `Role Others:` This class contains private and public actors that have shown interest in the development of a new grid infrastructure by participating in a research project. Actors are rather heterogeneous and have not a background in the energy grid sector. However, it also includes players from other sustainable energy areas such as combined heat and power plants that try to find their position within the new energy grid paradigm. This set of actors represents the reference group.

The size of a firm is also supposed to influence it's capabilities of successfully obtaining research grants, as well as to occupy central and a dominant position in the resulting research networks. However, size is difficult to compare between different forms of organizations such as private companies, public organizations and research institutions. Therefore we only use a rough classification of small (up to 25 employees, `firm small`), medium sized (up to 100 employees, reference groups) and large organizations (more than 100 employees, `firm large`).

While maturing, firms are able to increase their competences in how to successfully formulate a research grant application, establish an intensify formal and informal relationships to industry partners and public authorities, and develop routines how to manage research partnerships. Since we expect this benefits to increase with decreasing marginal effects, and furthermore the distribution of firm age in our sample is highly skewed (start-ups as well as traditional firms established over a hundred years ago), we use the natural logarithm of the ego's `age` in years instead as control variable.

Some further descriptive statistics of these actor based measures are provided in table 6 in the appendix.

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[5] We cross-validated the classification using a computational approach. For that, we collected approximately 550 Danish industrial publications related to energy system topics from the period 1995-2000 and used a fuzzy string matching approach in order to identify actors from the analysed research projects within the texts. We assume that actors that appear in a "energy context" can be considered established in the industry.

Structural effects of the ego-network: This set of variables captures structural characteristics of the actor's ego-network, which include dyadic and triadic tie-configurations with other actors. Literature suggests these effects to be among the most important driving forces of network dynamics. Given the context of our study, however, they mostly represent control variables and are not emphasized in the following analysis. Reason therefore is the local nature of these variables, referring to effects only in and on the close neighbourhood in the network space.

The most basic effect is defined by the `outdegree` of actor i, representing the basic tendency to form an arbitrary tie to possible alters j, regardless their individual characteristics. Since most social network structures observed in reality are rather sparse (meaning their density is way below 0.5), this effect is usually negative, meaning the costs of establishing a tie *per se* usually outweigh the benefits if no further characteristics make this tie particularly attractive (Snijders et al., 2010b).

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 (c.f. 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). In our case we make use of the measure for transitive triads, which measures transitivity for actor i by the number of other actors h for which there is at least one intermediary j forming a transitive triplet of this kind.

Degree related effects: Degree-related effects express global hierarchies in a way that they reflect actors positions in the overall network. In other words, they capture the tendency of actors to form and receive ties according to their amount of out- and in-degrees, independent of their particular position in the network. They are of particular interest against the background of our study, since they are in contrast to commonly applied triadic measures suitable to analyse the tendency of certain actors to establish central and thus dominant positions in the network structure.

`Out-degree popularity` captures the reputation and social recognition effect of the network on the activities of actor i. A positive parameter indicates that actors sending a higher amount of ties are also considered as more attractive to receive them. This effect leads to a convergence of in- and outdegrees on actor level. In our case that indicates that actors leading many research projects also happen to get often invited and to become research partners in other projects. These "knowledge integrators" (Bulathsinhala and Knudsen, 2013) are likely to accelerate the diffusion of knowledge and support other projects with their cumulated knowledge and other resources. Of particular interest for this study is the `Out-degree activity`, which is the tendency of actors with high outdegrees to establish even more. A positive parameter indicates a self-reinforcing mechanism leading to an increasing dispersion of out-degrees in the network (Barabási and Albert, 1999). It can be interpreted as the in network-structuralic impersonation of what is called

the "Matthew Effect" (c.f. Merton, 1968, 1988), cumulative advantage (Price, 2007) or preferential attachment (Barabási and Albert, 1999). Networks driven by this effect tend to stabilise towards a core-periphery structure around some very central, well connected an influential actors. To decrease the degree of collinearity especially with the effects of the ego-network structure, both `Out-degree popularity` and `Out-degree activity` are used in their square root. Finally, we also include an interaction term between `Out-degree activity` and `role incumbent`, to test if the posited Matthew effect works particularly strong for incumbents.

