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Smart innovation policy: How network position and project composition affect the diversity of an emerging technology

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ABSTRACT

Technological diversity is important to achieve long-term technological progress as diversity fosters recombinant innovation and renders undesirable lock-ins less likely. Many government policies influence the diversity of a technology, in particular by subsidizing collaborative innovation projects. This study investigates the influence of network position and the composition of innovation projects on the creation diversity of an emerging technology at a system level. We first conceptualize technological diversity and formulate hypotheses using a combination of innovation system and social network arguments. Empirically, we study the Dutch innovation system in relation to biogas energy technology.

Our results show that the more projects are related to each other through shared actors, the less likely they are to contribute to technological diversity. This supports the arguments that diffusion of knowledge and sharing knowledge bases lead to less diversity. With regard to composition, we found that including more partners in a project is negatively related to diversity, while a greater diversity of actors in a project contributes to technological diversity.

Overall, we conclude that a combination of innovation system and social network arguments provides a credible micro-level explanation for how the diversity of an emerging technology is created within an innovation system. These insights can be used to design "smart" innovation policy instruments that influence the level of technological diversity.

1. Introduction

The creation of technological diversity is considered pivotal in the development of emerging technologies (Dosi, 1982; Faber and Frenken, 2009; Rigby and Essletzbichler, 1997). Diversity aids in preventing a technological lock-in of a suboptimal alternative, it increases the chances of making recombinant innovations and it adds to the resilience of the technology against unexpected environmental changes.

Policymakers can influence technological diversity as part of their innovation agenda. Many policy programs stimulate research collaboration between actors in the innovation system, such as between large firms, small- and medium-sized enterprises, and knowledge institutes. The outcomes of these collaborations are knowledge and technological configurations that contribute to technological diversity, even if the increase in diversity is not among the policy's objectives. In addition, policymakers can also promote selection, for example by subsidizing the exploitation of a particular alternative, such as feed-in tariffs (Perez and Ramos-Real, 2009), or by establishing technology-specific regulations (Negro et al., 2012; Rennings and Rammer, 2011). As such, governments have several tools at their disposal to influence the technological diversity. Surprisingly, we still have little knowledge about how these different policy tools influence the level of diversity, as insights into the underlying driving mechanisms are currently lacking.

The question of what mechanisms explain diversity creation also remains unresolved in the innovation studies literature. The field of evolutionary economics provides a number of studies that describe the diversity of different technologies over time, such as airplanes (Frenken and Leydesdorff, 2000), steam engines (Frenken and Nuvolari, 2004), communication standards (Fontana et al., 2009) and tanks (Castaldi et al., 2009). These studies give case-related explanations for their observations, yet systematic mechanisms that explain diversity creation are lacking.

A related, but largely unconnected, strand of evolutionary literature that might explain the creation of diversity is that of innovation systems (Edquist, 1997; Hekkert et al., 2007), and the delineation

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to technological innovation systems in particular (Carlsson and Stankiewicz, 1991; Hekkert et al., 2007).[1] This approach highlights the collective nature of innovation and claims that new technologies are jointly developed by different types of actors that collaborate in networks under an institutional regime that is partly shaped by innovation policy (Carlsson and Jacobsson, 1997; Carlsson and Stankiewicz, 1991). This literature highlights so-called systemic problems that negatively influence the pace of innovation within an innovation system (Wieczorek and Hekkert, 2012). Network failures are specifically highlighted as a systemic problem. Networks can be too weak, which inhibits knowledge sharing, and too strong, which is seen as a cause for lock-in and detrimental for innovation (Klein Woolthuis et al., 2005; Weber and Rohracher, 2012; Wieczorek and Hekkert, 2012). However, except for the distinction between weak and strong networks the focus on systemic problems does not give any guidance as to what types of network lead to better innovation outcomes. Recently some scholars have taken up the challenge to analyze network structures as part of an innovation system analysis (e.g. Van Alphen et al., 2010; Binz et al., 2014; Ter Wal and Boschma, 2009; Yokura et al., 2013). But also in these studies, as in the studies on systemic problems, the link between networks and technological diversity is completely absent. This disconnection is striking as the literatures on innovation systems and technological trajectories both originate from evolutionary economics (Boschma et al., 2002; Nelson and Nelson, 2002).

In the management literature, the analysis of innovation networks is much more common. In these studies, social networks are used to explain the innovative performance of firms (e.g. Ahuja, 2000; Powell et al., 1996). These studies highlight that strategic network positions of actors induce new combinations of knowledge or resources that lead to new innovation (Ozman, 2009). These studies can intellectually fuel innovation systems research to enable better understanding of the networking element. However, these network studies also suffer from a number of limitations to adequately explain the creation of technological diversity. First, these studies try to explain the technological diversification of a firm (e.g. Cecere and Ozman, 2014; Leten et al., 2007), but they do not look at how this changes the diversity of the technology in the network or innovation system as a whole. Second, there is a strong focus on firms and firm networks, which does not do justice to the innovation systems premise that new inventions and technologies are the outcome of collaboration between *different* actor types (Phelps, 2010). Third, to the best of our knowledge, social network studies in management have not focused on the influence of innovation policy on the innovative performance of networks. Policies can change the conditions under which networks are formed, but it is unknown whether the arguments that are used in network literature are applicable to networks that are supported by policies in an uncertain environment.

Thus, both strands of scientific literature by themselves are insufficient to explain technological diversity. However, by incorporating insights from social network studies into an innovation systems framework, we are able to formulate testable hypotheses that may explain the policy-induced creation of technological diversity within innovation systems. In this article we study the contribution of policy-induced projects to technological diversity within the innovation system. In light of the studies mentioned above, we are specifically interested in how different characteristics of the project in terms of position in the network and the composition of project partners impact technological diversity. This leads to the following research question:

What is the influence of an innovation project's network position and partner composition on the creation of diversity of an emerging technology?

To answer this question, we first conceptualize technological diversity creation and formulate hypotheses related to the characteristics of the innovation project that are tested empirically on the Dutch innovation system in relation to the emerging technology of biogas energy generation. Biogas is a mixture of carbon dioxide and methane, predominantly produced from organic waste material in an oxygen-free environment (Negro et al., 2007; Raven, 2004). As this technology converts organic waste to sustainable energy, it has been intensively stimulated by the Dutch government during the past few decades through various policy schemes. Using government data on biogas energy innovation projects, we are able to map quantitatively the development of the innovation network and the change in technological diversity in the innovation system due to each innovation project.

Our main result is that the projects that contribute most to technological diversity are not too strongly embedded in a network, and consist of a set of actors that are limited in number, but diverse in types. In addition, we show that other concepts are less adequate in explaining technological diversity creation than our hypothesized concepts.

The first contribution of this paper is the integration of the literatures on technological trajectories, technological innovation systems and social networks. By using a social network approach, we are able to provide a systematic explanation for changes in technological diversity in a technological innovation system. Moreover, the combination of theories allows researchers to assess the performance of the technological innovation system in terms of technological diversity, which adds to the existing focus on technological diffusion (Bergek et al., 2008; Hekkert et al., 2007).

Second, we contribute to the social network literature by examining technological diversity created by collaborative policy-induced projects as a dependent variable. Thereby, we show that the network arguments that are commonly used to explain the innovation success of firms also apply to other dependent variables, actors and policy contexts.

