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Technological variety in innovation systems: the role of actors, networks, resources and institutions

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Abstract

This research aims to show how attributes of subsidized innovation projects of collaborating actors within an innovation system are related to the extent a projects adds to technological variety. We assume that within the innovation system, different technological varieties can be distinguished at different places in the system. These places are often collaborative innovation projects, that can be supported by government subsidies to overcome network failure. We conceptualize the innovation system to consist of an institutional environment with networks of collaborating actors in which resources are exchanged. These elements are used to predict technological variety of a project. Empirically, we study the Dutch technological innovation system around biogas technology. Our results show that regulative institutions in the form of project subsidies that stimulate collaboration contribute to technological variety. However, the more projects are related to each other through shared actors, the less likely they are to contribute to technological variety. Finally, more diversity of actors and resources contributes to technological variety, while including more partners in a project is negatively related to technological variety.

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Keywords: Innovation systems; technological variety, social networks, structural holes, resources, actors

1. Introduction

Technological innovation is needed for sustainable economic growth (Carlsson et al., 2009) and for solving societal challenges, such as climate change (Hekkert et al., 2007). For these reasons stimulating innovation is on the agenda of policy makers. In Europe for example, the Lisbon agenda aims to make Europe the most competitive economy in the world through innovation (European Commission, 2006), which has recently led to the Horizon 2020 research and innovation program (European Commission, 2010). Also national governments design policies to stimulate innovation. For example, the Dutch government first established a national platform to promote innovation (Innovation Platform, 2006) which was later replaced by a policy that aims to stimulate innovation in nine 'Top Sectors' through subsidies in R&D (Ministry of Economic Affairs, 2011).

A rationale for designing such innovation policies is to counteract so-called 'network failures', which mean that actors interact poorly with their environment during the innovation process (Carlsson and Jacobsson, 1997; Nooteboom and Stam, 2008). A consequence of network failure is a lack of collective vision, technological expectations, coordination of investments, and ultimately a negative outcome of the innovation process. Policies drawing on the network rationale are based on innovation systems thinking, which emphasizes that most radical innovations are the result of the collaboration between different actor types, such as large firms, small and medium sized enterprises and knowledge institutes. An innovation system is *"the network of institutions in the public and private sectors whose activities and interactions initiate, import, modify, and diffuse new technology"*. Network failure in the innovation system can be reduced by tying actors together through reciprocal flows of information and knowledge (Carlsson and Jacobsson, 1997). One policy instrument to reduce network failure is subsidizing collaborative innovation projects (Van Rijnsoever et al., 2012), as is currently done in the Dutch top sector policy to spur innovation in specific emerging technological fields.

Scientifically, a lot of attention has been dedicated to innovation systems. Studies that analyzed innovation systems have provided scientists and policy makers with insights on the necessary structural configurations of innovation systems (Nelson, 1994; Freeman, 1995), what key processes are necessary for innovation systems to function well (Hekkert et al., 2007; Bergek et al., 2008) and what systemic problems can be expected (Klein Woolthuis et al., 2005; Wieczorek and Hekkert, 2012). In these type of studies, the state of the innovation system itself is seen as a proxy for innovation success.

On a more disaggregate level, innovation systems have been approached from a social network perspective to model collaborating actors in innovation projects. Network ties between actors are seen as conduits for knowledge or resources (Leoncini et al., 1996; Ter Wal and Boschma, 2009). This approach is similar to studies about the performance of innovation networks (see for example Ahuja, 2000; Powell, Koput, & Smith-Doerr, 1996), which look at how network structure is related to measures of innovative performance, such as published scientific papers, or the number of innovations or patents.

Surprisingly, innovation system and social network studies alike have rather neglected a type of dynamic that is crucial for innovation: the creation of technological variety from which alternatives can be selected for retention (Dosi, 1982; van den Bergh, 2008; Faber and Frenken, 2009). Creating sufficient technological variety in an innovation system is important since it aids in preventing an early suboptimal technological lock-in and enables novel combinations that can lead to new innovations (Van den Bergh, 2008). Creating technological variety is not the end-goal of an innovation process, but rather a necessary step to obtain a desirable outcome.

A number of studies describe the development of variety over time for different technologies (see Frenken and Leydesdorff, 2000; Castaldi et al., 2009; Fontana et al., 2009). Although some give case related explanations for their observations, these studies do not attempt to systematically explain variety within the context of the innovation system that produces the technology. The disconnection between innovation systems and technological development is striking since both paradigms originate from evolutionary economics. Only the studies on innovation system functioning acknowledge the evolutionary processes of variety creation and selection (see Hekkert et al., 2007), but these do not provide many handholds on how to secure technological variety in innovation systems. Therefore, *this research aims to show how attributes of subsidized innovation projects of collaborating actors within an innovation system are related to the extent a projects adds to technological variety*.

Following evolutionary reasoning we assume that within the innovation system, different technological varieties can be distinguished at different places in the system. These places are often collaborative innovation projects (Powell et al., 1996; Ahuja, 2000; Laursen and Salter, 2006), that can be supported by government subsidies to overcome network failure. Further, following Carlsson and Stankiewicz (1991), we conceptualize the innovation system to consist of an *institutional environment* with *networks* of *collaborating actors* in which *resources* are exchanged. These elements are used to predict technological variety of a project.

Empirically, we study the Dutch technological innovation system around biogas technology. Biogas is a mixture of carbon dioxide and methane which is mostly produced from organic waste material in an oxygen-free environment (Negro et al., 2007). Since this technology converts organic waste to sustainable energy it has been stimulated by the Dutch government during the past decades with various policy schemes. Using government data on biogas innovation projects we are able to quantitatively map the development of components of this innovation system and the associated technological variety for each innovation project. To accomplish this we apply a combination of social network analysis and regression techniques.

Our study is the first to link innovation systems and technological development using this quantitative approach. Thereby, we enrich both the literatures about innovation systems and about technological trajectories. Further, we add to the social network literature in the context of innovation by showing the association between project connectedness and technological variety. Finally, we show that the diversity of actors and resources in a project is more important than the number of actors in a project. Our results are also of interest to policy makers since we give clear indications about which innovation system factors are important to variety creation.

2. Theory

In this section we formulate our hypotheses. We first discuss the technological variety of an innovation project as dependent variable. Next, we consider how technological innovation systems variables are associated with technological variety. None the hypotheses are formulated in a causal way, since we assume that the innovation system and the technology co-evolve (Nelson and Nelson, 2002; Markard et al., 2009).

2.1. Technological variety

Variety is defined as “the number of different technologies, products, processes and opportunities in a population of elements (Van den Bergh, 2008). It refers to the technological diversity from which alternatives that fit best with environmental demands can be selected (Rigby and Essletzbichler, 1997; Frenken et al., 1999). Until now, studies have always conceptualized technological variety on a system level. In contrast, we are interested in explaining technological varieties at different places within the system.

