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Maria Tsouri , Teis Hansen , Jens Hanson & Markus Steen

Utrecht University Human Geography and Planning

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Maria Tsouri[1], Teis Hansen[2,3], Jens Hanson[1], Markus Steen[3]

[1]*TIK centre, University in Oslo*
[2]*Department of Human Geography & CIRCLE, Lund University*
[3]*Department of Technology Management, SINTEF*

Corresponding author: Maria Tsouri, Centre for Technology, Innovation and Culture (TIK), University of Oslo, Postboks 1108 Blindern, NO-0317 Oslo, Norway

e-mail: maria.tsouri@tik.uio

Abstract

The paper explores knowledge recombination by analysing how knowledge networks in established technological fields influenced the formation of the emerging field of green shipping in the period 2007–2018. The authors build hypotheses to investigate whether important mechanisms for the evolution of single technology networks, embeddedness, proximity, and status apply across technological fields. By employing dynamic social network analysis models, they found that actors transferred knowledge across technological fields through (re)combination mechanisms, which affected the emergence of the new technological field, but in different ways. While embeddedness played an important role, status and geographical proximity were less important.

Keywords: knowledge recombination, network evolution, emerging technologies

JEL: D83, D85, O33

1. Introduction

The idea of innovation as a process of tapping into and combining existing knowledge is central in the geography of innovation literature. In general, knowledge in emerging technological fields is generated to solve a specific 'problem' (Dosi and Nelson, 2013). Knowledge from related technological fields is (re)combined in the development of possible 'solutions', thereby creating the emerging technological field (Kalthaus, 2016, König et al., 2011, Wagner et al., 2019). These 'solutions' are often supported by policy tools (e.g. subsidized R&D), motivated either by traditional market-failure arguments relating to underinvestment in R&D or by the need to stimulate knowledge creation in particular technological fields that may help to address grand societal challenges (Grillitsch et al., 2019, Laranja et al., 2008, Weber and Rohracher, 2012).

Knowledge creation in technological fields is shaped by networks and the geography of the existing technological knowledge. A wide range of theoretical and empirical research has underlined the crucial role of knowledge networks for the evolution of industries and technological fields (Balland, 2012, Glückler, 2007, Ter Wal, 2013, Ter Wal and Boschma, 2011, Zaheer and Soda, 2009). Much of the recent literature on the subject incorporates the geographical dimension, and is confined to the evolution of knowledge networks in single technological fields (Balland et al., 2013, Bauer et al., 2018, Broekel and Boschma, 2012, Ter Wal, 2013). The evolution of knowledge networks within technological fields is formed by embeddedness, proximity and status (popularity) mechanisms (Balland et al., 2016, Tsouri, 2019). However, there is scant evidence for whether and how these mechanisms apply across multiple technological fields, and particularly what role knowledge networks in established technological fields play in the formation of knowledge networks in new technological fields.

The purpose of this paper is to address this gap by exploring how actors in knowledge networks of established technological fields contribute to the recombination of knowledge and to the creation of a new technological field. Consequently, the aim of this study is twofold. Our first objective is to analyse how knowledge evolves and (re)combines across technological fields and over time to form the knowledge network of a new technological field. Second, we examine whether and how the mechanisms identified as central to knowledge network evolution within single fields (i.e. embeddedness, proximity, and status), also influence evolution across technological fields. Therefore, we develop a set of hypotheses to explore the dynamics that govern the evolution of knowledge networks in emerging technologies.

Our main contribution is to draw on the dynamics already described for single technology knowledge networks in established technological fields (Balland et al., 2016) and to explore whether existing knowledge recombines to foster the emergence and evolution of a new technological field. To do this we examine the role of embeddedness, proximity and status in the aforementioned process, which we expect differ in cases of knowledge transfer across technologies. Therefore, by examining processes of knowledge transfer across knowledge networks of related technological fields this paper expands the existing literature on knowledge network evolution (Bauer et al., 2018, Giuliani, 2013, Ter Wal, 2014).

Empirically, we explore the spatial and temporal dynamics of knowledge networks underpinning environmental innovation in the emerging technological field of 'green shipping'. By 'green shipping', we refer to fuels and energy solutions that can reduce or replace the usage of fossil fuels in maritime transport or shipping. To examine knowledge network dynamics, we employ data from the European framework programmes. In order to capture the (re)combinatory knowledge development, we analyse projects that have supported the emerging field of 'green shipping', as well as established fields of alternative fuels that have previously been developed and applied in other sectors and that are now used to reduce emissions from shipping.

The remaining part of this paper is organized in four sections. In the following section we review the literature on the evolution of knowledge networks and their role in technological fields, and we develop our hypotheses. In section 3 we present our research design and data, and in section 4 we present and analyse our findings. Our conclusions and discussion of limitations and future research are presented in section 5.

2. Literature review

The generation and diffusion of knowledge is a key element of the evolution of technologies (Cantner and Pyka, 1998, Iammarino and McCann, 2006, Saviotti and Mani, 1998, Verspagen, 2007). Emerging technologies require new knowledge, which is created from novel (re)combinations of existing knowledge elements (Asheim et al., 2007, Boschma et al., 2012, Grillitsch et al., 2018). Knowledge in emerging technological fields tends to be sparsely distributed, with no easily identifiable communities and with a variety of possible combinations and alternatives in knowledge resources (Etzkowitz and Klofsten, 2005, Tanner, 2016). Knowledge assets are not easily developed and whereas some forms of knowledge can easily be transferred across space, it is generally accepted that knowledge is a highly localized or 'sticky' resource (Bathelt et al., 2004).