Finally, our findings are of importance to policymakers as we demonstrate that subsidizing research projects alone is not enough to influence diversity. Network position and project composition are of great importance to this end. These insights can be applied to emerging technologies whose characteristics remain unobserved. By smartly subsidizing projects, governments can direct the diversity of an emerging technology to a desired optimal level (Van den Bergh, 2008).

2. Theory

In this section we first discuss the concept of technological diversity and how we view it at the level of innovation projects as our dependent variable. Next, we formulate our hypotheses and discuss three related concepts: resource variety, sector diversity and geographical proximity.

[1] Innovation systems have been approached from a variety of angles. The oldest approach is the national innovation system (Edquist, 1997; Faber and Hesen, 2004; Freeman, 1987, 1995), but the concept has been applied on a sectorial (Malerba, 2002), regional (Cooke, 2001; Cooke et al., 1997) and technological level (Carlsson and Stankiewicz, 1991; Hekkert et al., 2007; Nelson, 1994). Given that we are interested in explaining technological diversity at a system level, we focus in this paper on technological innovation systems.

2.1. Technological diversity

According to the evolutionary economics literature there are three reasons for why diversity is important to the development of emerging technologies (see Van den Bergh, 2008). First, diversity aids in preventing a technological lock-in of a suboptimal alternative. The risks of this are that the suboptimal alternative underperforms or that it does not fit the environment, which can prevent further development of the technology. Moreover, selecting a suboptimal alternative means that the chances of success of superior alternatives decrease (Cowan and Foray, 1997; Frenken et al., 2004). If there is too little diversity, a large chance exists that superior alternatives remain undiscovered or underdeveloped, which increases the chances of an undesired lock-in. Second, diversity increases the chances of making recombinant innovations. This means that different elements of existing alternatives can be recombined into novel superior alternatives (e.g. spillovers between options) that form the basis of future technology generations (Van den Bergh, 2008; Fleming, 2001). Third, diversity increases the resilience of a technology against unexpected environmental changes that are especially common in the emerging phase (Negro et al., 2008). Technological diversity provides flexibility and increases the chances of an appropriate response (Hannan and Freeman, 1989; Stirling, 2007). Thus, creating sufficient technological diversity is important for the long-term success of an emerging technology and should be considered as an important dimension in assessing how well innovation systems are functioning.

However, there are also downsides to diversity. It hampers the creation of standards and economies of scale, and the learning of routines that make exploitation of a technology profitable (Foray, 1997) and that contribute to the legitimacy of the technology (Abrahamson and Rosenkopf, 1993). Further, for actors, more diversity leads to more search, coordination and integration costs to keep track of and combine different alternatives (Leten et al., 2007). Finally, working on innovations that increase diversity is associated with a larger variability in the chances of success, but also higher potential rewards (Fleming, 2001), which makes diversity creation a risky endeavor. Given the pros and cons of diversity, it is likely that there is some optimal level of diversity in emerging innovation processes (Van den Bergh, 2008). Unfortunately, there is no fixed formula or recipe to determine the optimal level of diversity. What is possible, though, is to recognize situations with a clear shortage in diversity or abundance of diversity and develop policies accordingly.

In the context of innovation and technology, the use of the term "diversity" can easily lead to confusion. It is strongly related to the concept of variety, but the exact definition of both concepts is sometimes left implicit (e.g. Foray, 1997; Verspagen, 2007). In economics, variety describes differentiation within a given product group (e.g. Lancaster, 1975), while in biology the closely related concept of diversity is used to describe the number of species in a habitat (Pielou, 1966). In the field of innovation studies, Frenken et al. (1999) choose an intermediate position and state that "the biological definition of diversity implies that each time a distinguishable economic 'species,' be it an actor, an activity or an object, is created, the variety of the economic system increases" (p. 470). Stirling (1994, 2007) conceptualizes variety to be part of the higher-order construct diversity. Diversity itself is not explicitly defined, but it has three properties that are a "necessary but not sufficient property of diversity" (Stirling, 2007, p. 709): variety, balance and disparity. Variety is "the number of categories into which system elements are apportioned" (Stirling, 2007, p. 709). Balance refers to how many elements there are in each category, and disparity refers to how different the elements are. In this paper we consider diversity in such a way that it also takes into account variety and balance.[2] We therefore define diversity as the evenness in a distribution of elements among a number of categories in a system.

Most studies conceptualize technological diversity at an aggregated level over all alternative technological designs (Bakker, 2010; Frenken and Nuvolari, 2004; Frenken et al., 1999, 2004; Rafols and Meyer, 2010). In contrast, we are interested in explaining how single innovation projects contribute to technological diversity in the innovation system. As such, we take a micro-level approach.

To approach diversity at the micro level, we first define the boundaries of the technology. This is done by assuming that a technology or innovation fulfills a certain service or function (Castaldi et al., 2009; Van Rijnsoever and Oppewal, 2012; Saviotti and Metcalfe, 1984); in our case, this is the conversion of organic waste to biogas that can be used to generate energy.[3] This function can be achieved through different technological designs. These different designs form the basis of technological diversity. We use the idea of design spaces to systematically map the technological designs (Foray and Grübler, 1990; Frenken and Nuvolari, 2004). The idea is to distinguish between different dimensions of a technology that fulfill a certain function. Each dimension can assume different possible states, which are called "alleles." For example, biogas energy technology can be subdivided analytically into three dimensions: the energy source, the production method and the processing of gas. The alleles for energy sources are (1) manure, (2) organic waste, (3) energy crops, or (4) sewage; production method alleles are (1) mono-digestion or (2) co-digestion; alleles for processing are (1) cogeneration for electricity production, (2) upgrading to green gas, or (3) direct use of heat and electricity.[4]

Some designs are more common than others and might eventually become dominant (Murmann and Frenken, 2006; Utterback, 1996), while designs that are rarer contribute to more diversity. As such, we define diversity creation by a project as an increase in evenness in the distribution of technological designs.

If we limit the design space to only include designs that fulfill a specified function, we can also set the boundaries of the innovation system around the emerging technology to include only those actors, networks and institutions (Carlsson and Stankiewicz, 1991; Hekkert et al., 2007) that are related to the development of new designs with that function.

2.2. Networks of 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). Earlier studies have indeed shown that a firm's network position influences the innovative output of that firm in alliances (Ahuja, 2000; Powell et al., 1996; Schilling and Phelps, 2007). However, we chose to view the relationships between projects instead of actors. The projects are connected to each other through shared actors that act as knowledge conduits between projects. In essence, this is just a different projection of an actor-based network, but it has consequences for the network

[2] We do not take into account disparity because there is no satisfactory measure that satisfies all three criteria (Stirling, 2007). Stirling (2007) proposes an alternative that does include disparity, but that requires arbitrary assumptions about which aspects of diversity are important (see Rafols and Meyer, 2010). Consequently, we do not include disparity.

[3] It should be noted that biogas can also be used for other purposes. Moreover, these purposes can change over time. However, in this paper we focus exclusively on the application of biogas as an energy technology, which is a subset of the broader biogas technology field.

[4] This number of dimensions and alleles is the outcome of the high aggregation level of our conceptualization of the technology. An engineer could break down the technology into many more components and distinguish many more detailed alternative processes.

statistics (Borgatti and Everett, 1997; Latapy et al., 2008). We have two reasons for looking at projects. First, in line with innovation system thinking, new technological designs are the output of collaborative projects consisting of different actor types, new designs are not the output of actors themselves. The actor level is thus analytically inappropriate. Second, looking at relationships between actors would artificially inflate our network statistics, as all partners in a project are connected to each other.[5] A consequence from the choice of looking at project nodes is that we need to be careful that the arguments commonly applied to actor nodes are also applicable to project nodes.