Our approach is that we first assume that a technology or innovation fulfils a certain service or function (Saviotti and Metcalfe, 1984; Castaldi et al., 2009; Van Rijnsoever and Oppewal, 2012), in our case this is the conversion of organic waste to biogas. Drawing on Verspagen (2007) we conceptualize that the final goal of a technology (the fulfillment of a service) can be achieved through different technological routes. These can be compared to different paths on a map that all lead to the same destination. Some technologies are comprised of different components that fulfill different sub-services that are required for the technology as a whole to function (Henderson and Clark, 1990). Biogas technology for example consists of three components: the energy source, the production method and the processing of gas. Each component has potentially different paths that can be taken. For biogas technology, paths for energy sources are (1) manure, (2) organic waste, (3) energy crops or (4) sewage; production method paths are (1) mono-digestion or (2) co-digestion; processing paths are (1) cogeneration, (2) upgrade to green gas and (3) direct use. A technological route of a project is the combination of paths that is taken to reach the final goal of the technology. This idea is shown in figure 1. In the biogas technology example there are 4x2x3=24 different routes. Given that there are multiple innovation projects within the innovation system, some routes are taken more often than others. More popular routes might eventually become the dominant design (see Utterback, 1996), while routes that are 'of the beaten path' lead to more variety. Therefore, the variety of a project is the extent to which it's technological route has been or is taken over a period of time in comparison to other projects.

---------------Insert Figure 1 about here--------------

2.2. Institutions

Institutions can influence technological variety, they are informally defined by North (2005) as 'the rules of the game'. In innovation systems institutions can be seen as constraining the behavior of actors, but also as 'effective ways to get things done' (Nelson and Nelson, 2002). We focus on regulative institutions that aim to influence the behavior of actors in the innovation system (Blind, 2010). In case of network failure this change in behavior implies the promotion of collaboration between actors, for example through subsidies.

Within Dutch innovation policy roughly two types of subsidies are distinguished to spur innovation; research and exploitation. Research subsidies stimulate research and development of new knowledge and ideas, usually through consortia of different types of actors, such as firms and knowledge institutes. In this manner they overcome network failure. Further, research subsidies are explorative by nature and are thus likely to contribute to technological variety. Exploitation subsidies on the other hand aim at stimulating diffusion of existing innovations. They are usually granted to one or a very small number of actors and make the exploitation of the technology rentable by facilitating the learning of routines and the creation of economies of scale. Exploitation subsidies reinforce path dependence and give direction to the technological trajectory, thereby contributing to the selection of existing alternatives.

Hypothesis 1: Projects using research subsidies are more associated with technological variety, than projects using exploitation subsidies.

2.3. Networks between projects

Networks enable the exchange of knowledge and resources between actors (Schilling and Phelps, 2007), which allows firms to make novel combinations that can lead to successful innovations (Nelson and Winter, 1982), and enables firms to control their environment (Pfeffer and Salancik, 2003), which increases success changes of the innovation. Earlier studies indeed showed that network position influences innovative output of firms in alliances (Powell et al., 1996; Ahuja, 2000; Schilling and Phelps, 2007). Our network consists of projects of collaborating actors. Projects are connected to each other through shared actors, which act as knowledge conduits between projects.

There are several dimensions of a network that can influence innovation success (Powell et al., 1996; Ahuja, 2000; Tsai, 2002; Schilling and Phelps, 2007). The first is the degree of clustering which is the extent to which the network partners of an actor are also connected to each other (Wasserman and Faust, 1994). A major debate has focused on how clustering exactly influences innovation (Burt, 2001). There are two sides to this debate: the first side claims that a high degree of clustering around a particular node in a network is beneficial to innovation (Powell et al., 1996; Ahuja, 2000). Several explanations are given for this. First, clustering eases information transmission and enables nodes to compare information from different partners, which increase the reliability of the information (Schilling and Phelps, 2007). Second, clustering deepens the debate about problems and solutions between partners and contributes to a shared understanding (Powell et al., 1996) which allows partners to come up with novel solutions (Brown and Duguid, 1991). Third, clustering gives rise to trust, the development of shared norms and a shared identity (Coleman, 1988), which in turn facilitates collaboration and knowledge exchange (Schilling and Phelps, 2007).

The other side of the debate is that too much clustering has a negative influence on innovation. A high degree of clustering means that there are many redundant, but costly, network paths between actors (Burt, 2001). Actors thus largely share the same information sources (Schilling and Phelps, 2007). The result is knowledge and information that is too homogenous (Granovetter, 1973; Burt, 2001; Jack, 2005). Further, the development of shared conventions and norms can hamper creativity (Uzzi and Spiro, 2005). A lower degree of the clustering means that there are more 'structural holes' in a network (Burt, 2001, 2004). Structural holes can be seen as '*gaps in information flows between alters linked to the same ego but not linked to each other*' (Ahuja, 2000, p431). This means that two connected actors have access to different flows of information. Structural holes thus allow actors to combine diverse knowledge flows, and therby contribute to innovation (Schilling and Phelps, 2007).

The question is which mechanism prevails under what condition? We argue that this depends on the phase the innovation process is in. If there is more emphasis on the creation of variety, then knowledge diversity and a low clustering coefficient can be more desirable. However, if the emphasis is on selection and bringing new innovations to the market, it is more important that actors share visions, norms and ideas about the new technology (Borup et al., 2006; Hekkert et al., 2007). This is in line with reasoning by Burt (2004), who noted that most original ideas originate from nodes that bridge knowledge gaps in a network. However, the ideas from those that are better embedded in the network are more likely to be selected as innovation, since these ideas are more widely shared among others.

Given that our study looks at technological variety we hypothesize that clustering has a negative effect on variety creation. The less actors a project shares with other projects, the more likely it is to contribute to variety.

Hypothesis 2: Clustering around a project is negatively associated with technological variety.

Next to clustering, the number of ties a project has to other projects can also have an influence on technological variety. Powell et al. (1996) and Ahuja (2000) positively link network ties to R&D collaborations and product diversity of firms. Others attribute the direction of this relationship to the strength of the ties (Ruef, 2002; Jack, 2005). Originally, Granovetter (1973) made a distinction between strong and weak ties. Consequently, Marsden and Campbell (1984, p498) define tie strength as *'the 'closeness' or emotional intensity of a relationship*'. Strong ties are usually created between actors that are to some extent similar (Reagans, 2005), which means that partners are more likely to share norms and conventions. Examples of strong ties are family, friends and close co-workers. A drawback of strong ties in the context of innovation is that they demand conformity between partners. Partners that deviate from the shared norms and conventions risk a decline in social status (Homans, 1974), which is a disincentive for contributing to technological variety.

Weak ties on the other hand are heterogeneous by nature. They are relatively infrequent connections to other social clusters and the broader society (Jack, 2005). Weak ties allow for innovation and experimentation, because novel combinations can be made using information from sources outside the conventional social circle of an actor (Ruef, 2002). Weak ties are thus likely to contribute to technological variety, while strong ties are likely to decrease technological variety.