Within evolutionary economic geography, the ways in which territorial economies evolve over time has been premised first and foremost on the argument that innovation and new knowledge tends to develop on the basis of the existing knowledge base (Boschma and Frenken, 2006). This argument of related variety and/or diversification has been underpinned by various studies in which different proxies or indicators have been used (e.g. patents, skills, industry classification) for the knowledge structure of a given territory and how that has developed over time. Thus, this evolutionary characteristic of knowledge development also underpins the path-dependent manner in which territorial economic trajectories unfold over time. However, and as argued by Martin and Sunley (2010), this does not by default imply path dependence in a constraining sense, in which territories become locked-in to industrial paths. Instead, the basis for new development paths (path creation) or the renewal or reorientation of established industries can be provided either by new knowledge that develops on the basis of established knowledge or by new combinations of already established knowledge (Isaksen, 2014, Steen and Hansen, 2018). However, not all changes in territorial economic structures occur through related diversification. The contrasting process of unrelated diversification, which refers to the emergence of industries that are new to a territory (and possibly to the world) is more rare than related diversification (Grillitsch et al., 2018, Neffke et al., 2011).

Knowledge networks constitute channels and conduits for the knowledge transfer across organizations and geographical borders, enhancing knowledge diffusion and contributing to the evolution of technologies (Owen-Smith and Powell, 2004). The literature on knowledge networks focuses extensively on identifying mechanisms behind their evolution, taking into consideration different kinds of network properties, namely nodal, relational and structural properties (Phelps et al., 2012, Cassi and Plunket, 2015, Balland et al., 2019). As explained in detail in sections 2.1-2.3, the main mechanisms identified include the embeddedness of an actor, in either the social or structural context of the network, the proximity of two actors, and the actor's status (popularity), which refers to the relative position of an actor inside the network (Balland et al., 2016, Giuliani, 2013). The most recent studies explore these mechanisms in a dynamic way (Balland et al., 2016, Bauer et al., 2018, Ter Wal, 2014) but they are limited to the evolution of the knowledge network of a single technological field, sector or industry. Therefore, the literature to date has not captured the important role of knowledge (re)combination discussed above, although the specified mechanisms provide potentially relevant starting points for doing so.

Therefore, do the same mechanisms – embeddedness, proximity, and status – apply to the creation of new knowledge networks and thereby underpin the emergence and evolution of technological fields? We aim to test the mechanisms of knowledge networks in established technological fields, specifically on the evolution of the knowledge network of an emerging technology. In the following sections we disentangle each mechanism and discuss how it has been used in previous studies. On this basis we develop three sets of hypotheses to investigate the mechanisms' function in the (re)combination of knowledge for the emergence of new technological fields.

2.1 Embeddedness

According to Granovetter (1985) embeddedness can be defined as the mechanism whereby the behaviour of economic agents is regulated by their ongoing social relations. Embeddedness has positive effects on the parties in these relationships, fostering knowledge creation and diffusion (Uzzi, 1997). Gulati (1998) differentiates between two types of embeddedness: relational (social) and structural. Social embeddedness concerns the characteristics of the relationships on which the agents base their behaviour. In early literature, social embeddedness is expressed through the notion of strong ties (Granovetter, 1973, Krackhardt et al., 2003, Rost, 2011). Strong ties refer to repeated collaborations and interactions on the basis of interorganizational trust, thus enabling knowledge transfer (Ahuja et al., 2012, Broekel, 2019, Tsouri, 2019). The long-term creation of strong ties, apart from the benefits of enhancing trust and therefore knowledge transfer, may result in a densely connected network, which does not allow new external knowledge to be introduced (Fritsch and Kauffeld-Monz, 2010). To avoid this type of knowledge lock-in, actors obtain new knowledge through relationships with actors outside the densely connected part of the network. The characteristics of this relational network structure are referred to as structural embeddedness. Structural embeddedness formalizes the notions of weak ties (Granovetter, 1973) and structural holes (Burt, 2009); whereas weak ties are a relational element of actors loosely connected to the dense network core, structural holes refer to network ties as means of linking actors of separate network parts (Burt, 2009, Fritsch and Kauffeld-Monz, 2010). Therefore, the value of structural embeddedness stems from the ability of actors to have access to novel information and to enjoy efficiency and brokerage advantages, especially when exchanging knowledge.

The two types of embeddedness, social and structural, do not contradict each other. Instead, they are seen as playing different roles and are thus useful to agents for different purposes (Burt, 2000). Recent literature quantifies both types of embeddedness in order to describe knowledge diffusion and how it affects the evolution of knowledge networks of technological fields or sectors (Balland et al., 2016, Bauer et al., 2018, Broekel and Boschma, 2012, Cantner and Graf, 2006, Rost, 2011, Ter Wal, 2014, Tsouri, 2019). It is widely accepted that both types of embeddedness affect the formation of new ties or the strength of the ties in the knowledge network, thus suggesting path-dependent evolutionary trajectories of technological fields.

Based on the above-mentioned arguments we examine the effect of both social and structural embeddedness for the creation of new paths in the evolution of technological fields. In the case of social embeddedness, we assume that existing relationships of actors in established technological fields are transferred to emerging technological fields, due to scarcity of resources and the trust created by the previous collaborations. For structural embeddedness we assume that two actors collaborating with a third party in an established technological field might collaborate with each other in the emerging technological field, tapping into and recombining existing knowledge. These assumptions lead to the following set of hypotheses:

H1a: Social embeddedness in the established technological fields positively affects the formation of ties in the emerging technological field.

H1b: Structural embeddedness in the established technological fields positively affects the formation of ties in the emerging technological field.