As mentioned in the introduction, the literature on social networks and innovation does not treat technological diversity at the system level explicitly, rather it focuses on innovation success, which is a micro-level concept. The arguments that explain innovation success are often based on the creation of novelty, which is also key to diversity creation. Therefore, our hypotheses are based on two prominent and related concepts at the level of the node that influence novelty: the number of ties a project has and its degree of clustering (Ahuja, 2000; Powell et al., 1996; Schilling and Phelps, 2007; Tsai, 2002). We chose these two concepts as they have complementary explanatory mechanisms that are also applicable to diversity creation.

2.2.1. Number of ties

In the context of this paper, this concept is defined as the number of other projects with which a focal project shares actors. Powell et al. (1996) and Ahuja (2000) find a positive link between network ties in R&D collaborations and innovative output. However, this relationship does not necessarily hold for technological diversity creation. Sharing more actors with other projects means that newly developed knowledge and practices diffuse easily throughout the network (Alkemade and Castaldi, 2005; Valente, 1995). This leads to the creation of standards, the learning of routines, building economies of scale (Foray, 1997), lowering of search and coordination costs (Leten et al., 2007), and it gives legitimacy to a design (Abrahamson and Rosenkopf, 1993). These advantages make selection more attractive than diversity creation. Therefore we hypothesize a negative relationship between the number of ties and creation of technological diversity by a project.

Hypothesis 1. The number of ties a project has is negatively associated with technological diversity creation.

2.2.2. Degree of clustering

This concept refers to the extent to which the network partners of a node are also connected to each other (Wasserman and Faust, 1994). In our case it means the extent to which projects share actors with each other. By definition, for clustering to occur around a project it has to be connected to other projects (Kaiser, 2008). This means that arguments about clustering only apply to projects that have ties. If a focal project is connected to other projects via one or more actors, but those other "neighbor" projects are not connected to each other, then the degree of clustering is zero. The more the other neighbor projects are connected to each other, the higher the degree of clustering is.

A major debate has focused on how exactly clustering influences innovation (Burt, 2001) and the development of good ideas (Burt, 2004). There are two sides to this debate, one of which claims that a high degree of clustering around a particular node in a network is beneficial to innovation (Ahuja, 2000; Powell et al., 1996). Several explanations are given for this. First, clustering eases information transmission and enables nodes to compare information from different partners, thus increasing the reliability of the information (Schilling and Phelps, 2007). Second, clustering deepens the debate concerning problems and solutions between partners and contributes to a shared understanding (Powell et al., 1996) that allows partners to come up with novel solutions (Brown and Duguid, 1991). Third, clustering engenders trust, the development of shared norms and a shared identity (Coleman, 1988), which in turn facilitate 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 – and costly – network paths between actors (Burt, 2001). Thus, actors largely share the same information sources (Schilling and Phelps, 2007). The result is knowledge and information that is too homogeneous (Burt, 2001; Granovetter, 1973; Jack, 2005). Furthermore, the development of shared conventions and norms can hamper creativity (Uzzi and Spiro, 2005). On the other hand, a lower degree of clustering means that there are more "structural holes" in a network (Burt, 2001, 2004). Structural holes exist if a focal node is connected to two other nodes, but the two other nodes are not connected to each other. This means that the focal node has access to different flows of information. Structural holes allow the combination of diverse knowledge flows and thereby contribute to innovation (Schilling and Phelps, 2007) and new ideas (Burt, 2004).

Since technological diversity implies novel ideas and creativity, we follow the view of Burt (2004) and hypothesize that clustering has a negative effect on diversity creation. The fewer neighboring actors a project shares with other projects, the more likely it is to contribute to diversity. Thus:

Hypothesis 2. The degree of clustering around a project is negatively associated with technological diversity creation.

We note that the homogeneity of knowledge base arguments used in Hypothesis 2 can also be applied to Hypothesis 1. Both arguments are theoretically related and difficult to separate, since clustering is conditional upon having ties. However, the argument about diffusion throughout the network, which we used for Hypothesis 1, is not applicable to the degree of clustering. Clustering only leads to ties between the neighbors of a focal node, and does not connect the node to other parts of the network. As such, clustering does not contribute to the further diffusion of the node's knowledge throughout the network. In the methods we make clear how we test these different arguments.

2.3. Project composition

Innovation is often the result of collaborative projects between multiple partners (Tidd et al., 2001). We hypothesize that the composition of the project consortium can influence technological diversity. Following earlier studies (Powell et al., 1996; Ruef, 2002), we consider two attributes of project composition that can influence technological diversity: the number of partners and partner diversity.

2.3.1. Number of partners

This concept refers to the size of the project consortium in terms of distinct actors. 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" (p. 434). 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" (p. 118). It is easier to obtain this desired range of intellectual and

[5] For example, if we looked at the networks of actors that operate in the projects, the number of ties would largely be a function of the number of project partners, since all actors in a project are connected to each other.

scientific skills by including multiple partners, which would suggest a positive relationship with technological diversity creation.

However, alternative arguments can also be made. Lundvall et al. (2002) view innovation development as an interactive learning process between closely interacting partners. This intense collaboration facilitates the growth of trust and the building of shared norms and practices, which eases the generation and transfer of knowledge between partners (Coleman, 1988; Lundvall, 1985; Ruef, 2002; Schilling and Phelps, 2007). However, these intense collaborations also demand conformity between partners. Partners who deviate from the shared norms and conventions risk a decline in social status (Homans, 1974), which is a disincentive for contributing to novelty. These conforming processes can have a negative influence on the creation of technological diversity. Larger project teams are more complex and require more coordination, which demands more conformity to rules and standards, and thus less novelty (Tatikonda and Rosenthal, 2000). A similar argument is found in the social psychology of team size literature (Curral et al., 2001; Kozlowski and Bell, 2003), but convincing empirical evidence for this process is still lacking.

Arguments have thus been made for either a positive or a negative relationship. However, as the negative arguments lack solid empirical support we hypothesize a positive relationship:

Hypothesis 3. The number of project partners has a positive association with technological diversity creation.

2.3.2. Diversity of project partners

This concept refers to the differences in actor types within the consortium. Following the literature on innovation systems (Edquist, 1997) and science industry collaboration (Etzkowitz and Leydesdorff, 2000; Van Rijnsoever et al., 2014), 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 a maximum of 250 employees; more than 250 employees means that the firm is an 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, facilities or regulative support. Finally, IOs are organizations that facilitate dialog between partners; examples are branch organizations, lobby groups and special interest groups.

Powell et al. (1996) claim 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 (Laursen and Salter, 2006; Nieto and Santamaría, 2007; Nooteboom, 2000; Ruef, 2002). The straightforward argument is that diverse partners bring to the project their unique knowledge and skills, which can be combined to form novel concepts. This creates technological diversity. Therefore:

Hypothesis 4. The diversity of project partners has a positive association with technological diversity creation.

2.4. Other explanations

The arguments presented above are primarily based on knowledge-based arguments about the creation of ideas, sharing information and making novel combinations. However, the literature also discusses other concepts that can explain the relationships posed above. We discuss three prominent concepts that we shall also test empirically: resource variety, sector diversity and geographical distance.

