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Knowledge recombination for emerging technological innovations: The case of green shipping

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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. Previous research has demonstrated that embeddedness, proximity, and status are important mechanisms for the evolution of single technological fields. We investigate if these mechanisms also apply across technological fields. By employing dynamic social network analysis models, we find 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 and proximity played an important role, status was less important.

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 established technological fields is (re)combined in the development of possible 'solutions', thereby creating the emerging technological field (Antonelli et al., 2020; König et al., 2011). 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).

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; Salavisa et al., 2012; Ter Wal, 2013). Much of the recent literature 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; Giuliani, 2013; Ter Wal, 2013, 2014). Similarly, collaboration in emerging technological fields does not develop in isolation, but it is likely influenced by prior collaboration between organizations in established technological fields. However, there is scant evidence for which mechanisms influence the knowledge transfer across technological fields, and particularly what role knowledge networks in established technological fields play in the formation of knowledge networks in new technological fields.

The present work is an exploratory paper that empirically addresses this exact gap in the literature. Our first objective is to analyse how knowledge evolves and (re)combines across technological fields and over time to contribute to the knowledge network of a new technological field. Our second objective is to examine whether and how the mechanisms identified as central to knowledge network evolution within single fields, also influence evolution across technological fields. Specifically, we examine the role of embeddedness, proximity and status (Balland et al., 2016) for knowledge network evolution processes within and across fields.

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. We employ R&D data from the last two European framework programmes. In order to capture the (re)combinatory knowledge development, we analyse projects that have

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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 remainder 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 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 (Iammarino and McCann, 2006; Verspagen, 2007). Emerging technologies require new knowledge, which is created from novel (re)combinations of existing knowledge elements (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).

Within evolutionary economic geography, the ways in which economies evolve over time has been premised first and foremost on the argument that innovation and new knowledge tends to develop mainly on the basis of the existing knowledge base (Boschma and Frenken, 2006; Cheng, 2012). The 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 and how that has developed over time (Boschma, 2017). For the emergence of new technological fields, knowledge relatedness is necessary; either relatedness defined in terms of similarity, when the same knowledge is used in different technological fields, or in terms of complementarity, when different knowledge (re)combine to form new technological fields (Boschma, 2017; Broekel and Brachert, 2015).

Thus, this evolutionary characteristic of knowledge development also underpins the path-dependent manner in which 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 economies become locked-in to industrial paths. Path dependence in these terms implies evolution, rather than continuity, inertia and consequently lock-in situations (Martin, 2010). 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. This shift in knowledge path is needed in particular to support a transition from unsustainable to sustainable technologies, for instance in the areas of energy or transport. Due to the path dependence governing the technological change, (re)combination of knowledge of established “green” technological fields can make this technological shift easier to accomplish (Santoalha and Boschma, 2021; van den Berge et al., 2020).

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 (Balland et al., 2019; Cassi and Plunket, 2015; Tödtling et al., 2009). 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). While recent studies explore these mechanisms in a dynamic way (Balland et al., 2016; Bauer et al., 2018; Ter Wal, 2014), 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.

To identify the different technologies, we use the concept of technological fields, which is often used but rarely defined in the literature. Here we follow Peine (2009) and define a technological field as a “recognized area of technologies in which a specific set of components is repeatedly configured into systems.” The concept is thus quite open in that a technological field can be broad or narrow in technological variants and application domains (Markard et al., 2015). A timely question, therefore, is if 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? In the following we develop three sets of hypotheses to investigate these 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. 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 inter-organizational trust, thus enabling knowledge transfer (Ahuja et al., 2012; 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; Wen et al., 2021). 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 complementary 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; 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.

Therefore, we examine the effect of both social and structural embeddedness on knowledge network evolution across technological fields. For social embeddedness, we assume that existing relationships of actors in the knowledge network of established technological fields are transferred to the knowledge network of the emerging technological field, 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 established technological fields' knowledge networks positively affects the formation of ties in the emerging technological field's knowledge network.

H1b. Structural embeddedness in established technological fields' knowledge networks positively affects the formation of ties in the emerging technological field's knowledge network.