2.2 Proximity

Proximity refers to the relational property of connected actors as being close in terms of having similar characteristics. Actors that are proximate (having similar characteristics) tend to connect (McPherson et al., 2001). Proximity of actors constitutes a mechanism for reducing uncertainty and therefore for enabling knowledge transfer and network formation, as well as innovation (Boschma, 2005). Empirical evidence suggests that to great extent proximity in all its forms is important for knowledge production and diffusion (Balland et al., 2016, Boschma and Ter Wal, 2007, Broekel and Boschma, 2012, Cantner and Graf, 2006, Hansen, 2015, Tsouri, 2019).

To date, the literature has mainly highlighted the persisting important role of geographical proximity for knowledge network formation and for knowledge creation and diffusion (Torre, 2008). Proximity, although usually referring to geographical proximity, may also refer to different dimensions of similarity between the actors in a knowledge network (Boschma, 2005). According to Boschma (2005) actors can be proximate in five different ways: geographically, cognitively, socially, institutionally, and organizationally. Geographical proximity refers to the collocation of actors that can create spontaneous exchange of knowledge (Bathelt et al., 2004). Cognitive proximity is the overlapping of two actors in terms of their knowledge bases, whereas social proximity describes the micro-level embeddedness of actors (e.g. friendship, kinship, experience) (Boschma, 2005). Institutional proximity refers to cases when actors share common institutional and cultural contexts, thus providing stable conditions for knowledge transfer (Boschma and Frenken, 2009, Ponds et al., 2007). Finally, organizational proximity refers to the extent of sharing of organizational arrangements, involving the degree of autonomy and control of the organizational arrangements (Boschma and Frenken, 2009).

In the process of developing emerging technological fields, which are still characterized by considerable uncertainty regarding future development paths, actors may in particular use their networks to learn from other organizations and to access complementary skills. This involves collaboration in order to assess the relevance of (and potentially acquire) knowledge held by actors from other technological fields, or to engage directly in joint projects that provide complementary knowledge. Previous research suggests that geographical proximity is particularly conducive to the establishment of interorganizational collaborations motivated by the aforementioned purposes (Lorentzen, 2008), as they often involve interaction between partners characterized by low cognitive proximity (Hansen, 2014). Thus, geographical proximity may compensate for low cognitive proximity (Garcia et al., 2018). Consequently, the development of an emerging technological field may be affected by the location of the actors involved in the knowledge transfer process. Therefore, we expect geographical proximity to play a significant role in the formation of the new technological field.

While the proximity literature focuses on the possibility for substitution between spatial and non-spatial forms of proximity (Broekel and Mueller, 2018, Fitjar et al., 2016, Hansen, 2015, Kuttim, 2016), it gives little attention to the possibilities for substitution between different types of non-spatial proximity. However, research results indicate that other non-spatial forms of proximity may facilitate collaboration between cognitively distant partners (Werker et al., 2019). Janssen et al. (2019) find that shared organizational membership facilitates collaboration between firms with large cognitive distances. Hence, alongside geographical proximity, we expect institutional and organizational types of proximity will affect the formation of the emerging technological field. Accordingly, we have formulated the following hypotheses:

> H2a: Geographical proximity of actors positively affects the formation of ties in the emerging technological field.
>
> H2b: Institutional proximity of actors positively affects the formation of ties in the emerging technological field.
>
> H2c: Organizational proximity of actors positively affects the formation of ties in the emerging technological field.

2.3 Status (Popularity)

Similarly to embeddedness and proximity, the status (popularity) of an actor is an important driver for knowledge transfer and evolution of technological fields (Luo et al., 2009, Stuart, 1998). The popularity of an actor in social networks constitutes an attractive attribute driving preferential attachment (Barabási and Albert, 1999, Papadopoulos et al., 2012). Preferential attachment is a dynamic process, during which new actors entering the network prefer to connect with already well-connected actors (Barabási and Albert, 1999). This process results in the strengthening of the relative position of certain actors compared with the rest of the actors, augmenting their network status and making them more central (Autant-Bernard et al., 2014).

Popular actors are important for knowledge transfer and the evolution of technologies because they can act as intermediaries (Martin, 2013, Tsouri and Pegoretti, 2020). They accumulate knowledge over time due to their privileged position in the knowledge network and consequently their role becomes central to the evolution of a technology (Autant-Bernard et al., 2014, Wanzenboeck et al., 2014). Actors with high network status benefit from direct or indirect collaboration with a variety of actors and thus they provide a range of opportunities to foster knowledge creation and diffusion processes. Their actions impact the structure and dynamics of the knowledge network, ultimately shaping the dynamics and pace of evolution of the particular technological fields (Balland et al., 2016, Ter Wal, 2014).

Empirical studies addressing actors' status within the knowledge network have typically been limited to the evolution of a technological field and/or a specific network type (Balland et al., 2016, Bauer et al., 2018, Broekel and Graf, 2012, Graf, 2011). However, as popular actors inside knowledge networks have the propensity to tap into and diffuse knowledge, they may play a crucial role in the creation of novel knowledge combinations, the application of those knowledge combinations, and the generation of new technological fields, thereby creating bridges between different knowledge networks (Bathelt and Zeng, 2012, Cassi et al., 2008, Kauffeld-Monz and Fritsch, 2013). Taking into consideration the latter attribute of actors with high network status, we examine whether such actors in established fields play an important role in the development of the emerging technological field. This leads us to the following hypothesis:

> H3: The status (popularity) of actors in established technological fields affects positively the knowledge network of the emerging technological field.

3. Case, data and methods

3.1 The case of green shipping

International shipping is a large and rapidly growing source of greenhouse gas emissions, and these emissions are expected to increase in the years ahead (i.e. due to increasing global trade) unless new energy solutions are successfully developed and implemented. However, it is reasonable to say that the alternatives to fossil fuels are in early phases of development and therefore green shipping can be considered an emerging technological field. There are multiple obstacles to more sustainable shipping (Steen et al., 2019), which is generally considered a hard-to-abate sector, similar to heavy onshore transport and aviation (Sims et al., 2014, Pettit et al., 2018). However, promising developments are occurring in terms of new technology adoption, notably in shipping segments such as coastal ferry services (Bergek et al., 2018).