An important question that arises then is if the actors that connect projects in the innovation system are strong or weak ties? Ham and Mowery (1998) claim that intense collaborations are required to make public-private R&D projects a success. Similarly, Lundvall et al. (2002) view successful innovation as an interactive learning process between closely interacting partners. Both observations can be explained by the fact that intense collaborations facilitate the growing of trust, the building of shared norms and practices, which eases the transfer and generation of knowledge (Lundvall, 1985; Coleman, 1988; Ruef, 2002; Schilling and Phelps, 2007). Strong ties might not lie at the origin of technological variety, they are required for successful innovation. However, the partners in public-private R&D networks are usually quite heterogeneous by nature, coming from different institutional environments that place different demands on actors (Van Rijnsoever et al., 2012). This heterogeneity forms the basis for creating new technological variants, but also implies that the links in public-private R&D collaborations are weak ties by nature. If projects are to succeed past the variety creation stage, the key management challenge is to transform these weak ties into strong ties. The interactive learning process of innovation means that partners learn from exchanging information and practices (Levitt and March, 1988) and as a result become more similar. This similarity forms the basis for an increase in tie strength (Reagans, 2005). Interactive learning can thus contribute to making weak ties strong ties. To our argument this means that the ties that connect projects are either strong from the start of the project, because the partners had a higher changes of connecting in the first place, or that they have become strong through the interactive learning process. Further, the homogeneity that results from interactive learning also contributes to the legitimacy of practices, knowledge and of consequential technological routes that actors take. The more often a technological route is taken the more legitimacy it gains (Abrahamson and Rosenkopf, 1993), which can prompt others to adopt the same technological routes (DiMaggio and Powell, 1983). The legitimization process itself can thus reinforce partner homogeneity and the selection of technological routes.

The strong ties resulting from interactive learning and legitimacy creation ensure that projects that share actors will tend be similar to each other. The result is a decrease in technological variety. The more ties a projects has, the more both processes will take place. This results in a negative relationship between number of project ties and technological variety.

Hypothesis 3: The number of ties a project has is negatively associated with technological variety.

2.4. Project actors

Innovation is often the result from collaboration projects between multiple partners (Tidd et al., 2001; Van Rijnsoever et al., 2012). We consider two project attributes that can be of influence on technological variety: the number of partners and partner diversity (Powell et al., 1996; Ruef, 2002). The number of partners refers to the size of the project consortium in terms of distinct actors. Partner diversity, refers to the difference in actor types that are in the consortium. Following the literature on innovation systems (Edquist, 1997) and science industry collaboration (Etzkowitz and Leydesdorff, 2000), we distinguish five types of actors, Small or Medium-sized Enterprises (SMEs), Large Enterprises (LEs), Knowledge Institutes (KIs), Governmental Organizations (GOs) and Intermediary Organizations (IO). SMEs are firms with maximal 250 employees, more than 250 employees means that firm is a LE (European Commission, 2003). SMEs are usually credited with being more innovative than LEs, while the latter have more resources and experience (Chandy and Tellis, 2000). Knowledge institutes are not-for-profit institutes that conduct fundamental or applied research, such as universities or public research institutes. KIs bring in the fundamental scientific knowledge required for innovation (Laursen and Salter, 2004). GOs are public organizations that are tied to the national government or local governments.

They can contribute resources to a project, such as test-locations or facilities and regulative support. Finally, IOs are organizations that facilitate dialogue between partners. Examples are branch organizations, lobby groups and special interest groups.

Ruef (2002) argues that larger project teams encourage new combinations and ideas, whereas sole entrepreneurs are more likely to "*reproduce familiar routines based on their own life experience (p434).*" Powell et al. (1996) argue that *"research breakthroughs demand a range of intellectual and scientific skills that far exceed the capabilities of any single organization (p118)",* which points to the necessity of including multiple partners. However, this argument appears at to be odds with the arguments mentioned earlier that more strong ties lead to conformity and thus less innovation. Tatikonda and Rosenthal (2000) also pose a negative relationship by associating project size to higher complexity, which is hypothesized to negatively influence the success of an innovation project. However, they find little empirical support for this argument. A similar argument can also be found in social psychology of team size (Kozlowski and Bell, 2003), but the important nuance is added that the effect of team size depends on the nature of the task to be fulfilled.

Overall, the theoretical influence of project size is inconclusive. Given that the positive evidence about the influence number of project partners is derived from an innovation context, we hypothesize:

Hypothesis 4: The number project partners has a positive association with technological variety.

Though Powell et al. (1996) do not deny that the number of project partners have a positive influence on innovation, they add that in the context of breakthrough discoveries the diversity of partners is more important than the number of partners. This notion is much more widely shared in the literature (Nooteboom, 2000; Ruef, 2002; Laursen and Salter, 2006; Nieto and Santamaría, 2007). The general argument is that diverse partners bring-in their unique resources, knowledge and skills, which can be combined to novel concepts. This increases technological variety. Therefore we hypothesize:

Hypothesis 5: The diversity of project partners has a positive association with technological variety.

2.5. Resources

According to both the innovation systems perspective (Carlsson and Stankiewicz, 1991) and the social network literature (Powell et al., 1996; Lin et al., 2009) actors use can networks to exchange resources. This fits with ideas from the Resource Based View (Barney, 1991; Mahoney and Pandian, 2006), which argues that firms can gain a sustained competitive advantage by controlling *"valuable, rare imperfectly imitable and strategically unique resources (Lewin et al., 2004, p110)*." Eisenhardt and Martin (2000, p1106) define resources as: "physical, human and organizational assets that can be used to implement value-creating strategies". These resources can be transformed into innovations that form the source of a competitive advantage (Del Canto and Gonzalez, 1999). As such they play an important role in the innovation system (Hekkert et al., 2007). The diversity of resources that are used as input for an innovation determine the potential technological variety: the more diverse the input in the innovation process, the larger the degrees of freedom are for output variety. Specifically, unique or rare resources can contribute to original innovations. This does not mean that the total potential variety is always achieved, but we claim that resources diversity is a condition for technological variety. This leads to our final hypothesis:

Hypothesis 6: The diversity of resources has a positive association with technological variety.

3. Methods

3.1. Data

To test our hypotheses we analyzed project data provided by NL Agency, which is the executive agency of the Dutch Ministry of Economic affairs. NL Agency is responsible for the implementation of subsidy schemes that support the development sustainable energy technologies. One of these is biogas technology. NL Agency has documented in great detail all innovation subsidies for this technology between the year 2001 and 2013. The database contains information about the subsidy scheme used, the start- and end years, the technical specifications, the partners that are involved in the project and for research subsidies the resources they contribute. In total the database contains 404 innovation projects with 402 unique actors. However, for 28 projects it was not possible to retrieve technological specifications, which resulted in usable data about 376 projects.

Owners of biogas facilities are heavily dependent (for about 60%) on government subsidies to make their projects rentable (Peene et al., 2011). For this reason we assume that this project database approximates all the actors in the field of biogas technology and their activities when it comes to developing new innovations, and thus to cover all actors in the innovation system.

3.2. Measurement

Previous studies (Frenken et al., 1999, 2004; Bakker, 2010) measured *technological variety* on a system level, which is functional if one wishes to describe dynamics over time. However, we are interested in explaining technological variety within the system, for which we use our conceptualization of how often a technological route was taken in a specific period. It is therefore required to set a time window to calculate the frequency a route has been taken over. Without such a time frame all technology routes that have been taken in the past are included in our measure. One can argue that it is important to take the past use of routes into account, since technological trajectories are cumulative by nature (Dosi, 1982; Nelson and Winter, 1982; Verspagen, 2007). The path dependence of technological development ensures that the past states of the technology form the basis for future developments (Arthur, 1989). If path dependence is taken into account, the question becomes how to weigh past technological developments in determining current technological variety. The most simple, but rather extreme assumption, would be to weigh all past developments as equal, disregarding how long ago they took place. This is what we call a 'full rational' approach to technological variety. However, since technologies evolve over time, the cumulative historical past might not do justice to the current state of the technology. Another simple but equally extreme approach is to assess how often a route is taken only at a specific moment in time, thereby ignoring the past completely. This is what we call a ‘naïve’ approach to technological variety.