2.4.1. Resource variety

In addition to exchanging only information, actors can also use networks to exchange other resources (Lin et al., 2009; Powell et al., 1996). Eisenhardt and Martin (2000) define resources as "physical, human and organizational assets that can be used to implement value-creating strategies" (p. 1106). These resources can be transformed into innovations that form the source of competitive advantage (Del Canto and González, 1999). As we cannot determine the balance between different resources, we use a variety of resources instead of diversity (Stirling, 2007). The variety of resources that are used as inputs for an innovation determines the potential technological diversity. This does not mean that the total potential diversity is always achieved, but one can argue that resource diversity is a condition for technological diversity.

2.4.2. Sector diversity

Actors with the same principal activities, products and behavior are often seen as being part of the same sector (Pavitt, 1984). The knowledge and resources required for innovation are tied to the actors and are thus, in part, sector specific (Malerba, 2002). This restricts the potential for innovation and the creation of technological diversity. Interdisciplinary collaboration across sectors, however, opens up avenues for novel combinations and can thus lead to more diversity (Alves et al., 2007; Sampson, 2007). Using this argumentation, sector diversity is able to capture both the knowledge- and resource-based arguments above.

2.4.3. Geographical distance

The final argument is based on theories of clusters and regional innovation systems (Cooke, 2001). The claim is that knowledge is bound to a geographical location (Boschma, 2005; Zucker et al., 1998), and that it evolves over time based on the existing knowledge base (Boschma et al., 2014). As such, different regions have different knowledge bases. We measure geographical distance in two ways. First, we determine the physical distance between partners within projects. A large distance between partners means that their knowledge bases are more likely different, which increases the opportunity for making novel combinations and thus to create technological diversity. Second, we determine the geographical distance between projects. The argument here is that projects that are further removed from each other are more likely to create new varieties, since they draw knowledge from different local knowledge bases.

3. Methods

3.1. Case selection

We test our hypotheses on the case of biogas energy technology in the Netherlands, which is an example of an emerging technology. Emerging technologies are "science-based innovations that have the potential to create a new industry or transform an existing one" (Day et al., 2004, p. 2). Biogas technology falls into the latter category since it has the potential to transform the gas market by reducing the dependency on natural gas that is supplied by large corporations or foreign powers. Thereby, it decentralizes gas production, which is a major shift in current practices (Smink et al., 2014). As such, biogas energy technology is a suitable case to test our hypotheses on (see Bryman, 2013; Yin, 2003).

Moreover, biogas has large potential as a renewable energy technology. The World Bioenergy Association estimates that biogas may cover around one third of the current global use of fossil gas (WBA, 2013). In 2012, there were over 13,900 biogas installations

throughout Europe and this number is increasing (EBA, 2013). The technology is also suitable for upcoming countries such as China (Jiang et al., 2011) and developing countries (Bond and Templeton, 2011). Finally, in many countries biogas technology is stimulated by policy efforts. This also makes this case a well-suited case from a societal or policy point of view.

In the Netherlands, biogas technology is seen as a prominent option for obtaining renewable energy targets (SER, 2013). This country is a suitable location to study this technology. First, the Netherlands has the right conditions for the development of new variations of biogas energy technology, since it has a large, intensive agricultural sector, a strong gas sector and a strong knowledge infrastructure. Moreover, the technology is supported by the government through various subsidy schemes. Consequently, the required knowledge, resources, actors and institutions are present. Second, the Netherlands Enterprise Agency (NEA)[6] has documented all subsidized innovation projects in relation to this technology between the years 2001 and 2013. As owners of biogas facilities are heavily dependent (approximately 60%) on government subsidies to make their projects profitable (Peene et al., 2011), we can assume that the data approximates all the actors in the field of biogas energy technology and their activities when it comes to developing new innovations.

Given that we only study subsidized networks, we cannot generalize our findings to nonsubsidized networks. However, it should be noted that many emerging technologies are dependent on some form of government subsidy.

3.2. Data

Our data consists of granted subsidies that focused on the energy application of biogas technology. Each grant is seen as a separate project. This does not mean that each project is a separate biogas installation; it is also possible that a subsidy entails the expansion of existing sites with extra installations or capacity.

We distinguish between two generic types of subsidy instruments – research and exploitation – that influence variety and selection. Research subsidies stimulate research and the development of new knowledge and ideas, and are thus likely to contribute to technological diversity. They are usually granted to consortia of different actor types. Exploitation subsidies, on the other hand, aim to stimulate the diffusion of existing innovations and thus selection. They are usually granted to one actor and facilitate the learning of routines and the creation of economies of scale. Appendix 1 provides an overview of the subsidy schemes and how they were classified.

The project database contains information on the subsidy scheme used, the start and end years, technical specifications, and the partners involved in the project. In total, the database contains 404 innovation projects with 402 unique actors. In all, there were 291 exploitation projects and 113 research projects. For 28 projects it was not possible to retrieve technological specifications, which resulted in usable data for 376 projects.

3.3. Measurement

3.3.1. Technological diversity creation

As dependent variable we are interested in how much a focal project i influences technological diversity in a population of N projects. For this we operationalize the idea of design spaces using the technological specifications of the projects that were available in the database. It is reasonable to assume that the projects were realized according to the design that was described in the project application, since the Dutch government tracks the development of these installations (see www.b-i-o.nl). A measure that is commonly used in innovation studies for diversity (see Bakker, 2010; Frenken and Nuvolari, 2004; Frenken et al., 1999, 2004; Rafols and Meyer, 2010) is the entropy statistic introduced by Shannon (1948), which measures the randomness of a distribution. As such, it takes into account variety and balance (Stirling, 2007). The entropy statistic (H) is given by:

$$H = -\sum_s p_s \ \ln p_s \tag{1}$$

where p_s represents the proportion of projects with a specific design s. The technological diversity creation by project i is measured as the difference between the entropy of the existing population of projects (H_0) and the entropy of a hypothetical population in which the focal project does not exist (H_{-i}). This difference is denoted by dH_i.

$$dH_i = H_0 - H_{-i} \tag{2}$$

A positive value of dH_i indicates that diversity is created, a negative value indicates a reduction of diversity. H_0 can be obtained using Eq. (1), while H_{-i} is calculated as follows. Let the number of projects with the same design as project i in the population be given by n_{si}. Accordingly, the proportion of projects with the same design is given by p_{si}. However, since the focal project does not exist in the hypothetical population, there is one project fewer with that design in the population. Therefore, to calculate p_{si} we subtract 1 from both the nominator and the denominator.

$$p_{si} = \frac{n_{si} - 1}{N - 1} \tag{3}$$

Moreover, removing the focal project i has the consequence that the proportions of any other designs, denoted by p_{sj}, also change according to:

$$p_{sj} = \frac{n_s}{N - 1} \tag{4}$$

Thereby H_{-i} is calculated as:

$$H_{-i} = -(p_{si} \ \ln p_{si} + \sum\nolimits_{sj} p_{sj} \ \ln p_{sj}) \tag{5}$$

There are three issues with this measure that need to be addressed prior to the analysis. First, given that we have data from multiple years, it is necessary to determine whether past projects are part of the project population in a year for which we calculate entropy change. The simplest approach is to limit the population to projects that start at a specific moment in time, thereby ignoring the past completely. This is what we call a "naïve" approach to technological diversity. However, one can argue that it is important to include past projects in the population as technological trajectories are path dependent and cumulative by nature (Dosi, 1982; Nelson and Winter, 1982; Verspagen, 2007). If so, the question becomes how to weigh past projects in determining current technological diversity. A possible approach, then, is to take all past projects into account and weigh them as equal, regardless of how long ago they took place. This means that the population consists of all projects that are active up until a given moment in time. We call this the "full rational" approach to technological diversity. All other possibilities lie in between these naïve and full rational extremes. We calculated technological diversity using both approaches and empirically tested whether using either measure would influence our model results.