Among the proposed technological solutions that can contribute to the greening of shipping is the use of biofuels, hydrogen, and battery electric storage systems (DNV GL, n.d.).[1] These alternatives and/or supplements to fossil fuels were under development in other sectors (e.g. road transport) prior to their application in the maritime sector. The same technological fields offer complementary knowledge components to the emerging technological field of green shipping. The European Commission is currently supporting the aforementioned main types of alternative fuels and propulsion technologies, for example by subsidizing R&D projects in order to improve their efficiency and remove market entry barriers (EC, n.d.). For this reason, green shipping is a suitable example for studying how different knowledge components of established technological fields recombine to develop the knowledge network of the emerging technological field.

Figure 1 is a schematic representation of the emergence of the new technological field of green shipping within the traditional field of shipping. The established technological fields of biofuels, electricity storage and battery, and hydrogen constitute related technological fields, as they interact and have applications in shipping, thus contributing to the development of the green shipping technological field. These interdependencies result in different technological trajectories, either complementary or competing, within the emerging technological field (green shipping). With regard to the actor level, section 4 examines the effect of the knowledge

[1] See also http://www.emsa.europa.eu/main/air-pollution/alternative-fuels.html

transfer between actors in the established technological fields of green energy solutions on the knowledge transfer in the entire field of green shipping.

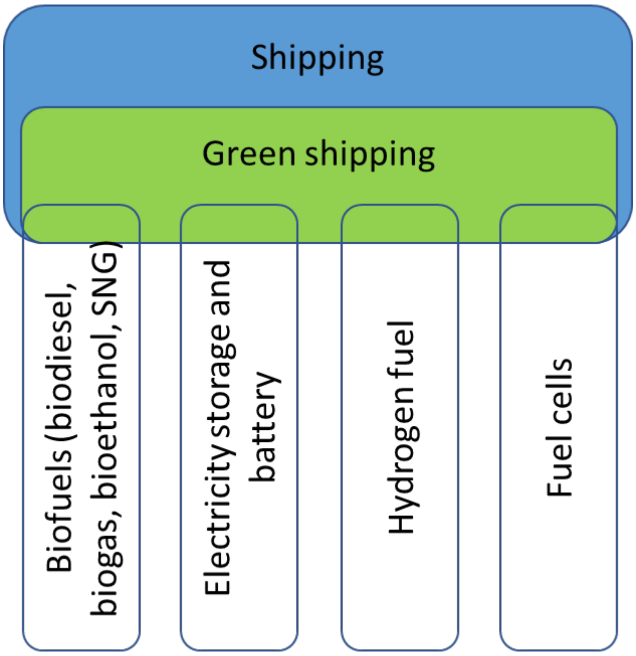

Figure 1 Schematic representation of the emerging technological field of green shipping with the contribution of the established technological fields of biofuels, electricity storage, and battery, fuel cells and hydrogen.

3.2 Data

To test our hypotheses and explore the mechanisms that govern the evolution of the knowledge network of emerging technological fields, we used data on R&D projects funded by the European Commission (CORDIS dataset). We used the R&D projects under the last two EU research framework programs – FP7 and Horizon2020 – and that spanned the twelve-year period from 2007 to 2018. The framework programs followed a scheme based on thematic areas. However, the relevant technological fields spanned several of these categories, so we started by identifying relevant projects through keyword searches. We identified all projects on shipping with alternative (green) fuels and/or energy carriers (hereafter referred to as green fuels) and labelled the category 'green shipping'. We also identified all R&D projects related to the established technological fields of biodiesel, bioethanol, biogas, synthetic natural gas

(SNG), electricity storage and battery, hydrogen fuel, and fuel cell. We include projects in these fields irrespective of application sector, also outside shipping, the application sector of our study. To isolate all projects that covered one of the above-mentioned technological categories, we performed a keyword filter in the project abstracts. Then we performed content analysis of the selected abstracts.

We identified 1136 EU-funded R&D projects (i.e. in the period 2007–2018) with a total of 3719 participating actors in the project categories. Based on the information on project participants, we created eight knowledge networks, each corresponding to one of the categories. The actors are considered connected if they participated in a project together (Autant-Bernard et al., 2007, Cantner and Graf, 2006). In terms of partner selection, the European framework programmes had a rather simple and basic constraint, namely the partners had to be located in at least two different EEA countries. This could possibly have biased the results in the selection of geographically distant or proximate partners. However, for the thematic areas of the projects included in our categories our stipulated requirement was at least four collaboration partners. With regard to project selection, the collaborative partners were numerous, which enabled us to draw unbiased conclusions from our knowledge networks (Autant-Bernard et al., 2007).

The sizes of the knowledge networks of the project categories, as well as the overlapping of projects and actors with regard to each green fuel with the actors of the green shipping knowledge network are presented in Table 1. The networks of the different green fuels varied in size and the extent to which they overlapped with the green shipping knowledge network. The biodiesel, bioethanol and SNG networks were smaller than the rest of the networks. Few actors were participating in both biodiesel and green shipping networks, while there were no overlapping projects during the period 2007–2018. Therefore, we excluded projects on biodiesel from the dataset.

Table 1 Network size and overlaps between networks in terms of projects and actors.