Since do not know exactly what a good timeframe is and how past developments should we weighed, we calculate both extreme approaches described above. We empirically explore how well they are related to each other, and if using either measure would influence our model results. Theoretically, one would expect that the naïve and full rational conception of technological variety are related to each other as long as the time window does not become too large or if no radical transitions occur.

To calculate our measures we first determined how often a path was taken in each component of the technology by all projects over the given time frame. For the naïve measure we only took into account projects that were active in a given year. The full rational measure took into account all projects that had been active in the past up until a given year. The remaining procedure to calculate technological variety is equal for both measures.

We assigned values to each project in the year it started for each path that could have potentially been taken. Since there were 9 distinct paths over 3 components (4, 2 and 3) each project got a total of 9 records. If a project had taken a specific path in a component it was assigned as value the total number of times the path had been taken by all projects over the given time frame. For example: if a project choose co-digestion as production method path, and 50 other projects had done the same thing, the project received the value 51 for co-digestion. If a path had not been taken by a project it received the value 0. Some projects took more than one path in a component. To correct for this we summed up all records per component and divided the outcome by the total number of paths the project had taken.

The three outcome variables were then multiplied to obtain a composite measure for the entire technological route of each project. The larger the value of this variable, the more often a route was taken by all projects, the lower the technological variety of a project. Both the naïve and full rational measures were heavily skewed since their values grew progressively for projects that started in later years. To obtain a better distribution we took the natural logarithm of these variables. Further, we multiplied the variables by -1, so that the larger values represent a higher technological variety.

Since our data is longitudinal, we need to correct for the effects of starting year somewhere in the data-analysis process. The most straightforward solution would be to add a nominal variable with years as categories to the final models that test our hypotheses. However, this method is rather inefficient, since it adds 12 degrees of freedom to models with a limited number of observations. In addition, some years have a very small number of observations which casts doubt on the reliability of the estimators for these categories. Therefore, we explored if a mathematical transformation of the year variable could approximate the same effect of a nominal variable. After fitting several transformations of the year variable, the natural logarithm gave the best fit with the technological variety variables. To completely separate the effects of the control variable from the independent variables we partialed out the effects of time prior to hypothesis testing (Greene, 1997). This was done by regressing the variety variables on the natural logarithm of the year variable. We used the residuals of these regressions as final corrected measures for technological variety. As expected, both variables were strongly correlated ($r=0.80, p<0.001$).

It should be noted that these variables do not say anything about the quality of the innovation or its novelty. Since all projects were part of an innovation subsidy scheme, we assume that they contribute something new to the technology.

Institutions were measured as the subsidy schemes the projects were financed from. These subsidy schemes were the most important regulative changes for biogas technology during the time period we studied. Based on the goals of the scheme subsidies were classified as research or exploitation. This classification was made by one of the authors and confirmed by a representative from NL Agency. In total there were 291 exploitation projects and 113 research projects.

Projects are connected to each other by actors that participate in multiple projects that are active at the same time, these actors are ties in a social network. To calculate network measures we only took into account projects that received research subsidies. A theoretical reason for this is that the hypotheses we formulated were about the development new knowledge and technological variety. Exploitation subsidies do not contribute to these aims. Second, most exploitation subsidy projects consist only of one actor that is not connected to the rest of the network or of one actor that combines an exploitation project with a research project. The latter cases are problematic, because they appear as a separate node in the network that is tied to a research project, while they are in fact the same actor that is also part of the research project. The result is a bias in network measures, which is removed by excluding exploitation projects.

Clustering was determined by calculating the undirected local clustering coefficient (see Wasserman and Faust, 1994) of a project in the year it started. The clustering coefficient represents the probability that two neighboring projects of a node are also connected. An issue is how distinguish projects that were unconnected to other projects (e.g. isolates) from projects that were connected, but who's neighbors were unconnected, since both received a value of 0. To distinguish 'isolates' an extra dummy variable was created. The clustering variable was regressed on the 'isolates-dummy'. The residuals of this regression form an 'isolates' corrected measure for clustering, which was used as independent variable in our models.

The *number of ties* a project has was a simple count of the number of actors a project shared with other active projects. The number of ties was strongly correlated with the clustering coefficient ($r=0.70, p<0.001$). This high correlation can partly be explained by the fact that both measures are partially calculated in the same manner; to have a cluster coefficient larger than 0 it is required that the number of ties is also larger than 0. To separate the effects of both measures we regressed the number of ties on the corrected clustering coefficient. The residuals of this regression are uncorrelated with the clustering coefficient and were used as used a measure for number of ties. This means that the effect of the number of ties can be interpreted as an effect independent of clustering.

Project consortium attributes were the *number of project partners* and the *diversity of project partners.* The former was a simple count of the number of partners that applied for a subsidy. The value of this variable for all projects ranged between 1 and 9 with a mean of 1.56 in a project. If only research projects are taken into account the mean becomes 3. To calculate the diversity of partners all actors were first classified according to the aforementioned types: SME, LE, KI, GB and IO. Next, for each project we applied the entropy formula (F1) by Thiel (1972) that is often applied in innovation studies to calculate technological diversity (Frenken et al., 1999, 2004; Bakker, 2010)[1]:

F1: $$H = -\sum_{i=1}^{n} p_i \ln p_i$$

In this formula p_i is the share of an option within system i and n is the total number of available options in system i. We applied the same principal to calculate diversity of actor types in a project.

To calculate *diversity of resources* we first established which resources were contributed to a project by the participating actors. We only had resource data available for the projects that received a research subsidy. The database classified resources into the following categories: (1) Capital Feedstock, (2) Instruments: technology (3), Instruments: equipment, (4) Licenses, (5) Location: ground, (6) Location: building, (6) Location: research facility, (7) Patents, (8) Knowledge: technology, (9) Knowledge: market, (10) Knowledge: law, (11) Manpower and (12) Network. For each resource type we created a dummy variable that indicated if the resource was present or not in the project. Unfortunately, it is not possible to calculate the relative shares for this diverse set of resources, since they are incomparable. This means cannot apply the entropy formula. Resource diversity was therefore calculated as sum of the nine resource dummy variables. Since the resulting variable was quite skewed, we took its natural logarithm. Theoretically, this implies that there can be a positive relationship, but that the increase in technological variety decreases when extra resource types are added.

Table 1 displays the descriptive statistics and correlation matrix of all variables for the research projects; we have full data for 82 projects.

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[1] We could not use the entropy formula to calculate technological variety in this study, since this measures is not project specific.

---------------Insert Table 1 about here--------------

3.3. Analysis

Hypothesis 1 was tested on all projects with simple independent samples t-test, Subsidy type was the independent variable and both measures of technological variety were dependent variables. The remaining hypotheses were tested for the research projects only. Since all variables were of a continuous nature, an Ordinary Least Squares (OLS) regression model was fitted for each measure of technological variety. There was no need to add time as control variable, since time effects are already taken into account in the dependent variables.