5 Results

Table 1 reports a set of analyses of a multinominal logistic regression based on a stochastic actor-based approach. In the first model we test for the basic ego-network effects together with actor characteristics. Among the ego-network effects, the measure for `transitive ties` shows a high positive coefficient as well as significance at one percent level, indicating a tendency for local clustering. Surprisingly, the effect of `balance` is negative and significant, even though relatively small in magnitude. While literature advocates for a tendency of actors to form their network relatively homophyl with respect to the choosen partners characteristics in general (McPherson et al., 2001), and their network structure in particular (Burt, 1982), in our case the opposite appear to be true at first glance. This might be on the one hand an indication for the efficient functioning of policies that aim at connecting diverse actors that might potentially complement their respective competencies. On the other hand, given the other results of our analysis, this might be also interpreted as part of an incumbent strategy with the intention to assess and acquire, or even block potentially threatening emergent technologies. On the European level (Erlinghagen and Markard, 2012) found for instance that established firms showed a strong tendency to acquire start-up companies with promising technological capabilities.

Among the set of actor specific variables, first striking insight is the high positive and significant coefficient of `role incumbent`, providing first evidence that the smart grid research network indeed over time tends to be dominated by incumbent actors. As expected, actors of the `role entrant` also show a higher likelihood to establish outgoing ties compared to the reference group of public organizations, research institutions and adjacent companies. However, due to the comparably higher coefficient as well as significance level of `role incumbent`, actors operating in the "old regime" still seem to gradually move to central positions and thus shape the direction of research and development of technologies. Also `size large` shows a positive and significant coefficient, depicting the benefits of size in obtaining research grants, managing research projects and collaborations.

Table 1: Stochastic Actor-Oriented Model: Probability of Tie Creation Ego→Alter

	Model I		Model II		Model III	
Variable	Coef.	Std. Er.	Coef.	Std. Er.	Coef.	Std. Er.
Structural ego-network effects						
outdegree	-4.314***	0.540	-5.913***	0.342	-6.264***	0.453
reciprocity	1.143	0.622	1.411**	0.582	1.034	0.594
transitivity	1.791***	0.345	0.319	0.228	0.229	0.191
Actor level effects						
size small	0.990	0.873			1.601**	0.681
size large	2.644***	0.832			1.629**	0.726
role incumbent	3.424***	0.611			2.759***	0.476
age (ln)	-0.793**	0.267			-0.448**	0.227
Degree related effects						
out-pop ($\sqrt{}$)			0.085**	0.029	0.077**	0.030
out-act ($\sqrt{}$)			0.372***	0.047	0.413***	0.073
out-act ($\sqrt{}$) * role incumbent					1.430***	0.347

Note: *, **, *** indicate significance at 10, 5, 1 percent level, two-tailed

In model II, we test for the set of degree related effects. First interesting result is that the `transitive ties` parameter completely looses significance, showing that of global hierarchy indeed seems to have an stronger effect as the local one, thus global centralization outweighs

local clustering in the further evolution of the network. Thus, the former significance of local hierarchical effects are likely to be only a first-order effect of the underlying global one.

Among the degree related effects, both `outdegree popularity` and `outdegree activity` show a high positive an significant coefficient, where `outdegree activity` dominates.[6] This findings indicate that the current selection environment in the technological niche of public funded smart grid R&DD indeed shows a tendency to develop towards a global hierarchy, which over time ultimately leads to a centralised network structure with a high dispersion of degrees. In such network structures, some actors move over time in a reinforcing manner towards a dominant position. This fact *per se* is, however, neither surprising nor worrisome but rather a natural tendency that can be observed in many real world networks.

In our final model we jointly test both sets of effect to instigate if actor characteristics still impact the network development when simultaneously testing for endogeneous structural effects. While ego-network effects remain roughly unchanged compared with the former model, the investigation of actor level effects reveal some interesting insights. Again, the effects of `size large` and `role incumbent` are significant and show the highest coefficient, whereas both drops for `role entrant`. The two degree relate effects `outdegree popularity` and `outdegree activity` both remain significant and increase in magnitude. Overall, the results of this final model suggests incumbents indeed to be in a favourable position to inherit dominant roles in the research network over time. While they are generally more likely to establish outgoing ties, preferential attachment and accumulated advantages reinforces this tendency over time, both in terms of in- and outdegrees. Finally , the interaction term `role incumbent * outdegree activity` also shows a high positive coefficient, significant at one percent level, providing further evidence for the advantageous effects incumbents enjoy in the development of their network position.