2.2. Proximity

Proximity refers to the relational property of connected actors as being close in terms of having similar characteristics. Proximity mechanisms of different types reduce uncertainty and thereby enable knowledge transfer and network formation, as well as innovation (Balland et al., 2016; Broekel and Boschma, 2012; 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. 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. 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). Institutional proximity refers to cases when actors share common institutional and cultural contexts, thus providing stable conditions for knowledge transfer. Finally, organizational proximity refers to the extent of sharing of organizational arrangements, involving the degree of autonomy and control of the organizational arrangements.

Previous research has focused on the role of geographical proximity for the establishment of inter-organizational collaborations, and the relations between geographical and non-geographical proximity dimensions (Garcia et al., 2018; Hansen, 2014, 2015). While proximity literature considers the possibility for substitution of non-spatial dimensions for geographical proximity (Broekel and Mueller, 2018; Fitjar et al., 2016; Hansen, 2015; Kuttim, 2016), it gives little attention to the possibilities for substitution between the different non-spatial proximity dimensions. Indeed, Werker et al. (2019) suggest that other non-spatial dimensions of proximity may facilitate collaboration between cognitively distant partners.

Particularly, in the process of developing emerging technological fields, which are still characterized by considerable uncertainty regarding future development paths, actors may 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. Hence, we expect that institutional and organizational types of proximity will affect the formation of the knowledge network of the emerging technological field. Accordingly, we have formulated the following hypotheses:

H2a. Institutional proximity of actors positively affects the formation of ties in the emerging technological field's knowledge network.

H2b. Organizational proximity of actors positively affects the formation of ties in the emerging technological field's knowledge network.

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). The status (popularity) of an actor in social networks constitutes an attractive attribute driving preferential attachment. This 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). Actors with high network status benefit from direct or indirect collaboration with a variety of actors and 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 single technological field and/or a specific network type (Balland et al., 2016; Bauer et al., 2018; Broekel and Graf, 2012). However, as popular actors have the propensity to tap into and diffuse knowledge, they may play a crucial role for novel knowledge (re)combinations, thereby creating bridges between different knowledge networks (Cassi et al., 2008; Kauffeld-Monz and Fritsch, 2013). Therefore, we examine whether actors with high network status in established technological fields play an important role in the development of the emerging technological field and its knowledge network. This leads us to the following hypothesis:

H3. The status (popularity) of actors in established technological fields affects positively the formation of ties in the emerging technological field's knowledge network.

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 (Bach et al., 2020), which is generally considered a hard-to-abate sector, similar to heavy onshore transport and aviation (Pettit et al., 2018). However, promising developments are occurring in terms of new technology adoption, notably in shipping segments such as coastal ferry services.

The proposed technological solutions that can contribute to the "greening" of shipping are many and include for instance changes in design, materials and technologies that can allow for more efficient operations. The main challenge for shipping is however to switch from fossil fuels to alternative energy solutions with lower or zero carbon emissions (ABS, 2021). These alternative energy solutions include biofuels, hydrogen, fuel cells and battery electric storage systems (DNV, GL, n.d.), which we focus upon in this paper.[1] These alternatives and/or supplements to fossil fuels were under development in other application domains (e.g. road transport, power, heating) prior to their application in shipping, which is essential given the purpose of the paper to examine the recombination of knowledge from established technological fields into an emerging technological field. For example, hydrogen has been applied in microgeneration in Japan and forklifts in the US, while battery electric storage, such as lithium batteries, found early niches in military and consumer electronics sectors in the 70s, before starting to diffuse into for example automobiles (Dijk et al., 2013; Scrosati, 2011; Staffell et al., 2019).

These technological fields offer related and 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.