4. Results

Prior to the testing of our hypotheses, we visualized the innovation system by drawing network graphs. The graphs include all projects over the entire time period. The figure ignores the fact that not all projects were active at same moment, but it provides intuitive insights about how projects and actors are formally related.

---------------Insert Figure 2 about here--------------

Figure 2a shows the network graph for the project level. Nodes are projects, ties are actors. The size of the node indicates how much each project contributes to technological variety (based on the Full Rational measure); the larger the node, the more technological variety[2]. Further, the color of node indicates what the project type is: green nodes are research projects, while red nodes are exploitation projects. The first noticeable observation is that there is a giant component that mostly consists of research projects, but that also has peripheral exploitation projects. Further, there are many isolated exploitation projects. If exploitation projects are connected this means that a single actor received subsidies for multiple projects over the years, since all exploitation projects consist of one actor. Overall, research projects are much better connected than exploitation projects ($t=4.51$, $p<0.001$). Figure 2b shows how the actors in the projects are connected to each other. Nodes are actors, the ties indicate that actors participate in the same project. The ties between actors are by definition research projects[3]. The color of the node indicates the actor type: red are SMEs , green are LEs, dark blue are KIs, light blue are GBs and purple are IOs. Most actors are SMEs (284), followed by LEs (50), GBs (28), IOs (25) and finally KIs (15). There are significant differences in how connected the actor types are ($F=11.68$, $p<0.001$): KIs have most connections (3.00 on average), while SMEs are least connected (1.05 on average). Figure 2b shows that that most isolated projects are indeed single SMEs, while only one KI is unconnected. The giant component consists of a variety of actor types, and is also a source of technological variety.

Next, we move on to testing our hypotheses, here we do take into account that different projects were active in different years. Both independent sample t-tests confirm that the technological variety of research subsidies is larger than of exploitation subsidies ($t_{naïve}=4.08$, $p<0.001$; $t_{full\ rational}=5.57$, $p<0.001$), which supports hypothesis 1. This means that

[2] There are number of ties with no nodes attached, this is because for these projects we did not have the technical specifications and thus were unable to calculate technological variety.

[3] Note that the position the projects in figure 2a is not the same as the position of the related actors in figure 2b.

institutions in the form of directed subsidies do influence technological variety in the innovation system.

Table 2 presents the results of our OLS models. To allow for comparison of effect sizes we present standardized estimators. The adjusted R^2 is good for both models: 0.30 for the 'full rational' model and 0.39 for the 'naïve' model. Further, the variance inflation factors remain at acceptable levels. The distributions of the residuals approached normality, but they also revealed that in both models one case was an outlier with a standardized residual larger than 4. We reran the models to test if removing the outlier had any effect on our results. This was not the case. Both models show identical results, which is evidence that in this case setting a time frame did not affect the outcome of the models.

---------------Insert Table 2 about here--------------

There is a negative effect of clustering on technological variety, which is in line with the thesis that structural holes are good for variety. This supports hypothesis 2. Beyond the effect of clustering, the number of ties are also negatively related to technological variety, which is evidence for the arguments that strong ties lead to more knowledge homogeneity and legitimacy, but not to more technological variety. Hypothesis 3 is thereby supported. The number of project partners also has a negative association with technological variety, which contradicts hypothesis 4. The diversity of project partners and resources on the other hand has a positive influence on technological variety, which supports hypotheses 5 and 6. An additional analysis (result not shown here) revealed that the significant negative effect of number of projects partner is the result of adding diversity of partners and diversity of resources to the model, otherwise there would have been no significant effect. As discussed earlier, the theoretical arguments for the number of project partners are more contradictory than those for partners diversity. These results are evidence for the thesis that adding a partner to a project is only beneficial to technological variety if it increases the diversity of partners or resources. We explored this issue further by adding for each actor type the number of project partners to the model. These models show that the negative effect of number of partners is caused by SMEs ($\beta_{naïve}$=-0.39, $p<0.001$; $\beta_{full\ rational}$=-0.29, $p<0.05$), LEs ($\beta_{naïve}$=-0.38, $p<0.01$; $\beta_{full\ rational}$=-0.30, $p<0.05$) and IOs ($\beta_{naïve}$=-0.22, $p<0.05$; $\beta_{full\ rational}$=-0.19, $p<0.1$)[4]. This means that this case technological variety does not originate from firms or intermediaries. Since KIs are not negatively related to technological variety, it seems that their fundamental new knowledge can contribute to technological variety. However, the results do not show that having more than one KI adds extra technological variety.

5. Conclusion and discussion

5.1. Conclusion

This study aimed to show how attributes of subsidized innovation projects of collaborating actors within an innovation system are related to the extent a projects adds to technological variety. This was done by quantitatively investigating the Dutch biogas innovation system using government data about project subsidies. Our results show that regulative institutions in the form of project subsidies that stimulate collaboration

[4] The rest of the model remained unchanged, for reasons of space it is not shown here.

contribute to technological variety. However, the more projects are related to each other through shared actors, the less likely they are to contribute to technological variety. Finally, more diversity of actors and resources contributes to technological variety, while including more partners in a project is negatively related to technological variety.

5.2. Theoretical implications

As argued in the introduction, our study is the first to explicitly link innovation systems to technological variety using a quantitative approach and social network analysis. We have added to innovation systems literature by demonstrating an approach that does not use the state of the system as indicator for innovation success, but rather the technology itself. Knowing how system configuration and technological variety are related helps with substantiating claims about the system performance based on the system itself. This is especially important in the earlier stages of the innovation process where the creation of technological variety is most important, but where data is often lacking. Further, we contributed to research about describing technological trajectories by explaining the development of technological variety using innovation systems.

We also contributed to the literature about social networks and innovation. We demonstrated that clustering is negatively associated to technological variety, which is in line with claims by Burt (2001, 2004). However, it should be noted that technological variety does not equate innovation success, it is only a condition for success. This can explain the difference in results with other social network studies, that focus more on successful innovation. Moreover, on the project level we demonstrated that the diversity of actors and resources in a project is more important than the quantity of project partners. This supports ideas about the complexity of larger teams and the social psychology of team size, but it contradicts claims by Ruef (2002). A possible explanation for these differences is that Ruef looked at patents/trademark applications and self reported measures that resemble innovation success, not variety. Overall, this means that it is important to treat variety creation and successful innovation as separate concepts.

5.3. Policy implications

Our results provide clear handholds on how to influence technological variety creation using subsidy instruments designed to overcome network failure. If policy makers aim to increase technological variety in the innovation system, subsidy schemes should reward small consortia, consisting of diverse actor types that contribute diverse resources with at least one knowledge institute. Allowing actors to participate in multiple consortia at the same time hampers technological variety.

However, policy makers should note that although technological variety is required for successful innovation, there is an optimal balance between variety and selection (Van den Bergh, 2008). It is not the aim of this study to indicate what this optimal point is, but the idea of optimal variety implies that variety should not be over-stimulated. In general it can stated that in the earlier phases of the innovation process there is a larger chance of network failure and a larger need for variety creation than in later phases when there is more emphasis on selection. Following the network rationale, European and national governments can thus most easily make legitimate contributions to the innovation process by stimulating technological variety in earlier phases.