[6] The NEA is the executive agency of the Dutch Ministry of Economic affairs. In Dutch it is called RVO – formerly it was known as NL Agency. The NEA is responsible for the implementation of subsidy schemes that support the development of sustainable energy technologies.

Second, our measure of technological diversity is sensitive to the number of projects that are in the population. As the population increases, the mean and variance of entropy change dH_i will decrease, since the influence of single projects is smaller as the population becomes larger. This results in variables with means that are dependent on the population size in a given year, causing heteroscedasticity. These effects are stronger for the full rational approach than for the naïve approach, since the former is based on the cumulative number of designs while the latter only on the number of designs in the most recent year.

Third, some projects had more than one active allele per dimension (this was especially the case for energy sources). Whether these designs are truly unique, or whether they are a variation upon an existing design, is arbitrary. Since the entropy statistic views projects with multiple active alleles as truly unique, these designs cause too large a change in entropy, which does not do justice to their actual contribution to technological diversity.

We corrected for the difference in means caused by time and the multiple active alleles by partialing out these effects (Greene, 1997). We regressed both the technological diversity creation variables on dummies for each year and on the number of active alleles per dimension. We used the residuals of these regressions as corrected measures for technological diversity creation. In the final regression models we deal with the issue of heteroscedasticity.

For our independent variables we only took into account projects that received research subsidies. A theoretical reason for this is that the hypotheses we formulated concerned the development of new knowledge and the creation of technological diversity. Exploitation subsidies do not contribute to these aims. Second, most exploitation subsidy projects either consist of only one actor not connected to the rest of the network or of one actor combining an exploitation project with a research project. The latter cases are problematic, because the actor appears as a separate node in the network that is tied to a research project, but is in fact the same actor who is also part of the research project. The result is a bias in network measures, which is removed by excluding exploitation projects. All network measures were calculated using the igraph software package (Csárdi and Nepusz, 2006) of the R program (R Development Core Team, 2013).

3.3.2. Number of ties

This variable comprised a simple count of the number of actors a project shared with other active projects.

3.3.3. Degree of clustering

This variable 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. One issue is how to distinguish projects that are not connected to other projects (isolates) from projects that were connected, but whose neighbors are unconnected, since both receive a value of 0. To distinguish "isolates," an extra dummy variable was created. The clustering variable was then regressed on the isolates dummy. The residuals of this regression form an isolates-corrected measure for clustering, which was used as an independent variable in our models.

The number of ties was strongly correlated with the clustering coefficient ($r = 0.70$, $p < 0.001$). This is because clustering is conditional on having ties. To separate the effects of both measures, we regressed the number of ties on the corrected clustering coefficient. The residuals of this regression were uncorrelated with the clustering coefficient and were used as an unconfounded measure for the number of ties. As the variance that captures the homogeneity effect of sharing knowledge has been removed, we can use the number of ties variable to test the diffusion argument from Hypothesis 1. As clustering around a node does not lead to more diffusion of its knowledge, the clustering variable only contains the variance of the shared knowledge, and can thus be used to test Hypothesis 2.

3.3.4. Number of project partners

This was a simple count of the number of partners that applied for a subsidy in a project.

3.3.5. Diversity of project partners

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 Shannon's (1948) entropy formula (F1) to calculate the diversity of project partners.

3.3.6. Resource variety

To calculate this variable, we first established which resources were contributed to a project by the participating actors. The database classified resources into the following categories: (1) Feedstock, (2) Technology, (3) Equipment, (4) Licenses, (5) Land, (6) Buildings, (7) Research facilities, (8) Patents, (9) Technological knowledge, (10) Market knowledge, (11) Judicial knowledge, (12) Manpower, (13) Capital, and (14) Network. Unfortunately, it is not possible to calculate the relative shares for this diverse set of resources because they are not comparable. This means we cannot apply the entropy formula. Therefore we looked at the number of different elements (Stirling, 2007) and calculated resource variety as the number of resources in a project. Since the resulting variable was heavily skewed, we took its natural logarithm.

3.3.7. Sector diversity

This variable was based on 15 different sectors in the database in which actors could classify themselves in the project application: (1) Agriculture, (2) Consultancy, (3) Energy, (4) Engineering, (5) Finance, (6) Food processing, (7) Government, (8) Knowledge, (9) Law, (10) Project management, (11) Recreation, (12) Transport, (13) Trustee, (14) Waste Processing, and (15) Water regulation. These sectors are broader than the conventional NACE codes that are often used to classify firms in sectors (EU, 2010), but it should be noted that our list of actors is broader than firms only. Moreover, this list is tailored to our empirical case and thus gives better insights into the core activities of the actor than the NACE classification would. We calculated sector diversity for each project by applying the entropy formula (F1).

3.3.8. Geographical distance within projects

This was measured by calculating the average distance to a calculated geographical center of actors in each project, using the geographical coordinates of each actor. This was done using the *fossil* package (Vavrek, 2011) of the R program.

3.3.9. Geographical distance between projects

This was measured as the distance between the calculated geographical center of a project and the calculated geographical center of all projects. Since this variable was heavily skewed, we took the natural logarithm.

Table 1 displays the descriptive statistics and correlation matrices of all variables for the research projects only. It should be noted that the two network variables are correlated despite the fact that they were statistically separated. This is because the research projects are a subset of the data, while the partialing-out procedure was conducted on the entire dataset. However, the correlation is substantially lower than it originally was.

Table 1
Descriptive statistics and correlations for the research subsidy projects.

	Mean	Standard deviation	Diversity creation: naive	Diversity creation: full rational	Number of ties	Degree of clustering	Number of project partners	Diversity of project partners
Diversity creation: naive	0.058	0.112						
Diversity creation: full rational	0.029	0.108	0.935					
Number of ties	1.700	2.446	−0.090	−0.072				
Degree of clustering	0.242	0.409	−0.245	−0.164	−0.300			
Number of project partners	3.506	2.191	−0.136	−0.098	0.183	0.249		
Diversity of project partners	0.502	0.427	0.037	0.016	0.218	0.129	0.603	
Number of KIs	0.259	0.580	0.078	0.044	0.262	−0.020	0.280	0.354
Number of LEs	0.341	1.086	0.081	0.050	−0.036	−0.124	0.352	0.057
Number of SMEs	1.941	1.409	−0.140	−0.088	0.003	0.302	0.696	0.227
Number of IOs	0.224	0.472	−0.009	−0.018	−0.030	0.087	0.246	0.417
Resource variety	1.559	0.555	−0.018	−0.001	0.035	0.149	0.507	0.393
Sector diversity	−0.057	0.084	0.047	0.017	0.064	0.215	0.471	0.500
Geographical distance within projects	3.292	2.148	−0.082	−0.094	0.170	0.315	0.594	0.505
Geographical distance between projects	3.835	0.667	0.189	0.153	−0.107	−0.188	−0.122	−0.048

	Number of KIs	Number of LEs	Number of SMEs	Number of IOs	Resource variety	Sector diversity	Geographical distance within projects
Number of KIs							
Number of LEs	−0.010						
Number of SMEs	0.033	−0.127					
Number of IOs	0.221	−0.104	0.056				
Resource variety	0.126	0.026	0.509	0.134			
Sector diversity	0.162	0.136	0.354	0.075	0.450		
Geographical distance within projects	0.091	0.040	0.529	0.096	0.494	0.624	
Geographical distance between projects	0.117	0.074	−0.187	0.074	0.06	−0.145	−0.301

3.4. Analysis

Prior to testing our hypotheses, we visualized the innovation network by drawing network graphs. This was done using the sna package (Butts, 2008) of the R program. The graphs include all research and exploitation projects over the entire time period, but they ignore the fact that not all projects were active at the same moment. However, they provide intuitive insights concerning how projects and actors are formally related.