Knowledge networks	No. projects 2007–2018	Overlapping projects with green shipping (2007–2018)		No. actors 2007-2018	Overlapping actors with green shipping (2007–2018)	
		Green fuels (2007–2018)	Green fuels (2007–2013)		Green fuels (2007–2018)	Green fuels (2007–2013)
Green Shipping	82	–	–	586 (209)	–	–
Biodiesel (excluded)	52	0	0	308	29	15
Bioethanol (excluded)	46	1	0	277 (127)	49 (37)	28 (17)
Biogas (excluded)	111	1	0	591 (213)	55 (51)	42 (25)
Electricity storage and battery	409	16	8	1771 (617)	148 (114)	109 (95)
Fuel cells	343	11	7	967 (470)	92 (85)	76 (75)
Hydrogen	343	11	7	965 (480)	100 (94)	78 (76)
SNG	53	3	2	300 (153)	53 (46)	37 (35)

For the analysis we included only the actors that participated in more than one project during the entire period (2007–2018). We made this choice to ensure that we included actors that repeat a collaboration by participating in a later project. The dataset included the entire population of actors participating in EU-funded R&D projects on green shipping, biofuels (except biodiesel), hydrogen fuel, fuel cells, and electricity storage and battery, based in countries of the European Economic Area (EEA, comprised the EU member states plus Norway, Switzerland and Iceland) in the years 2007 to 2018 inclusive. To allow for dynamic analysis of the data, we divided the data into two periods according to the year in which the projects started. The first period covered 2007–2013 (corresponding to FP7), while the second period spanned 2014–2018 (corresponding to Horizon2020). During FP7 bioethanol and biogas projects proved to have few common actors, and did not overlap with the green shipping network for the entire period (2007–2018). Moreover, the analysis showed that there were no overlapping ties between the bioethanol and biogas networks (2007–2013) and the green shipping network (2007–2018). Accordingly, we excluded these two categories.

3.3 Methods

Social Network Analysis (SNA) is the method for analysing social structures by using network and graph theory. It represents the social structures in terms of nodes (individuals, firms, events) and ties between them (relationships, interactions). We depicted the data in a network form, in which actors were represented as nodes, whereas collaborations, which indicated knowledge transfer, were represented as ties. In that way, the data could be summarized in nine one-mode square sociomatrices (actor × actor): the 'green shipping' sociomatrix depicted the network of green shipping for the entire period (2007–2018), and two sociomatrices for each green fuel (SNG, electricity storage, fuel cells, and hydrogen) respectively covered the periods 2007–2013 and 2014–2018.

Longitudinal and dynamic analysis of network data, notably in terms of explaining how knowledge network structures change over time, presents certain difficulties. Due to their nature, network data violate basic assumptions in most standard econometric techniques. As all actors are members of the same network, the observations are not independent and the models suffer from structural autocorrelation and excess of zeros (Snijders et al., 2010). To overcome this problem, we used stochastic actor-oriented models (SAOMs), implemented in the RSiena software treated network data as 'snapshots' repeated in continuous time, similarly to panel data. SAOMs are based on Markov's process in continuous time, estimated with the method of moments through Monte Carlo simulations. The Monte Carlo algorithm produces a number of simulated networks, estimating the parameters that minimize the deviation between the original network and the simulated networks (Balland et al., 2016, Snijders et al., 2010).

When the simulations converge to the original network, the parameters are kept constant for calculating the standard errors. We used SAOMs because they perform dynamic network analysis in actor, dyad, and structural levels. Due to these characteristics we were able to use entire networks as variables and examine how one network affected the evolution of another network.

3.4 Networks as variables

Following the methodology proposed by Balland et al. (2016), we used actor, dyadic and structural effects as variables. The most significant difference was that we examined how other knowledge networks, such as green fuels and/or energy carriers (their evolution and elements), affected the evolution of a new technological field (green shipping). Given that we analysed multiple networks, we defined green shipping (2007–2018) as the dependent variable, while the remaining eight knowledge networks constituted explanatory variables. To express multiple network effects (when the structure of one network affected the evolution of another network), we represented the dependent variable with the tie variables denoted as x_{ij}, while the tie variables denoted by w_{ij} represented the network of an explanatory variable (Ripley et al., 2018).

Our aim was to explain the evolution of the green shipping knowledge network during the entire period under consideration (2007–2018). We wanted to understand how collaborations between actors in green shipping (dependent variable) evolve and therefore changed between FP7 (2007–2013) and Horizon2020 (2014–2018). This was expressed by the rate of change (non-existing ↔ existing ties) for the network, from FP7 to Horizon2020. Our explanatory variables and effects were derived from the evolution of the established fields (SNG, electricity storage, fuel cells and hydrogen) during FP7 (2007–2013). In that way we detected how the early evolution of established knowledge networks shaped the knowledge network of green shipping during a later period (2014–2018).

Social embeddedness. This variable was used to estimate how established knowledge networks shaped the knowledge network in the emerging field (H1a). To express this property, we employed the rate of change (non-existing ↔ existing ties) of the established knowledge networks (SNG, electricity storage, fuel cells, hydrogen) during FP7. It is portrayed by the change of a tie between nodes i and j of one network W (that is $i \overset{W}{\rightarrow} j$), leading to a change of a tie between nodes i and j of another network X (that is $i \overset{X}{\rightarrow} j$).

Structural embeddedness. This variable showed the probability that two actors, which were connected with a third actor in the established networks, were connected in the new network (H1b). In single network evolution structural embeddedness is usually represented by triadic closure, whereas in multiple network setting structural embeddedness can be operationalized with the effect of closure of shared ties: $\sum_{j \neq h} x_{ij} w_{hi} w_{hj}$. This refers to the shared W ties of the established knowledge network (explanatory variable) contributing to the tie $i \overset{X}{\rightarrow} j$, of the green shipping knowledge network (dependent variable).