5.4. Limitations

This research suffers from two major limitations. The first limitation is the measurement of concepts. Technological variety was calculated based on the technological characteristics in the government data base. We do not know for certain if the intended technological route of a project was actually taken during realization. It is likely that this is the case, since the route described is likely to fit with the capabilities of the project partners, but this cannot be validated. Further, we measured only regulative institutions through subsidy programs, but it is possible that other types of institutions (both regulative or non-regulative) were also of influence. Next, we measured the number of ties per project, but we had to rely on theoretical arguments to determine the strength of these ties. Although the results support our argument for strong ties, we cannot empirically verify this.

The second limitation is generalizability. We only took into account projects that were subsidized by the government, which leaves the possibility that we missed unsubsidized projects. There is a large dependency of the sector on government funding, but the possibility of missed projects cannot be excluded entirely. Furthermore, our results are strictly speaking only valid for subsidized projects in the Dutch biogas innovation system between 2001 and 2013. For generalization, further research is required in different countries and on different technologies.

6. References

Abrahamson, E., Rosenkopf, L., 1993. Institutional and Competitive Bandwagons: Using Mathematical Modeling as a Tool to Explore Innovation Diffusion. The Academy of Management Review 18, 487–517.

Ahuja, G., 2000. Collaboration networks, structural holes, and innovation: A longitudinal study. Administrative Science Quarterly 45, 425–455.

Arthur, W.B., 1989. Competing Technologies, Increasing Returns, and Lock-in by Historical Events. Economic Journal 99, 116–131.

Bakker, S., 2010. Hydrogen patent portfolios in the automotive industry – The search for promising storage methods. International Journal of Hydrogen Energy 35, 6784–6793.

Barney, J., 1991. Firm Resources and Sustained Competitive Advantage. Journal of Management 17, 99–120.

Bergek, A., Jacobsson, S., Carlsson, B., Lindmark, S., Rickne, A., 2008. Analyzing the functional dynamics of technological innovation systems: A scheme of analysis. Research Policy 37, 407–429.

Van den Bergh, J.C.J.M., 2008. Optimal diversity: Increasing returns versus recombinant innovation. Journal of Economic Behavior & Organization 68, 565–580.

Blind, K., 2010. The use of the regulatory framework for innovation policy, in: Smits, R.E.H.M., Kuhlmann, S., Shapira, P. (Eds), The Theory And Practice Of Innovation Policy: An International Research Handbook. Edward Elgar Publishers, Cheltenham.

Borup, M., Brown, N., Konrad, K., Van Lente, H., 2006. The sociology of expectations in science and technology. Technology Analysis & Strategic Management 18, 285–298.

Brown, J.S., Duguid, P., 1991. Organizational Learning and Communities-of-Practice: Toward a Unified View of Working, Learning, and Innovation. Organization Science 2, 40–57.

Burt, R.S., 2001. Structural holes versus network closure as social capital, in: Lin, N., Cook, K.S., Burt, R.S. (Eds), Social Capital: Theory and Research. Transaction Publishers, New Brunswick, NJ, pp. 31–56.

Burt, R.S., 2004. Structural holes and good ideas. American Journal of Sociology 110, 349–399.

Del Canto, J.G., Gonzalez, I.S., 1999. A resource-based analysis of the factors determining a firm's R&D activities. Research Policy 28, 891–905.

Carlsson, B., Jacobsson, S., 1997. Diversity creation and technological systems: a technology policy perspective, in: Edquist, C. (Ed), Systems of Innovation: Technologies, Institutions and Organizations. Pinter Publishers, London.

Carlsson, B., Stankiewicz, R., 1991. On the nature, function and composition of technological systems. Journal of Evolutionary Economics 1, 93–118.

Castaldi, C., Fontana, R., Nuvolari, A., 2009. "Chariots of Fire": The Evolution of Tank Technology, 1915-1945. Journal of Evolutionary Economics.

Chandy, R.K., Tellis, G.J., 2000. The Incumbent's Curse? Incumbency, Size, and Radical Product Innovation. The Journal of Marketing 64, 1–17.

Coleman, J.S., 1988. Social Capital in the Creation of Human Capital. American Journal of Sociology 94, S95–S120.

DiMaggio, P.J., Powell, W.W., 1983. The Iron Cage Revisited: Institutional Isomorphism and Collective Rationality in Organizational Fields. American Sociological Review 48, 147–160.

Dosi, G., 1982. Technological paradigms and technological trajectories : A suggested interpretation of the determinants and directions of technical change. Research Policy 11, 147–162.

Edquist, C., 1997. Systems of Innovation approaches - Their Emergence and Characteristics, in: Edquist, C. (Ed), Systems of Innovation. Pinter, London.

Eisenhardt, K.M., Martin, J.A., 2000. Dynamic capabilities: what are they? Strategic Management Journal 21, 1105–1121.

Etzkowitz, H., Leydesdorff, L., 2000. The dynamics of innovation: from National Systems and “Mode 2” to a Triple Helix of university-industry-government relations. Research Policy 29, 109–123.

European Commission, 2003. COMMISSION RECOMMENDATION of 6 May 2003 concerning the definition of micro, small and medium-sized enterprises. Official Journal of the European Union 124, 36–41.

European Commission, 2006. An innovation-friendly, modern Europe: COMMUNICATION FROM THE COMMISSION TO THE EUROPEAN COUNCIL (INFORMAL MEETING IN LAHTI – FINLAND, 20 October 2006).

European Commission, 2010. COMMUNICATION FROM THE COMMISSION EUROPE 2020: A strategy for smart, sustainable and inclusive growth. Brussels.

Faber, A., Frenken, K., 2009. Models in evolutionary economics and environmental policy: Towards an evolutionary environmental economics. Technological Forecasting and Social Change 76, 462–470.

Fontana, R., Nuvolari, A., Verspagen, B., 2009. Mapping technological trajectories as patent citation networks. An application to data communication standards. Economics of Innovation and New Technology 18, 311–336.

Freeman, C., 1995. The “National System of Innovation” in historical perspective. Camb. J. Econ. 19, 5–24.

Frenken, K., Hekkert, M., Godfroij, P., 2004. R&D portfolios in environmentally friendly automotive propulsion: Variety, competition and policy implications. Technological Forecasting and Social Change 71, 485–507.

Frenken, K., Leydesdorff, L., 2000. Scaling trajectories in civil aircraft (1913-1997). Research Policy 29, 331–348.

Frenken, K., Saviotti, P.P., Trommetter, M., 1999. Variety and niche creation in aircraft, helicopters, motorcycles and microcomputers. Research Policy 28, 469–488.

Granovetter, M.S., 1973. The strength of weak ties. American journal of sociology 1360–1380.

Greene, W.H., 1997. Econometic Analysis , 3rd ed. Prentice-Hall, Upper Saddle River, New Jersey.

Ham, R.M., Mowery, D.C., 1998. Improving the effectiveness of public-private R&D collaboration: case studies at a US weapons laboratory. Research policy 26, 661–675.

Hekkert, M.P., Suurs, R.A.A., Negro, S.O., Kuhlmann, S., Smits, R.E.H.M., 2007. Functions of innovation systems: A new approach for analysing technological change. Technological Forecasting and Social Change 74, 413–432.