All variables were of a continuous nature, but our dependent variables suffered from heteroscedasticity. To control for this we fitted a series of weighted least squares (WLS) regression models for both measures of technological diversity creation, with the hypothesized independent variables as predictors. The cases were weighed by the squared number of projects that were in the population at that point in time.[7] In each model we added the independent variables from our hypotheses.

The relationships we tested are likely of a causal nature, since network and consortia formation precede the realization of the innovation project. However, this depends on the plausible assumption that projects were realized according to the designs specified in the application. In addition, we cannot fully exclude rivaling underlying explanations (see Campbell and Stanley, 1966). This is a common problem with research designs in innovation research (Van Rijnsoever et al., 2012), and cannot be remedied completely unless we resort to formal experimental design. However, we did test the three rivaling explanations that might reveal spurious correlations, by fitting a series of models in which we added either resource diversity, sector diversity or geographical distance as additional variables. If these extra variables are significant, and our hypothesized effects become insignificant, then there is reason to doubt the causality of our relationships. Furthermore, it is possible that some of the projects were actually an expansion of existing installations by the same actors. This implies interdependencies between projects, which violates the assumption of independent observations. To control for these effects, we also fitted a linear mixed model with a random intercept dependent on the actors participating in the projects. For this procedure the projects in the database have a number of observations that is equal to the number of project partners, which means that the number of observations increases. As our research looks at projects and not at actors within projects, we primarily use the random intercept models to check whether there are any effects from the violation of the independent observations assumption.

4. Results

Fig. 1a shows the network graph for the project level. Nodes are projects and ties are actors. The size of the node indicates how much technological diversity each project creates, based on the corrected naïve measure; the larger the node, the more technological diversity is created. The color of the node indicates what the project type is: green nodes are research projects and red nodes are exploitation projects. The first noticeable observation is that there is one large connected component in the network 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 because all exploitation projects consist of one actor. A series of independent sample t-tests demonstrate that the technological diversity creation by research subsidies is larger than by exploitation subsidies ($t_{\text{naïve}} = 10.42$, $p < 0.001$; $t_{\text{full rational}} = 3.95$, $p < 0.001$). This means that innovation policy in the form of directed research subsidies to collaborative projects does have an influence on the technological diversity creation by a project.

Fig. 1b shows how the actors within the projects are connected to each other. The nodes are actors and the ties indicate that actors participate in the same project. The ties between actors by definition concern research projects. The color of the node indicates the actor type (see Section 2.3): red nodes are SMEs, green are LEs, dark

[7] The dispersion in variance over time was curvilinear. In 2001 the variance was low, after which it increased in 2002. Then it gradually declined over the year. A squared term is better able to capture this effect.

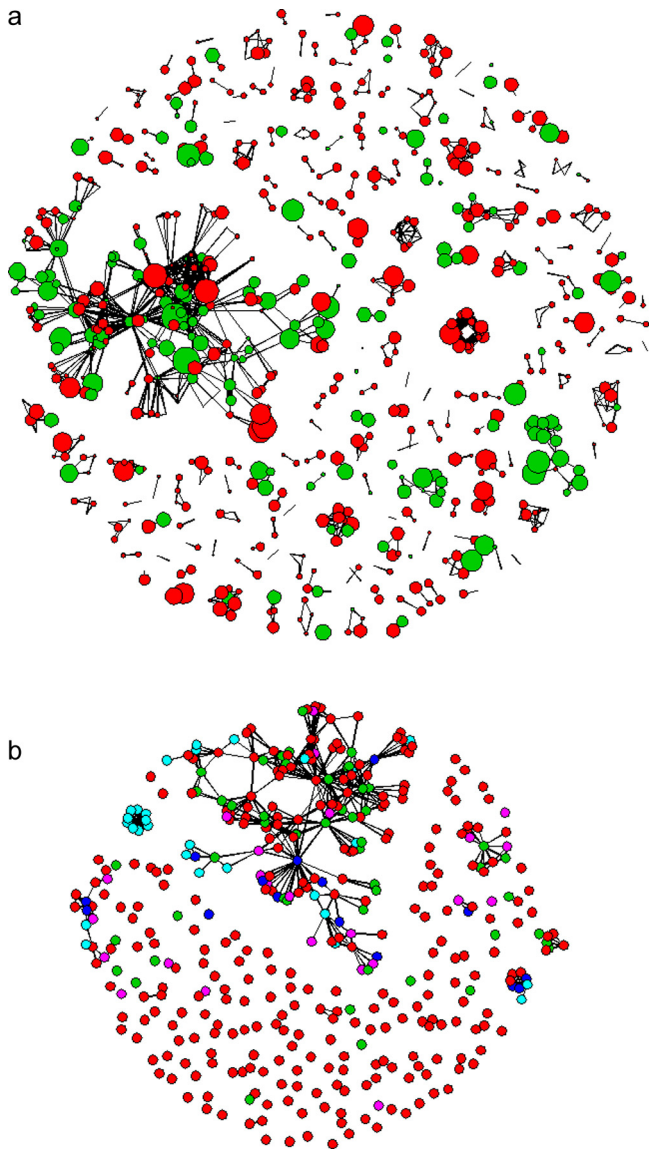

Fig. 1. (a) Network graph for the project level. Nodes are projects and ties are actors. The size of the node indicates how much technological diversity each project creates, based on the corrected naïve measure; the larger the node, the more technological diversity is created. The color of the node indicates what the project type is: green nodes are research projects and red nodes are exploitation projects. (b) Network graph for the actor level. Nodes are actors, ties indicate that actors participate in the same project. The color of the node indicates the actor type: red nodes are SMEs, green are LEs, dark blue are KIs, light blue are GBs and purple are IOs. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

blue are KIs, light blue are GBs and purple are IOs. Most actors are SMEs (284), followed by LEs (50), GOs (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 the most connections (three on average), while SMEs are least connected (1.05 on average). Fig. 1b shows that most isolated projects are indeed single SMEs, while only one KI is unconnected.

Table 2 presents the results of our regression models. The adjusted R^2 is 0.192 for the naïve WLS model, which is good. The full rational model scores substantially lower with 0.068. This can be explained by the fact that this model suffers most from heteroscedasticity. Furthermore, variance inflation factors ranged between 1.16 and 1.57, which is acceptable, and the distributions of the residuals approached normality. There are almost no differences in results between the models that had the naïve or full rational measure of technological diversity creation as a dependent variable. This shows that setting a time frame in this case did not affect the outcome of the models. Finally, the results of the random intercept models strongly resemble those of the WLS models, which means that the interdependencies between projects did not influence our testing of the hypotheses.