Goodness-of-fit evaluation and robustness

Since the class of stochastic actor-oriented models is still under development, there exists no direct equivalent to the R^2 indicator of least squares regression models. Latest advances, however, offer a set of instruments to asses the model fit in stochastic settings. Score tests for each variable proposed by Schweinberger (2012), lead to overall satisfying results and gradually increase from model I to III. Also, we perform the Monte Carlo Mahalanobis Distance Test proposed by Lospinoso and Snijders (2011). Here we test the null hypothesis that auxiliary statistics such as indegrees, outdegrees and geodesic distance of observe data is distributed the results of Monte Carlo simulations on the estimated coefficients of our SAOM model, using the network in period one as point of departure. The purpose is to evaluate how well our stochastic model simulates transformation from the initial to the final network in terms of different degree distributions. We thereby also provide first validation of the ability of our model to predict future developments of research networks based on our estimated coefficients. The results are illustrated in figure 7. The results suggest that our model is very well suited to predict the indegree and geodesic degree distribution, where the simulation results are very close to the observed values.

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[6]Note that all parameters in SAOM are standardised (divided by their mean), thus making a direct comparison of their magnitude possible

Same holds for most forms of triad constellations. The only weakness of the model up to now appears to be the inconsistent identification of low outdegrees. While the model performs very well for high outdegrees, the simulated statistics for nodes with zero up to two outdegrees deviates highly from the observed values. However, since we are primarily interested in the distribution of the high degrees (the dominant nodes in the network), we consider the accuracy of prediction on the low end only as second priority. While we still work on the improvement of the model fit, we are yet overall satisfied with the results.

6 Conclusion

In this paper we analyse the role of incumbents in public funded research networks. Drawing from innovation system, socio-technical transitions and network evolution literature, we discuss possible effects of their participation in technological niches (in our context, research networks in public funded R&DD projects) on the network structure. We provide a set of arguments why and how incumbents might be able to substantially alter the niche's dynamic and thereby over time inherit a dominant position.

To do so, we conduct a stochastic actor based network analysis, where we model the hierarchy and power structure in the network with directed ties between research project leader and partners. By doing so, we are able to analyse up to now unobserved cumulative and self-reinforcing effects of network dynamics. We find path-dependent and cumulative effects in the development of the research network, which favour incumbent actors, thus in the long run it appear as likely to lead to a structure dominated by them. We assume the leader of such projects as mainly influencing the context of conducted research as well as the selection of further participants, thus strongly influencing the development of technological trajectories in such niche networks.

While the findings may indicate a quick adaptation of the established sector to the new technological challenges, it seems more likely that incumbent players are willingly altering technological trajectories in a way that favours compatibility with the existing system, at the extent of the innovative and sustainable performance of the new technology. Our findings provide implications for research and policy alike.

While we fully acknowledge that established companies are capable of innovating, we think that the network dynamics that we find, are an indicator for a high share of add-on type of innovations. The extent to which such a development is likely to lead away from the established unsustainable regime is questionable. Whether these increasingly incumbent-dominated networks are favourable or not is a rather normative discussion, which would go beyond the scope of this research.