Proximity. We examined the effects of geographical (H2a), institutional (H2b), and organizational (H2c) dimensions of proximity. These variables were dyadic explanatory variables, added as constant dyadic dummy covariates. Geographical proximity takes the value one when two actors were located in the same region (NUTS2), otherwise it takes the value zero. Institutional proximity takes the value one if two agents were located in the same country, as they are acting under the same institutional context, otherwise it takes the value zero. Finally, organizational proximity takes the value one when two actors were of the same organizational type (universities, research centres, private firms, public agencies, other types of organizations), and zero otherwise. The three dyadic covariates were treated as constant. The geographical location, institutional setting, and organizational kind of an actor can change over time. However, such change does not happen easily and is considerably slower than the change in the collaborations between the actors (Broekel, 2015).

Status. We examined the effect of the actors' status in the established knowledge networks on the ties of the green shipping network (H3). This refers to a preferential attachment mechanism (Barabási and Albert, 1999) whereby new actors in a network connect with already central actors, which augments the central actors' popularity. In studies of single network evolution conducted to date this concept has been operationalized by endogenous degree centrality (popularity effect) (Balland et al., 2016). However, this was problematic in our case, for two reasons: (1) in a multiple network context, actor popularity is not endogenous to the dependent network, but refers to the popularity of actors in the explanatory networks, and (2) the R&D project data we used would give a false indication of the degree of actor centrality, as this measurement depends heavily on the size and numbers of partners in projects. Therefore, a more global centrality measurement is needed, the eigenvector centrality (Bonacich, 2007). Eigenvector centrality measures the influence of a node in the network and is an enhanced measure of degree centrality, based on the assumption that connections to more centrally positioned actors contribute more to the popularity of the actor under consideration compared with connections to peripheral nodes. We operationalized eigenvector centrality of actors, adding the eigenvector centrality score as a covariate variable. We measured the eigenvector centrality of actors for the knowledge networks of green fuels during the period 2007–2013 and examined its effect on the green shipping knowledge network for 2014–2018.

Control variables. As we were dealing with undirected networks, we did not differentiate between in- and out- degree. Therefore, we could not use these types of controls. We examined the effect that the density of the established networks had on the evolution of the new network. This effect measures the overall tendency of actors to create ties. We also used another type of control, namely the basic rate parameter of the green fuel networks, representing the amount of network change through time for each established knowledge network.

4. Empirical analysis

The descriptive statistics of the dyadic variables and the correlation between them are shown in Table 2. All variables were dummy variables, taking only the values 0 and 1. Neither the explanatory variables, nor the proximity variables were highly correlated. Most of the dyadic variables positively affected each other, but the magnitude of the effect does not appear to have been large.

Table 2 Descriptive statistics and correlations of the dyadic variables used in the analysis.

	Min	Max	Mean	SD	Gr. Ship	El. Stor	F. Cell	Hydrogen	SNG	Geo. Prox.	Inst. Prox.
Green shipping 2007–2018	0	1	0.005	0.073	–	–	–	–	–	–	–
Electricity storage 2007–2013	0	1	0.01	0.101	0.011	–	–	–	–	–	–
Fuel cells 2007–2013	0	1	0.007	0.085	0.015	0.13	–	–	–	–	–
Hydrogen 2007–2013	0	1	0.007	0.084	0.016	0.088	0.585	–	–	–	–
SNG 2007–2013	0	1	0.002	0.04	0.014	0.054	0.072	0.178	–	–	–
Geographical proximity	0	1	0.01	0.101	0.015	0.026	0.019	0.02	0.007	–	–
Institutional proximity	0	1	0.085	0.279	0.007	0.016	0.021	0.017	0.004	0.335	–
Organizational proximity	0	1	0.372	0.483	0.002	-0.011	-0.006	-0.005	-0.006	0.013	0.018

To explain the evolution of green shipping network over time and to test our hypotheses, we employed the model described in the preceding section. The results of the analysis are presented in Table 3. All estimations of the parameters were based on 1000 simulations, an amount that is considered reliable (Balland et al., 2016, Snijders et al., 2010). The overall convergence rate of the model is 0.1742 < 0.8, while the convergence ratios of each variable are less than 0.1, making the algorithm approximation excellent. As the underlying idea behind the model is the effect of the rate of change (non-existing ↔ existing ties) of the established networks on the rate of change in the dependent network, the coefficients are interpreted as log-odds ratios of the time formation. In other words, they represent how the log-odds ratio of the dependent network will change with the change of one unit in the explanatory variables.

Table 3 Analysis of the evolution of green shipping technological field (2007–2018)

Dependent variable: Green shipping 2007–2018			
	Coefficients	Standard Errors	p-values
Social embeddedness:			
Electricity storage 2007–2013	0.5992*	0.2786	0.0842
Fuel cells 2007–2013	0.4180	0.4387	0.3844
Hydrogen 2007–2013	-0.0678	0.4218	0.8771
SNG 2007–2013	1.1401**	0.3992	0.0356
Structural embeddedness (X: mixed from W):			
Electricity storage 2007–2013 (str.emb)	0.4332***	0.0682	0.0014
Fuel cell 2007–2013 (str.emb)	0.3321*	0.1430	0.0679
Hydrogen 2007–2013 (str.emb)	-0.0369	0.1295	0.7871
SNG 2007–2013 (str.emb)	0.4952***	0.0741	0.0011
Proximities:			
Geographical proximity	0.0454	0.2356	0.8549
Institutional proximity	0.2879*	0.1162	0.0560
Organizational proximity	0.3555**	0.103	0.0182
Status (eigenvector centrality):			
Electricity storage 2007–2013	-0.3608	0.4006	0.4091
Fuel cells 2007–2013	-0.3695	0.7951	0.6617
Hydrogen 2007–2013	0.1526	0.9976	0.8845
SNG 2007–2013	1.768***	0.2333	0.0006
Controls:			
Degree (density) green shipping 2007–2018	-4.0707***	0.1186	< 0.0001
Rate green shipping 2007–2018	22.2581***	1.172	< 0.0001
Rate electricity storage 2007–2013	4.8573***	0.0848	< 0.0001
Rate fuel cell 2007–2013	3.3765***	0.0707	< 0.0001
Rate hydrogen 2007–2013	3.4175***	0.0664	< 0.0001
Rate SNG 20072013	0.7627***	0.0305	< 0.0001
Significance: *p<0.1, **p<0.05, ***p<0.01			