Henderson, R.M., Clark, K.B., 1990. Architectural Innovation - the Reconfiguration of Existing Product Technologies and the Failure of Established Firms. Administrative Science Quarterly 35, 9–30.

Homans, G.C., 1974. Social Behaviour: Its Elementary Forms, Revised Ed. ed. Harcourt Brace Jovanovich, Inc., New York.

Innovation Platform, 2006. The Dutch Innovation Platform.

Jack, S.L., 2005. The role, use and activation of strong and weak network ties: A qualitative analysis. Journal of Management Studies 42, 1233–1259.

Klein Woolthuis, R., Lankhuizen, M., Gilsing, V., 2005. A system failure framework for innovation policy design. Technovation 25, 609–619.

Kozlowski, S.W.J., Bell, B.S., 2003. Work groups and teams in organizations. Handbook of psychology.

Laursen, K., Salter, A., 2004. Searching high and low: what types of firms use universities as a source of innovation? Research Policy 33, 1201–1215.

Laursen, K., Salter, A., 2006. Open for innovation: The role of openness in explaining innovation performance among UK manufacturing firms. Strategic Management Journal 27, 131–150.

Leoncini, R., Maggioni, M.A., Montresor, S., 1996. Intersectoral innovation flows and national technological systems: network analysis for comparing Italy and Germany. Research Policy 25, 415–430.

Levitt, B., March, J.G., 1988. Organizational Learning. Annual Review of Sociology 14, 319–340.

Lewin, A.Y., Weigelt, C.B., Emery, J.D., 2004. Adaption and Selection in Strategy and Change: Perspectives on Strategic Change in Organizations, in: Poole, M.S., Van de Ven, A.H. (Eds), Handbook of Organizational Change and Innovation. Oxford University Press, Oxford.

Lin, Z., Yang, H., Arya, B., 2009. Alliance partners and firm performance: resource complementarity and status association. Strategic Management Journal 30, 921–940.

Lundvall, B.A., 1985. Product Innovation and User-Producer Interaction.

Lundvall, B.A., Johnson, B., Andersen, E.S., Dalum, B., 2002. National systems of production, innovation and competence building. Research Policy 31, 213–231.

Mahoney, J.T., Pandian, J.R., 2006. The resource-based view within the conversation of strategic management. Strategic management journal 13, 363–380.

Markard, J., Stadelmann, M., Truffer, B., 2009. Prospective analysis of technological innovation systems: Identifying technological and organizational development options for biogas in Switzerland. Research Policy 38, 655–667.

Marsden, P. V, Campbell, K.E., 1984. Measuring Tie Strength. Social Forces 63 , 482–501.

Ministry of Economic Affairs, 2011. Naar de top: Het bedrijvenbeleid in actie(s) (To the top: industry policy in action(s). The Hague.

Negro, S.O., Hekkert, M.P., Smits, R.E., 2007. Explaining the failure of the Dutch innovation system for biomass digestion—A functional analysis. Energy Policy 35, 925–938.

Nelson, R.R., 1994. Analyzing the functional dynamics of technological innovation systems: A scheme of analysis. Industrial and Corporate Change 3, 47–63.

Nelson, R.R., Nelson, K., 2002. Technology, institutions, and innovation systems. Research Policy 31, 265–272.

Nelson, R.R., Winter, S.G., 1982. An Evolutionary Theory of Economic Change. The Belknap of Harvard University Press, Cambridge, Massachusetts.

Nieto, M.J., Santamaría, L., 2007. The importance of diverse collaborative networks for the novelty of product innovation. Technovation 27, 367–377.

Nooteboom, B., 2000. Learning by interaction: Absorptive Capacity, Cognitive Distance and Governance. Journal of Management and Governance 4, 69–92.

Nooteboom, B., Stam, E., 2008. Micro-foundations of Innovation Policy.

North, D.C., 2005. Understanding the Process of Economic Change Princeton Economic History of the Western World. Princeton University Press, Princeton.

Peene, A., Velghe, F., Wierinck, I., 2011. Evaluatie van de vergisters in Nederland (Evaluation of digestors in the Netherlands. Gent.

Pfeffer, J., Salancik, G., 2003. The External Control of Organizations: A Resource Dependence Perspective. Stanford Business Books.

Powell, W.W., Koput, K.W., Smith-Doerr, L., 1996. Interorganizational Collaboration and the Locus of Innovation: Networks of Learning in Biotechnology. Administrative Science Quarterly 41, 116–145.

Reagans, R., 2005. Preferences, identity, and competition: Predicting tie strength from demographic data. Management Science 51, 1374–1383.

Rigby, D.L., Essletzbichler, J., 1997. Evolution, Process Variety, and Regional Trajectories of Technological Change in U.S. Manufacturing. Economic Geography 73, 269–284.

Van Rijnsoever, F., Welle, L., Bakker, S., 2012. Credibility and legitimacy in policy-driven innovation networks: Resource dependencies and expectations in Dutch electric vehicle subsidies.

Van Rijnsoever, F.J., Oppewal, H., 2012. Predicting early adoption of successive video player generations. Technological Forecasting and Social Change 79, 558–569.

Ruef, M., 2002. Strong ties, weak ties and islands: structural and cultural predictors of organizational innovation. Industrial and Corporate Change 11 , 427–449.

Saviotti, P.P., Metcalfe, J.S., 1984. A Theoretical Approach to the Construction of Technological Output Indicators. Research Policy 13, 141–151.

Schilling, M.A., Phelps, C.C., 2007. Interfirm Collaboration Networks: The Impact of Large-Scale Network Structure on Firm Innovation . Management Science 53 , 1113–1126.

Smits, R.E.H.M., Kuhlmann, S., 2004. The rise of systemic instruments in innovation policy. International Journal of Foresight and Innovation Policy 1, 4–32.

Tatikonda, M. V, Rosenthal, S.R., 2000. Technology novelty, project complexity, and product development project execution success: a deeper look at task uncertainty in product innovation. Engineering Management, IEEE Transactions on 47, 74–87.

Theil, H., 1972. Statistical decomposition analysis: with applications in the social and administrative sciences. North-Holland Publishing Company Amsterdam.

Tidd, J., Bessant, J., Pavitt, K., 2001. Managing Innovation: Integrating Technological, Market and Organizational Change. John Wiley & Sons, Chichester.

Tsai, W.P., 2002. Social structure of “coopetition” within a multiunit organization: Coordination, competition, and intraorganizational knowledge sharing. Organization Science 13, 179–190.

Utterback, J.M., 1996. Mastering the Dynamics of Innovation. HBS Press, Boston, Massachusetts.

Uzzi, B., Spiro, J., 2005. Collaboration and Creativity: The Small World Problem. American Journal of Sociology 111, 447–504.

Verspagen, B., 2007. Mapping technological trajectories as patent citation networks: A study on the history of fuel cell research. Advances in Complex Systems 10, 93–115.

Ter Wal, A.L.J., Boschma, R., 2009. Co-evolution of Firms, Industries and Networks in Space. Regional Studies 45, 919–933.

Wasserman, S., Faust, K., 1994. Social Network Analysis: Methods and Applications. Cambridge University Press, Cambridge.

Wieczorek, A.J., Hekkert, M.P., 2012. Systemic instruments for systemic innovation problems: A framework for policy makers and innovation scholars. Science and Public Policy 39, 74–87.