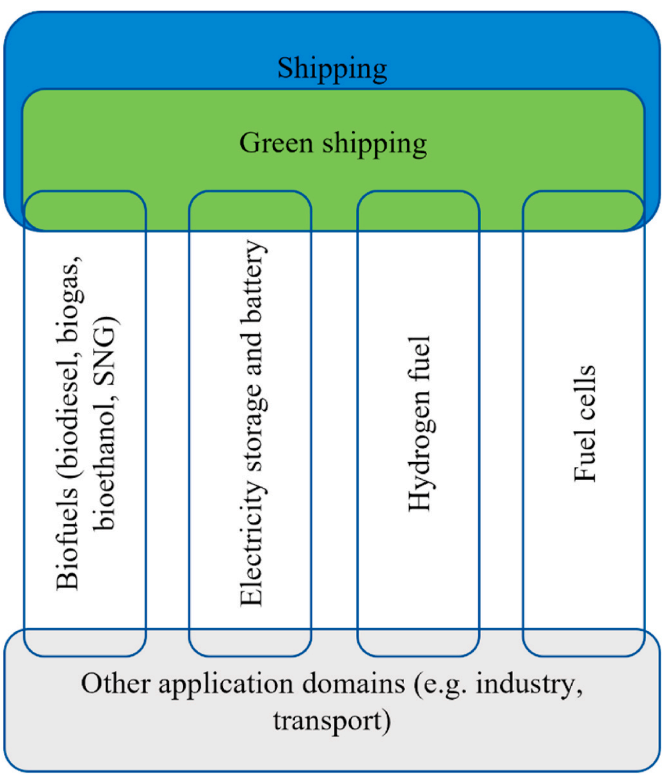

Fig. 1. Schematic representation of the emerging technological field of green shipping with the contribution of the established technological fields of biofuels, electricity storage and battery, fuel cells and hydrogen. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

Fig. 1 is a schematic representation of the emerging technological field of green shipping within the traditional field of shipping. The established technological fields of biofuels,[2] electricity storage and battery, and hydrogen and fuel cells constitute related technological fields that are also associated with other application domains (e.g., land based transport, power, heating). These interact with, and are applied in, shipping and thereby contribute 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). Regarding the actor level, section 4 examines the effect of the knowledge transfer between actors in the established technological fields of green energy solutions on the knowledge transfer in the entire field of green shipping.

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 – 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 (‘propulsion’, ‘marine’, ‘vessel’, ‘engine’, ‘ship’, ‘boat’ and combinations between them) and content analysis. 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 cells. We include projects in these fields irrespective of application sector, i.e., also outside the application sector (shipping) of our study. To isolate all projects that covered one of the above-mentioned technological categories, we performed keyword searches in the project abstracts (‘biogas’, ‘biodiesel’, ‘bioethanol’, ‘electricity storage’, ‘electric storage’ ‘battery’, ‘fuel cell’ ‘hydrogen’, ‘synthetic natural gas’, ‘SNG’). Then we performed content analysis of the selected abstracts.

We identified 1136 EU-funded R&D projects (i.e., in the period 2007–2018), in which a total of 3719 actors participates. 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). 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 the identified 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

[1] Note that also other alternative energy solutions to conventional (marine) fossil fuels exist for shipping, including liquefied natural gas, ammonia, methanol, and also wind-propulsion (sails, kites etc.).

[2] Biofuels covers the technological fields of bioethanol, biogas, biodiesel and synthetic natural gas among others. We selected these specific biofuels, as we test the knowledge network of each alternative fuel separately, to examine whether they constitute related or unrelated (established) technological fields vis-à-vis the emerging technological field of green shipping. We included the entire population of actors for each related established technological field in our analysis.

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.

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 2007–2018 inclusive. Therefore, the entire population of actors included in the analysis is 981 actors that participate in at least one knowledge network and in at least two projects. 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 Horizon 2020). 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

Using Social Network Analysis (SNA), 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 ten one-mode square sociomatrices (actor × actor) of the same size, including the entire population of actors: the 'green shipping' sociomatrix depicted the network of green shipping for the entire period (2007–2018), one sociomatrix depicted the network of green shipping for the period 2007–2013, and two sociomatrices depicted 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), a permutation method that does not assume variable independence. Implemented in the RSiena software network data is treated as 'snapshots' repeated in continuous time, similarly to panel data (Balland et al., 2016; Snijders et al., 2010). 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 examined both the evolution of the knowledge network of the emerging technological field (green shipping) and the effect of knowledge networks of established technological fields on the evolution of the green shipping knowledge network. We defined green shipping (2007–2018) as the dependent variable in both models examined. 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 Horizon 2020 (2014–2018). This was expressed by the rate of change (non-existing ↔ existing ties) for the network, from FP7 to Horizon 2020. Our explanatory variables and effects were derived from the evolution of the early emerging network of green shipping (2007–2013) in the first model, and of the knowledge networks of the established fields (SNG, electricity storage, fuel cells and hydrogen) during FP7 (2007–2013) in the second model.