Hypothesis H1a refers to the social embeddedness of green fuels' knowledge networks on the knowledge network of green shipping. This is shown by the effect on the change in ties of the green shipping network (2007–2018) by the change in ties of the green fuels' knowledge networks. This effect represents the shaping of the knowledge network of the new field. Interpreting the significance of the p-values for every knowledge network (2007–2013) of every green fuel, it appears that the change of ties in all of them did not significantly affect the change of knowledge ties in the new technological field, although all of the coefficients were positive. The change in the knowledge ties of the established fields of SNG and electricity storage and battery had a significant positive effect on the evolution of the green shipping network. The two coefficients were both significant but of different intensity (electricity storage and battery = 0.5992 and SNG = 1.1401). Both the SNG and the electricity storage and battery networks constituted strong drivers for the evolution of green shipping network, suggesting that ties in early electricity storage and battery and SNG networks (2007–2013) mattered for the evolution of the ties in the green shipping knowledge network. Hypothesis H1a is only confirmed for the electricity storage and battery and SNG networks, as we did not observe any standard pattern.

Similarly, hypothesis H1b refers to the structural embeddedness of the change of ties in the green shipping knowledge network (2007–2018) on the weak ties and structural holes of the established green fuels knowledge networks (2007–2013). Overall, structural embeddedness was a strong driver towards the shaping of the green shipping knowledge network, confirming hypothesis H1b, with the exception of the hydrogen fuel network. More specifically, when one actor was connected with two other actors in the knowledge networks of electricity storage and battery (= 0.4332), fuel cells (= 0.3321), and SNG (= 0.4952), this significantly affected the connection of those two actors in the green shipping knowledge network. The SNG network had the strongest effect on structural embeddedness in terms of significance and intensity.

Further, the geographical proximity of the actors did not seem to affect the evolution of green shipping knowledge network. We used collocation of actors at NUTS2 level, assuming that two actors that are located in the same region were geographically proximate, thereby rejecting hypothesis H2a. However, institutional proximity significantly affected the evolution of the green shipping knowledge network (= 0.2879), confirming hypothesis H2b. We defined institutional proximity as occurring when two actors were located in the same country, acting in the same institutional setting (e.g. laws, norms, language). Finally, an important determinant for the evolution of the green shipping knowledge network was when actors shared the same organizational structure (= 0.3555). When two actors were of the same organizational type, they were more likely to create a tie in the green shipping knowledge network, thus confirming hypothesis H2c.

In terms of the actors' status in the established knowledge networks of green fuels, their eigenvector centrality did not seem to affect the evolution of the green shipping network, thus in general leading to our rejection of hypothesis H3.[2] The only exception was the eigenvector centrality of actors in the SNG knowledge network (= 1.768), which had a significant positive effect on the change of ties in the green shipping knowledge network, in this case confirming hypothesis H3. As an enhanced measure of degree centrality, eigenvector centrality shows the connectivity of an actor with other central actors in the network. In other words, the status of an actor in the SNG knowledge network, positioned in such a way that it is connected with central actors, affects the evolution of the green shipping network.

All control variables in the model are significant. The density of the green shipping network had a negative effect on the evolution of the network. The value of the density parameter was not very important, as it correlated with all other statistics, which made it difficult to interpret. The basic rates of all of the networks were positive and significant, but the basic rate referred to the effect they had on the evolution of their own networks. For example, the basic rate of green shipping (rate green shipping 2007–2018) referred to the rate of change of ties (evolution) of the green shipping knowledge network. This specific rate was positive and

[2] We controlled the robustness of the results of status repeating the model with degree centrality, and the results were similar in significance. However, degree centrality with data on R&D projects does not reflect the real status of an actor, as it can be affected by the size of project.

significant, and therefore important, showing a significant amount of endogenous evolution in the green shipping network and in turn signifying strong path dependency.

5. Conclusions

The evolution of knowledge networks has received considerable attention in the geography of innovation literature in the last decade (Balland et al., 2016, Bauer et al., 2018, Ter Wal, 2014). Research has focused on the evolution of single technological fields and their knowledge networks (Ahuja et al., 2012, Balland et al., 2019, Broekel and Boschma, 2012, Giuliani et al., 2019), while there has been no evidence for how knowledge is transferred across technological fields. However, the latter is important for the generation of new knowledge and the emergence of new technological fields (Wagner et al., 2019).

The purpose of our paper is to address this gap. We have identified different mechanisms that influence the evolution of the knowledge networks of technologies – embeddedness, proximity and status – that represent actor relations and the structural characteristics of the knowledge networks (Ahuja et al., 2012, Balland et al., 2016). We have explored how these mechanisms work across technological fields, recombining existing knowledge and creating diversified knowledge networks, and thus how they contribute to foster the development of knowledge networks in emerging technological fields. In this paper we have presented evidence of how these mechanisms play different roles in the formation of the emerging technological field, by (re)combining the knowledge existing in established related technological fields.

Empirically, we have explored the emerging field of green shipping, and the different green fuels (electricity storage and battery, hydrogen, fuel cells, and SNG) as established fields, which through their application in shipping contribute to the development of the new field. We have demonstrated that some mechanisms in green fuel networks, such as structural embeddedness and different dimensions of proximity, are strong drivers for the evolution of the emerging green shipping field.