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Appendix

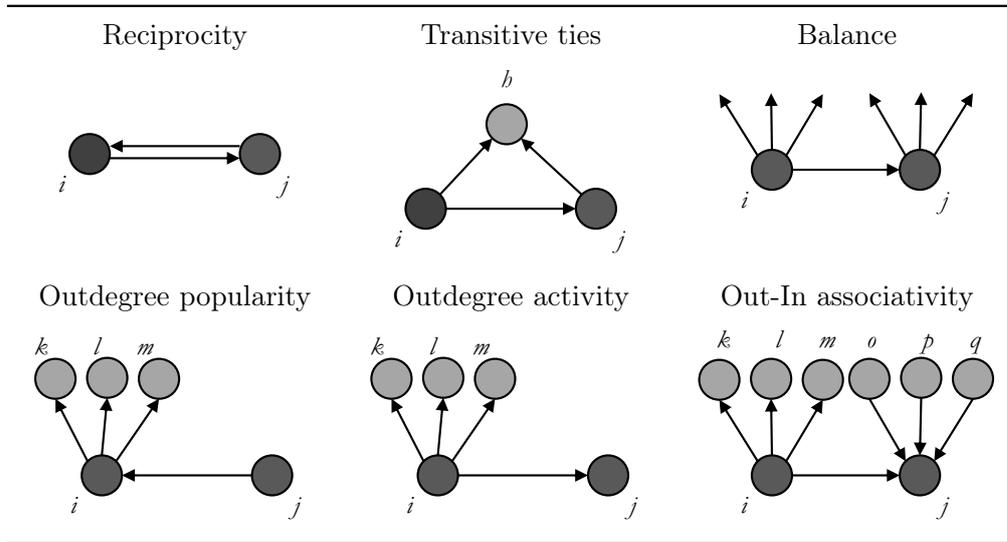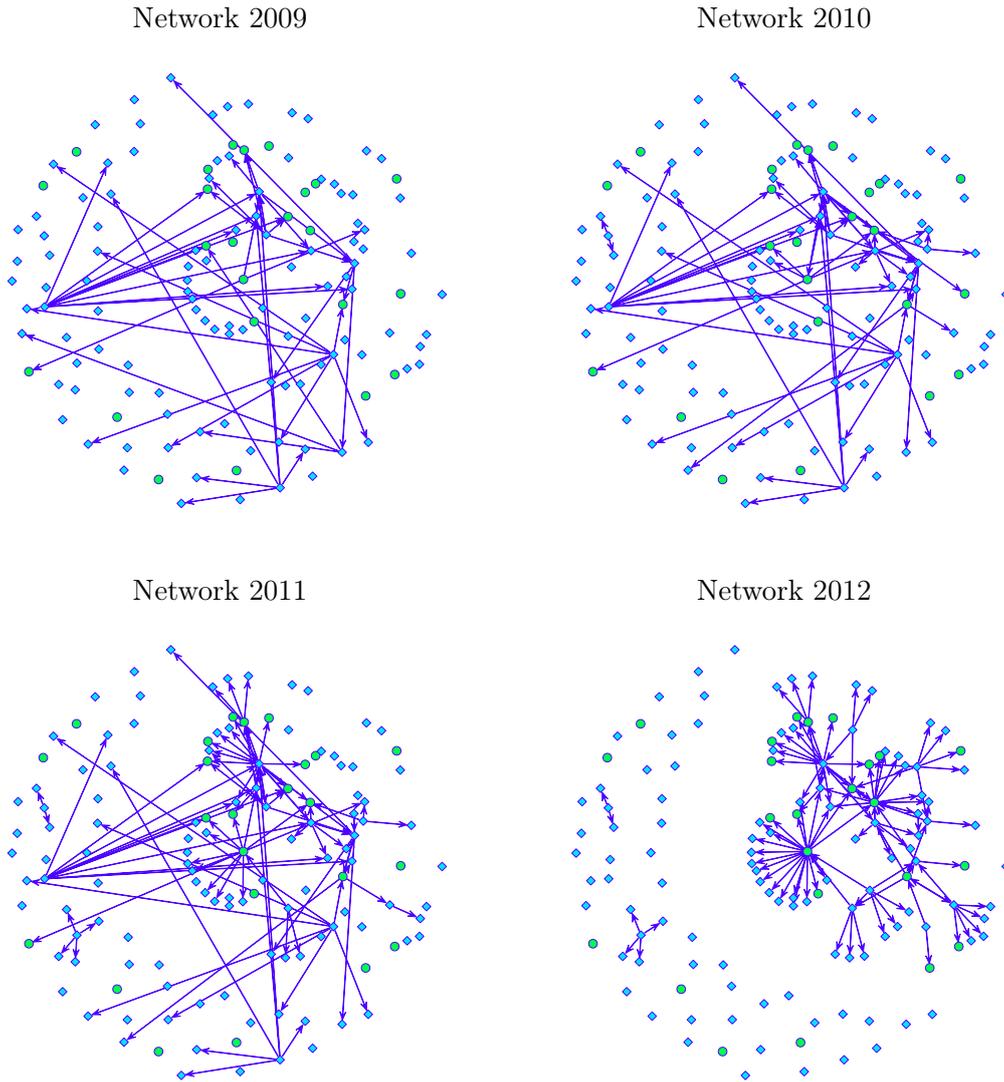Table 2: Illustration of Ego-Network and Degree-Related Effects

Reciprocity	Transitive ties	Balance
Outdegree popularity	Outdegree activity	Out-In associativity

Table 3: Network Development in Public Funded R&D in Smart-Grid Research

Network 2009

Network 2010

Network 2011

Network 2012

Note: Research network on basis of joint public funded research projects. Ties are directed from project-leader ⇒ project partner. Circles represent incumbents, squares all remaining types of organisations. The graphical presentation was done with the R package *Igraph*.