Table 2a presents the results of our hypotheses tests. In three models, the number of ties is negatively related to technological diversity creation, which is in line with the arguments that more ties lead to more knowledge homogeneity and legitimacy, but not to more technological diversity. This supports the diffusion argument from Hypothesis 1. There is also a negative association between clustering and technological diversity creation in all models. The homogeneity argument from Hypothesis 2 is thereby supported. The number of project partners has a negative association with technological diversity creation in all models. Since we expected a positive relationship, Hypothesis 3 is not supported. This result is in line with the argument that larger teams are more complex to manage, which demands more conformity to rules and standards, and thus results in less novelty (Tatikonda and Rosenthal, 2000). The diversity of project partners, on the other hand, has a significant positive relationship with technological diversity creation in all models, which supports Hypothesis 4.

We explored the lack of support for Hypothesis 3 further by conducting additional analyses. We added for each actor type the number of project partners to the models. The results (see Table 2b) of all models present a negative association between the number of project partners and the creation of technological diversity. However, significant positive relationships also appear for specific actor types. The number of LEs and SMEs is positively related to technological diversity creation in three models, while the number of KIs shows a positive association with naïve models only. IOs are not related to technological diversity creation. However, the positive estimators for the specific actor types are smaller than the negative estimator for the number of project partners, which means a net negative effect of adding an extra actor. These results confirm the negative association between the number of project partners and technological diversity.

The correlation matrix (Table 1) shows that the three variables that test the additional processes are strongly correlated with each other, with correlations up to 0.62. Moreover, most of these variables are also correlated with the number or diversity of project partners. However, the correlations with the dependent variables are modest. Table 3 shows the results of the regression models in which these additional explanations are added. The effects that test our hypotheses remain significant, which lends support to the claim that the hypothesized relationships are likely causal. Resource variety (Table 3a) is, in the naïve random intercept model, slightly negatively related to technological diversity creation; in all other models there is no relationship. Sector diversity is significantly positively associated with technological diversity creation in both naïve models. Finally, geographical distance within projects has a small positive effect in the full rational model. However, the effect is not found in the random intercept model, which indicates that the effect can be attributed to individual characteristics. This is in line with the claim that social networks are able to overcome the barriers of geographical distance (Boschma, 2005). There is also no effect of geographical distance between projects. We thus conclude here that sector diversity can add to explaining technological diversity creation. The effects of geographical distance and resource variety do not contribute to explaining technological diversity creation in this case. However, none of these three variables form an alternative explanation that casts doubt on the causality of our hypotheses.

Table 2
Results from the regression models predicting technological diversity creation with (a) hypothesized effects only and (b) actor type counts.

	WLS-model		Random intercept model	
	Naive	Full rational	Naive	Full rational
(a)				
Intercept (random: variance)	–	–	0.000	0.066
Intercept (fixed)	0.043***	0.677***	0.040***	0.528***
Number of ties	−0.003*	−0.041	−0.004***	−0.077***
Degree of clustering	−0.030***	−0.265[a]	−0.031***	−0.369***
Number of project partners	−0.006**	−0.083*	−0.004***	−0.050*
Diversity of project partners	0.036***	0.425*	0.023***	0.328**
No. obs.	85	85	298	298
Adj. R^2	0.192	0.068		
(b)				
Intercept (random: variance)	–	–	0.000	0.080
Intercept (fixed)	0.037***	0.627***	0.032***	0.398**
Number of ties	−0.002	−0.039	−0.003***	−0.066***
Degree of clustering	−0.024*	−0.229	−0.022***	−0.271*
Number of project partners	−0.017***	−0.214[a]	−0.016***	−0.219***
Diversity of project partners	0.054***	0.582*	0.045***	0.664***
Number of KIs	0.016**	0.065	0.014***	0.065
Number of LEs	0.012*	0.093	0.012***	0.166*
Number of SMEs	0.014**	0.165	0.013***	0.209**
Number of Ios	−0.003	0.112	−0.005	0.007
No. obs.	85	85	298	298
Adj. R^2	0.260	0.048		

[a] $p < 0.1$.
* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.

Table 3
Results from the regression models predicting technological diversity creation with (a) resource variety, (b) sector diversity and (c) geographical distance.

	WLS-model		Random intercept model	
	Naive	Full rational	Naive	Full rational
(a)				
Intercept (random: variance)	–	–	0.000	0.056
Intercept (fixed)	0.037**	0.755**	0.032***	0.499**
Number of ties	−0.003*	−0.043	−0.004***	−0.080***
Degree of clustering	−0.032***	−0.291[a]	−0.031***	−0.363***
Number of project partners	−0.007**	−0.086[a]	−0.005***	−0.061*
Diversity of project partners	0.035**	0.398*	0.021***	0.293**
Resource variety	0.007	−0.013	0.007*	0.064
No. obs.	82	82	294	294
Adj. R^2	0.203	0.060		
(b)				
Intercept (random: variance)	–	–	0.000	0.064
Intercept (fixed)	0.058***	0.780***	0.045***	0.594***
Number of ties	−0.003*	−0.041	−0.004***	−0.076***
Degree of clustering	−0.033***	−0.265[a]	−0.031***	−0.359***
Number of project partners	−0.007***	−0.092*	−0.004***	−0.054*
Diversity of project partners	0.030**	0.393*	0.021***	0.304**
Sector diversity	0.122*	1.567	0.077[a]	1.387
No. obs.	85	85	298	298
Adj. R^2	0.238	0.070		
(c)				
Intercept (random: variance)	–	–	0.000	0.094
Intercept (fixed)	0.032	0.801[a]	0.038**	0.733**
Number of ties	−0.032*	−0.305[a]	−0.033***	−0.443***
Degree of clustering	−0.003***	−0.051*	−0.004***	−0.084***
Number of project partners	−0.006**	−0.114*	−0.004***	−0.067**
Diversity of project partners	0.035**	0.454*	0.025***	0.417***
Geographical distance within projects	0.003	0.072[a]	0.000	0.046
Geographical distance between projects	0.002	−0.068	0.001	−0.082
No. obs.	83	83	292	292
Adj. R^2	0.203	0.097		

[a] $p < 0.1$.
* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.

5. Conclusion and discussion

5.1. Conclusion

In this paper we studied the influence of network position and the composition of collaborative innovation projects on the creation of diversity of an emerging technology. We tested our hypotheses on data about collaborative innovation projects around biogas energy technology. With regard to network position, our results show that the more projects are related to each other through shared actors and the more clustering there is, the less likely they are to contribute to technological diversity. This supports the arguments that collaboration leads to knowledge diffusion and to more homogenous knowledge bases, which decrease diversity creation. With regard to composition, we found that including more partners in a project is negatively related to diversity creation, while a greater diversity of actors contributes to technological diversity. We applied two different measures of our dependent variable, used different model specifications and tested three alternative explanations. Overall, our findings proved to be robust. As such, we conclude that a combination of innovation system and social network arguments provides a credible micro-level explanation for how diversity is created in innovation systems. Moreover, our results demonstrate that subsidizing (collaborative) research projects alone is not enough to stimulate diversity creation; the position of new projects in networks and the composition of project partners are of great importance to this end.

5.2. Limitations

This research suffers primarily from a number of limitations.