	Mean	Standard Deviation	Technological variety: naïve	Technological variety: full rational	Clustering	Number of ties	Number of project partners	Diversity of project partners
Technological variety: naïve	0.72	1.96						
Technological variety: full rational	0.69	1.33	.88***					
Clustering	0.25	0.41	-.30**	-.28**				
Number of ties	1.71	2.49	-.22*	-.18	-.31**			
Number of project partners	3.59	2.19	-.26*	-.14	.23*	.18		
Diversity of project partners	0.52	0.42	.17	.21	.10	.22*	.59**	
Resource diversity	1.56	0.56	.08	.15	.15	.04	.51**	.39**

Table 1: Descriptive statistics and correlation for the research subsidy projects (Valid N=82), *: p<0.05, **: p<0.01, ***: p<0.001.

	Technological Variety					
	Naïve			Full rational		
	Est.		VIF	Est.		VIF
Clustering	-0.38	***	1.22	-0.38	***	1.22
Number of ties	-0.37	***	1.22	-0.33	***	1.22
Number of project partners	-0.50	***	1.88	-0.37	***	1.88
Diversity of project partners	0.49	***	1.59	0.44	***	1.59
Resource diversity	0.21	*	1.38	0.23	*	1.38
N	82			82		
Adj R^2	0.39			0.30		

Table 2: Results from the OLS model predicting both measures of technological variety. *: p<0.05, **: p<0.01, ***: p<0.001.

Figure 1: Conceptualization of technological paths and routes over different components. Each component fulfills a sub-service that together form the total technological service. Arrows indicate different paths that can be taken. The bold arrows combined form an example route.

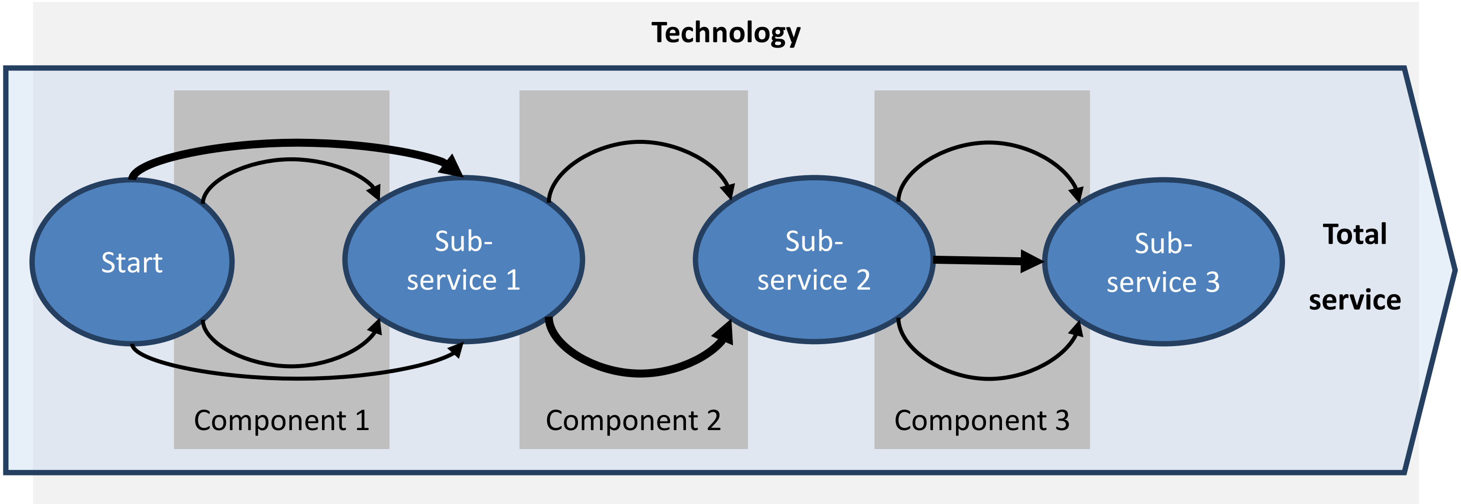
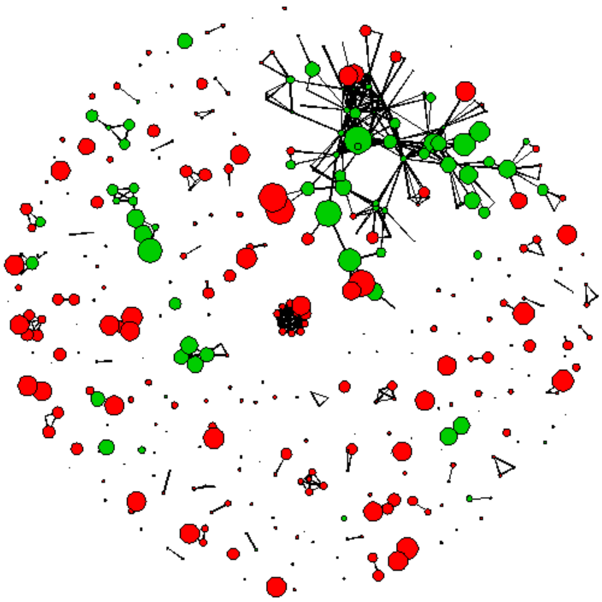
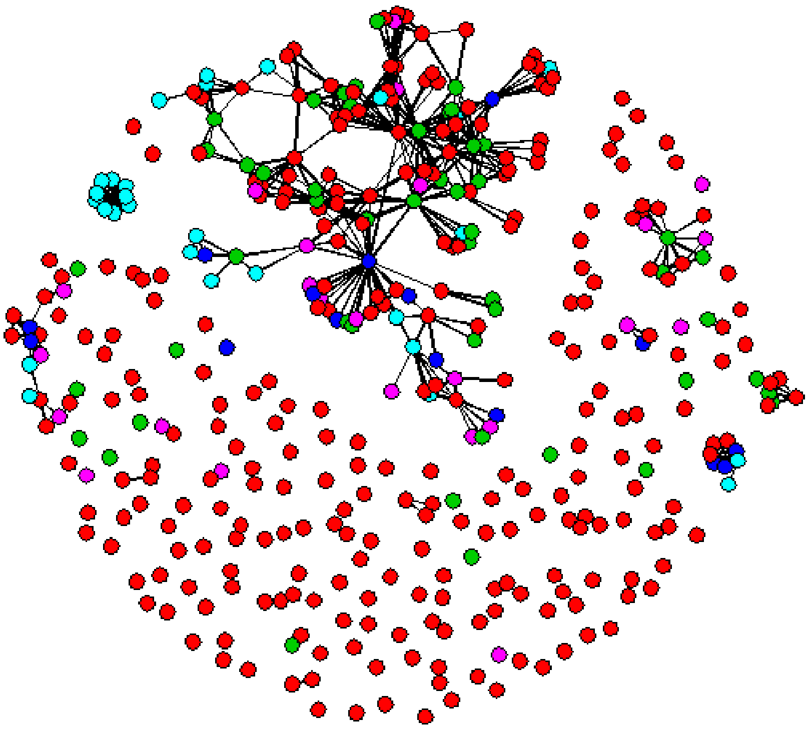


Figure 2: Network graphs of projects (figure 2a) and actors (figure 2b).



2a



2b