Table 4: Network turnover frequency

Periods	$0 \Rightarrow 1$	$1 \Rightarrow 0$	$1 \Rightarrow 1$	Jaccard
$1 \Rightarrow 2$	22	3	42	0.627
$2 \Rightarrow 3$	30	2	62	0.660
$3 \Rightarrow 4$	53	39	53	0.366

Table 5: Network density indicators

Periods	1	2	3	4
density	0.003	0.004	0.005	0.006
average degree	0.341	0.485	0.697	0.803
Network rate	0.383	0.490	1.406	-
number of ties	45	64	92	106
Mutual ties	0	2	4	3
Asymmetric ties	45	60	84	100

Table 6: Descriptive Statistics

Variable	Min.	Max.	Mean	Std. Dev.
size small	0	1	0.356	0.481
size large	0	1	0.432	0.497
Role: Incumbent	0	1	0.182	0.387
Role: Newcommer	0	1	0.106	0.309

Table 7: Goodness-of-Fit: Monte Carlo Mahalanobis Distance Test
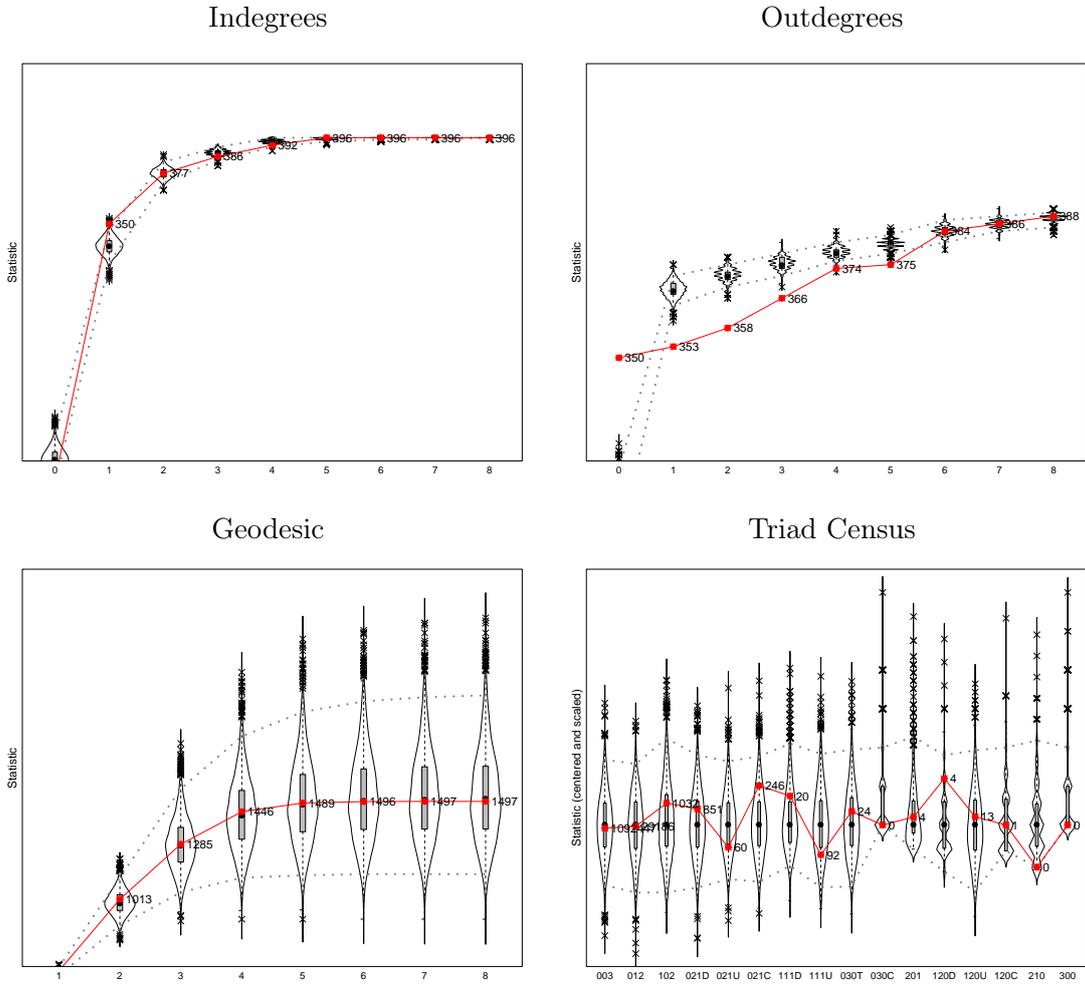
X-axis: P-value obtained by the Monte Carlo Mahalanobis Distance Test proposed by Lospinoso and Snijders (2011), testing null hypothesis that auxiliary statistics of observe data is distributed according to plot.

Y-axis: Value of auxiliary statistic (indegree, outdegree, geodesic distance, triad census). Solid red line the observed values equal auxiliary statistic.

"Violin plots" show simulated value of statistic as kernel density estimate and box plot of 95% interval.