Theoretically we used a technological innovation systems approach with a strong focus on networks of collaborating actors. Thereby we placed less emphasis on the role of institutions. Our study only took into account regulative institutions in the form of subsidized innovation projects. Although the effects of other changes in the institutional environment were statistically captured by including "year dummies" in our models, we did not take these other institutions systematically into account. Future research should try to make the effect of institutions more explicit. This can be done by comparing regions or countries that have different institutional structures. Another element that deserves more attention is the role infrastructure plays in diversity as this can limit the implementation of alternatives (Van der Vooren and Alkemade, 2012).

The second limitation regards measurement of the dependent variable, which was calculated based on the technological characteristics in the government database. We do not know for certain whether the proposed design was exactly realized the way it was intended. It is likely that this is the case, but it cannot be validated.

Third, we cannot be absolutely certain about cause and effects. We excluded three theoretically plausible alternative explanations, but we cannot be absolutely certain that there are no other underlying variables that can explain our findings. However, while we do not have any theoretical indications that this might be the case, further research is required to verify our claims.

The final limitation is generalizability. We only took into account projects that were subsidized by the government, and it is theoretically possible that nonsubsidized projects are missing. However, in our case this is highly unlikely since the costs of installation are substantial (between €0.2 m and €1 m) and the technology is not profitable without subsidies. Furthermore, the NEA, as the responsible government agency, is also not aware of any other installations or actors beyond those listed in their database. Therefore we assume that our database covers all projects. If projects are missing because they were not subsidized, but still executed, then this could indeed potentially influence technological diversity. However, the entropy measure for diversity is quite robust against minor changes. The measures of technological diversity in this paper are only strongly influenced if a large volume of projects that all have the same technological configuration is missing. We have no evidence that this is the case, but strictly speaking, our results are only valid for subsidized projects in the Dutch biogas energy innovation system between 2001 and 2013. However, our study does inform theories about the diversity creation of emerging technologies that change existing markets. In addition, the research subsidies we studied operate in a similar manner to many innovation subsidy schemes, such as those on the European level – e.g. Horizon 2020 (European Commission, 2013). However, for further empirical generalization, research is required in different countries and time frames and in relation to different applications of this particular technology or other emerging technologies, such as electric vehicles or stem cell therapy. Important criteria for suitable technology domains are: a full overview of all innovation projects in the technological innovation system over time, a clear design space according to which the technological outputs of each project can be classified, a complete overview of the actors that participate in the networks of projects, and a clear overview of the development of the institutions that support or hinder the projects. Finally, for a robust empirical result, it is better to have a large sample size. Our empirical case fulfills these criteria, although we would have preferred a larger sample of research projects to gain more statistical power.

5.3. Theoretical implications

The current paper has implications for evolutionary economics theories about technological diversity creation in innovation systems, and management theories about social networks and innovation. In addition, we provide avenues for further research.

This study is the first to offer a systematic micro-level explanation of how diversity of emerging technologies is created from networks of collaborating actors in a technological innovation system. As such, we have made a fruitful connection between the strands of evolutionary economics literature about technological diversity and innovation systems. This connection goes beyond the case-related explanations that are often given in studies about technological diversity. Moreover, it adds a technology-based performance dimension to the literature regarding technological innovation systems. We encourage scholars to explore this connection between these literatures further.

In addition, we demonstrated that arguments from social network studies are applicable to other contexts than those that have traditionally been used in the field of management. Our approach of studying subsidized projects of diverse actors in innovation systems instead of single firms yielded results that are in line with arguments from social network studies. Moreover, the social network variables outperformed alternative explanations.

Our focus on networks is consistent with literature on technological innovation systems, which claims that network building is a crucial process for the success of an emerging technology (Hekkert et al., 2007). We have taken the next step by showing what the consequences are of different network configurations when it comes to diversity. Future scholars of innovation systems need to take the purpose of the network building activities explicitly into account. As such, our results imply that the innovation system literature can benefit from insights into social network studies.

We demonstrated that sharing knowledge bases is negatively related to technological diversity creation. However, we cannot ascertain which part of the effect of clustering can be attributed to structural holes. Therefore we do not interpret our results as full support for the thesis of Burt (2001, 2004) about structural holes,

but it does provide evidence for it. Our results do support the argument that sharing knowledge bases leads to less diversity creation, which underlies the structural holes argument, but it is not in line with claims by social network studies that look at successful innovation (Ahuja, 2000; Powell et al., 1996). A likely explanation for this is that technological diversity creation at the system level is not equal to innovation success for a project. For an innovation to be successful, it needs to have a certain degree of novelty, which means that it does contribute to diversity at the system level. However, not all novel innovations become successful. Thus, technological diversity and innovation success should be treated as separate concepts, both with their own explanatory variables and mechanisms. An interesting avenue for further research would be to look at whether the success needs of projects and the system needs for diversity can be aligned. Since innovation success has been shown to be inversely linked to some of our independent variables (e.g. number of ties, clustering and number of project partners), it is worthwhile investigating the trade-off between the creation of technological diversity at the system level and the chances of successful innovation of a project.

In this paper we only looked at different diversities of biogas energy technology. An additional avenue for further research is to study technological diversity creation at the level of the energy portfolio, which implies more of a service or user perspective than a single technology perspective (Saviotti and Metcalfe, 1984). In our case, this means including other technologies such as wind energy or solar energy, but such a user perspective is also conceivable in other contexts.

5.4. Policy implications

Our results provide clear signposts for policymakers that wish to effectively influence the diversity creation of emerging technologies. First, we showed that diversity is not effectively increased by just subsidizing more collaborative projects. To encourage diversity it is important to: (1) subsidize those projects that are not well embedded in the current innovation system, which means that they don't have too many ties and that they can bridge structural holes between projects, and (2) subsidize projects that have a limited number of partners, but that are diverse in actor types. If policymakers wish to encourage selection in the innovation system, they should fund: (1) projects with partners that are also active in other projects, (2) projects that link unconnected projects to each other, and (3) large projects with many partners of the same type.

Second, a problem that is often encountered with emerging technologies is that the technological characteristics that are needed to determine the level of diversity in a system often remain unobserved, either because information about projects is lacking or because there are no clear technological dimensions. In those cases, information about network position and project composition can be used to determine whether a project likely adds to diversity. Therefore, it is important for governments to monitor all the projects active in the innovation system of an emerging technology. This enables policymakers to determine the current network structure and thus where valuable additions can be made.

Finally, to effectively influence the diversity of an emerging technology it is important to recognize that the relative contribution to diversity of each additional project will be less when many projects are already financed.

By taking these implications into account, policymakers can turn existing instruments into "Smart" policy instruments that effectively steer the level of diversity. It is not only the project participants that benefit from these instruments, but also the entire technological innovation system.

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Appendix 1. Classification of the subsidy programs

Subsidy program	Goals	Research	Exploitation	Number of projects
Duurzame Energie Nederland (DEN)	Network creation Knowledge distribution	x		57
Energie Onderzoek Subsidie (EOS)	Research of new sustainable energy technologies Knowledge distribution	x		37
Reductie Overige Broeikasgassen (ROB)	Promotion, development and application of new techniques to reduce greenhouse gas (excl. CO_2)	x		17
Unieke Kansen Regeling (UKR)	Stimulating the transition to sustainable energy Promoting market introduction of new sustainable energy technologies	x		2
Milieukwaliteit Elektriciteitsproductie (MEP)	Production of sustainable electricity		x	96
Overgang Milieukwaliteit Elektriciteitsproductie (OVMEP)	Transition regulation for biomass digestion installations that produce electricity		x	60
Subsidie Duurzame Energie (SDE)	Production of sustainable energy: electricity, heat and green gas		x	135

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