In order to form ties in the network of the new technological field or to repeat ties created in the established technological fields, actors invest effort, trust and resources. The actors involved in green shipping were to different degrees embedded in the knowledge network of the analysed green fuel networks. The actors in the green shipping network were both structurally and socially embedded in the established technological fields of electricity storage and battery and SNG. This shows that the social ties and the structure of the knowledge network of established technological fields affect the creation of the new field. The actors exploited both strong and weak ties in the electricity storage and battery and SNG knowledge networks to form or reinforce relationships in the green shipping network. Additionally, structural embeddedness in the fuel cell R&D network influenced network formation in green shipping. In other words, actors in the green shipping network tended to connect with friends of friends from the fuel cells network. However, they did not consider any type of embeddedness in the hydrogen fuel field in the creation of the green shipping field. These findings are in line with the literature suggesting that embeddedness is a key driver for the formation of interorganizational networks (Balland et al., 2016). In our case, looking at knowledge recombination across technological fields, we found variance in the degree of actor embeddedness in the different established technological fields and how it affected the formation of the emerging technological field network. However, in general we found that structural embeddedness had a more intense effect than social embeddedness. The strong effect of structural embeddedness, expressed by triadic closure in the emerging knowledge network, highlights the importance of the weak ties in the established networks (Ter Wal, 2014). Weak ties constitute important knowledge sources for the early stage of the emerging network.

The literature on the evolution of knowledge networks in single technological fields suggests that status is an important driver, as knowledge is concentrated in few actors (Balland et al., 2016, Giuliani, 2013). However, this is not the case across technological fields. The only green fuel for which the status of an actor is important for the emergence of the green shipping field is SNG. Thus, in general, network formation in an emerging technological field is not driven by the status of actors in existing technological fields. In other words, we have shown empirically that preferential attachment does not appear to work as a driver across fields, thus suggesting that reputation and information about who is reportedly knowledgeable does not travel across technological fields. Although the status of the actors in certain established networks (e.g. SNG) may affect the evolution of the new network, in general actors venturing into a new technological field rely more on other drivers than their own popularity in established fields.

The effects of the different dimensions of proximity vary for the formation of the knowledge network of the emerging technological field. In contrast to the positive effect that geographical proximity has been shown to have on the evolution of established technological fields (Ter Wal, 2014), the geographical proximity of the actors did not affect the evolution of the emerging field in our study. Ter Wal (2014) suggests that geographical proximity plays an important role in the formation of knowledge networks at early stages, but this happens in the case of a single technology. In this setting, actors are more likely to know each other when they are geographically close, and the localization element is reduced in importance when knowledge starts to become widely diffused in the field. However, our focus was on the role of knowledge recombination across technological fields for the emergence of a new field, since (re)combination of existing knowledge from established fields has been shown to be important (König et al., 2011, Wagner et al., 2019). Taking this into consideration, our findings reveal that geographical proximity does not seem to play an important role in knowledge network formation under such circumstance. These new knowledge components can be very geographically dispersed, rare and difficult to acquire, which might explain why geographical proximity of actors does not play an important role in the formation of relationships between actors in the emerging technological field.

Instead of geographical proximity, we found that institutional proximity played an important role in the formation of the ties in the emerging field. In some cases, geographical and institutional proximity appear to substitute each other (Autant-Bernard et al., 2007, Ponds et al., 2007). Undoubtedly, a set of common laws, norms or culture facilitates the transfer of knowledge between actors. Being under the same institutional context enhances the necessary trust between actors for the emergence and evolution of the new technological field, compensating for the lack of geographical proximity. Similarly, organizational proximity of actors enables the formation of ties in the emerging technological field. Organizational proximity can substitute for geographical proximity (Broekel and Mueller, 2018, Cassi and Plunket, 2015, Lorentzen, 2008), as interacting with similar types of organizations provides agents with the necessary trust and reliability for collaborating in an emerging technological field.

Overall, we did not find an identifiable pattern in the effect of all the established networks on green fuels. In other words, the evolution of each network of green fuels affected the evolution of the green shipping knowledge network in different ways. The factors behind this differentiation remain still to be examined in future research. Potentially influential factors include the different levels of maturity of the related technologies, and thus the degree of applications to other sectors, their relatedness and compatibility with the emerging technological field, or whether the knowledge networks of the established technological fields include specific actors in privileged positions that are capable of transferring their properties to the new technological field.

In general, our findings are in line with the existing literature on knowledge network evolution and the way that the mechanisms of embeddedness, status and proximity function (Ahuja et al., 2012, Balland et al., 2016). However, with regard to the interaction across technological fields, their effect and importance is varied. All three mechanisms in the established technological fields have positive effects on the emergence and evolution of the new field. However, the significance and intensity of this effect depends heavily on the particular characteristics of the established field (Balland et al., 2016).

Furthermore, the interactions between established and emerging technologies, which we have studied from a knowledge network perspective, is an important theme in sustainability transitions studies. Hence, future research could connect these studies more strongly, for instance by investigating how network dynamics evolve across technological fields with differing interactions modes (e.g. complementary interactions, whereby technologies positively influence each other, as opposed to competitive interactions whereby technologies can influence each other negatively). This could contribute to a better understanding of why certain technologies gain momentum and develop successfully whereas other technologies do not. Moreover, in the context of technology and knowledge related to sustainability (as in the case of green shipping), the factors enabling or constraining the generation of novelty may be highly influenced, for example by strong opposition from actors with vested interests in existing industries and technologies (e.g. in fossil fuels). How this form of opposition potentially influences the development of knowledge networks for emerging environmental innovation both across sectors and space is an interesting topic for future research.

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