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 $i \xrightarrow{W} j$), leading to a change of a tie between nodes i and j of another network X (that is $i \xrightarrow{X} j$).

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 settings 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 $i \xrightarrow{X} j$, of the green shipping knowledge network (dependent variable).

Proximity. We examined the effects of institutional (H2a), and organizational (H2b) dimensions of proximity. These variables were dyadic explanatory variables, added as constant dyadic dummy covariates. Institutional proximity takes the value one if two agents were located in the same country, as they are acting under the same

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

Knowledge networks	No. Projects	Overlapping projects with green shipping (2007–2018)		No. actors	Overlapping actors with green shipping (2007–2018)	
	2007–2018	Green fuels (2007–2018)	Green fuels (2007–2013)	2007–2018	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)

institutional context, otherwise it takes the value zero. 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 two dyadic covariates were treated as constant. The 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 status 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 degree 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. Controlling for the effect of geographical proximity on the green shipping network evolution, we use a dummy matrix which takes the value one when two actors were located in the same region (NUTS2), otherwise it takes the value zero. As a status control we have used the degree centrality of the actors in the green fuel networks. Finally, in order to control for the effect of triads in the green fuel networks and how they affect the change of a tie in the green shipping network, we use the basic effect of triadic closure.

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.

To explain the evolution of green shipping network over time, we first explore the dynamics of the emerging network (green shipping). We employed the model described in the preceding section, testing the effect of the rate of change (non-existing ↔ existing ties) during the early period of the emerging technology on the rate of change (non-existing ↔ existing ties) of the entire green shipping network (2007–2018). 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 $0.2898 < 0.8$, 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 explanatory network 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.

The results of the analysis confirm the effect of the three mechanisms (embeddedness, proximity and status) in the evolution of the green shipping field. The rate of change (non-existing ↔ existing ties) of the early network of green shipping significantly affects the later formation of the technological field. However, in the formation of an emerging technological field, like green shipping, the contribution of established technological fields is important. Therefore, we test the effect of the rate of change (non-existing ↔ existing ties) of the established technological fields' networks on the rate of change (non-existing ↔ existing ties) of the emerging field network. The results on the dynamics across technological fields are presented in Table 4. We use the same model structure, and all estimations of the parameters were based on 1000 simulations. The overall convergence rate of the model is $0.1138 < 0.8$, while the convergence ratios of each variable are less than 0.1.

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. The change of ties in most green fuel knowledge networks (2007–2013) affected significantly the change of knowledge ties in the new technological field. The change in the knowledge ties of the established technological fields of SNG, fuel cells and electricity storage and battery had a significant positive effect on the evolution of the green shipping network. SNG, fuel cells, and electricity storage and battery networks constituted strong drivers for the evolution of green shipping network. Therefore, hypothesis H1a is confirmed for all green fuels except for hydrogen.

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 fuel 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. When one actor was connected with two other actors in the knowledge networks of electricity storage and battery, fuel cells, and SNG, 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, institutional proximity significantly affected the evolution of the green shipping knowledge network, confirming hypothesis H2a. Similarly, organizational proximity constituted an important determinant for the evolution of the green shipping knowledge network, hence, confirming hypothesis H2b. Therefore, actors located in the same country, under the same institutional setting, and/or sharing the same organizational structure, were more likely to create a tie in the green shipping knowledge networks.

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.[3] The only exception was the eigenvector

[3] 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.

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	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	–	–
Institutional proximity	0	1	0.085	0.279	0.007	0.016	0.021	0.017	0.004	–
Organizational proximity	0	1	0.372	0.483	0.002	−0.011	−0.006	−0.005	−0.006	0.018

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			
Green Shipping 2007–2013	4,3524***	0,3335	<0.0001
Structural Embeddedness (X:mixed from Y)			
Green Shipping 2007–2013	0,2331***	0,0115	<0.0001
Proximity			
Institutional Proximity	0,2755**	0,1156	0.0174
Organizational Proximity	0,269***	0,0895	0.0027
Status/popularity (eigenvector)			
Green Shipping 2007–2013	2,2602***	0,1987	<0.0001
Controls (density)			
Green Shipping 2007–2018	−4,4732***	0,1086	<0.0001
Green Shipping 2007–2013	−3314***	0,0278	<0.0001
Controls (proximity)			
Geographical proximity	0,1574	0,2956	0.5945
Controls (basic rates)			
Green Shipping 2007–2018	46,2805***	5,3234	<0.0001
Green Shipping 2007–2013	1,7984***	0,0526	<0.0001
Controls (degree status/popularity)			
Green Shipping 2007–2013	0,0177***	0,0009	<0.0001
Controls (triadic closure)			
Green Shipping 2007–2013	−0,0626***	0,021	0.0029

centrality of actors in the SNG knowledge network, which had a significant positive effect on the change of ties in the green shipping knowledge network. 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.

When we added the control variables, 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 significant, and therefore important, showing a significant amount of endogenous evolution in the green shipping network and in turn signifying strong path dependency. Geographical proximity is not significant, as expected, given the nature of the data in R&D projects. The same holds for the triadic closure of the early green fuel networks. It is rational that when three actors are closely connected with each other in another field, this does not affect the establishment of new ties in the emerging technological field. Finally, when we express the status of an actor through degree centrality, we observe the same results with the use of eigenvector centrality.

Table 4
Analysis of the evolution of green shipping (2007–2018) across technological fields.

Dependent Variable: Green Shipping 2007–2018	Coefficients	Standard Errors	p-values
Social Embeddedness			
Electricity Storage 2007–2013	0,601**	0,2792	0.0316
Fuel Cell 2007–2013	0,6343**	0,3132	0.0431
Hydrogen 2007–2013	0,2502	0,3512	0.4764
SNG 2007–2013	1,2503***	0,3049	<0.0001
Structural Embeddedness (X:mixed from Y)			
Electricity Storage 2007–2013	0,4332***	0,0682	<0.0001
Fuel Cell 2007–2013	0,3321**	0,143	0.0204
Hydrogen 2007–2013	−0,0369	0,1295	0.7757
SNG 2007–2013	0,4952***	0,0741	<0.0001
Proximity			
Institutional Proximity	0,2879**	0,1162	0.0134
Organizational Proximity	0,3555***	0,103	0.0006
Status/popularity (eigenvector)			
Electricity Storage 2007–2013	−0,3608	0,4006	0.3680
Fuel Cell 2007–2013	−0,3695	0,7951	0.6422
Hydrogen 2007–2013	0,1526	0,9976	0.8785
SNG 2007–2013	1768***	0,2333	<0.0001
Controls (density)			
Green Shipping 2007–2018	−4,0707***	0,1186	<0.0001
Electricity Storage 2007–2013	−2,3332***	0,0158	<0.0001
Fuel Cell 2007–2013	−2,6663***	0,012	<0.0001
Hydrogen 2007–2013	−2,7438***	0,0194	<0.0001
SNG 2007–2013	−3,3705***	0,0646	<0.0001
Controls (proximity)			
Geographical proximity	0,0454	0,2356	0.8472
Controls (basic rates)			
Green Shipping 2007–2018	22,2581***	1172	<0.0001
Electricity Storage 2007–2013	4,8539***	0,0911	<0.0001
Fuel Cell 2007–2013	3,3704***	0,0657	<0.0001
Hydrogen 2007–2013	3,4159***	0,0657	<0.0001
SNG 2007–2013	0,761***	0,0316	<0.0001
Controls (degree status/popularity)			
Electricity Storage 2007–2013	−0,0001	0,0006	0.8677
Fuel Cell 2007–2013	0,0008	0,0023	0.7280
Hydrogen 2007–2013	0,0014	0,0028	0.6172
SNG 2007–2013	0,0283***	0,0022	<0.0001
Controls (triadic closure)			
Electricity Storage 2007–2013	−0,0117	0,0334	0.7262
Fuel Cell 2007–2013	0,0184	0,0356	0.6054
Hydrogen 2007–2013	−0,0131	0,0296	0.6582
SNG 2007–2013	−0,0192	0,0258	0.4569

5. Conclusions

In this paper we set out to explore knowledge (re)combination across technological fields through a knowledge network perspective. 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), 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 (Salavisa et al., 2012; Wagner et al., 2019).

Previous research has identified different mechanisms that influence the evolution of knowledge networks of established 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). Our paper provides the first analysis of the role of these mechanisms in influencing knowledge transfer across 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 technological fields, which through their application in shipping contribute to the development of the emerging field. We have demonstrated that some mechanisms in green fuel networks, such as embeddedness and institutional and organizational proximities, are strong drivers for the evolution of the emerging green shipping field.

In terms of embeddedness, the actors in the green shipping network were, to differing degrees, both structurally and socially embedded in the established technological fields of fuel cells, electricity storage and battery, and SNG. The actors exploited both strong and weak ties in the knowledge networks of established technological fields to form or reinforce relationships in the knowledge network of the emerging technological field. Our findings expand the understanding of embeddedness as a key driver for the formation of inter-organizational knowledge networks (Balland et al., 2016; Ter Wal, 2014; Wen et al., 2021), by showing that the social ties and the structure of the knowledge network of established technological fields affect the creation of the emerging field. Therefore, we found that embeddedness constitutes an important driver of knowledge transfer and (re)combination, not only within single technological fields, but also across technological fields.

In contrast, we found that network formation in an emerging technological field is not driven by the status of actors in established technological fields, with exception for SNG. This contrasts studies of knowledge networks in single technological fields where status is an important driver (Balland et al., 2016; Giuliani, 2013). 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 status in established fields.

Finally, we found that the different dimensions of proximity vary for the formation of the knowledge network of the emerging technological field. Institutional proximity played an important role, as did organizational proximity, suggesting that interaction with similar types of organizations provides agents with the necessary trust and reliability for collaborating in an emerging technological field (Hansen, 2014; Tsouri, 2019). In contrast to the positive effect that geographical proximity has been shown to have on the evolution of single technological fields (Ter Wal, 2014), the restrictions in the selection of partners in EU funded R&D projects did not permit us to detect a similar effect across technological fields (Autant-Bernard et al., 2007).

Although we did not find a strong pattern in the effect of all the established networks on green shipping, our overall findings are significant for understanding the knowledge transfer across technological fields and the evolution of knowledge networks of emerging technological fields (Tödtling et al., 2009). The evolution of each network of green fuels affected the evolution of the green shipping knowledge network in different intensities. For instance, we saw a lacking effect from the embeddedness in the knowledge network of hydrogen fuel field on the emergence of the green shipping technological field, and status was only important in the case of SNG. The factors behind this differentiation remain still to be examined in future research. Potentially influential factors include the different levels of maturity of the established technological fields, 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.

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). With regard to the interaction across technological fields, the effect and importance of the three mechanisms is varied. All three mechanisms previously found important for single technological fields have positive effects on the emergence and evolution of the new technological field. However, the significance and intensity of this effect depends heavily on the particular characteristics of the established technological field (Balland et al., 2016). Based on network data, our results lend further credence to the importance of related variety, and how new knowledge evolves based on existing knowledge bases (Boschma and Frenken, 2006; Cheng, 2012). While notions of related variety and diversification have rested mainly on indicators such as patents, skills or industry classifications (Boschma, 2017), we show a similar pattern in terms of knowledge networks. Indeed, we show path dependence occurring at the network level, in the sense of a less constrained view on path dependence suggested by Martin and Sunley (2010), indicating opportunities for path renewal. As such, we use knowledge networks as a novel approach to studying how emerging green technological fields rest, and build upon established fields (Santoalha and Boschma, 2021; van den Berge et al., 2020).

Overall, our findings thus suggest that knowledge creation for green shipping benefits from knowledge development in existing technological fields, previously deployed in other sectors such as transport. However, the realization of knowledge transfer, and indeed, the use of knowledge for implementation of low-emission solutions likely depends on a wider mix of policies such as public procurement of ferry services or demand for low-emission logistical services from buyers (Bergek et al., forthcoming). A key question is thus how favourable knowledge creation policies can be combined with measures to ensure market deployment, as well as policies that destabilise and disincentivise fossil fuel usage.

In more general terms, one key policy implication is that the knowledge networks that are necessary for developing new technological fields, such as clean tech, can benefit from networks in already established fields, and needn't be built from scratch. Many countries and regions now embrace so called mission-oriented, or smart specialisation, policy approaches, which entail prioritization of certain areas and technological fields. Our approach, can support the identification of areas in which match-making between established and emerging fields seems favourable. Furthermore, the interactions between established and emerging technological fields, 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.

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