The firm's knowledge network and the transfer of advice among corporate inventors – A multilevel network study

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Abstract

Knowledge networks consisting of links between knowledge elements and social networks composed of interactions between inventors both play a critical role for innovation. Taking a multilevel network approach, this study integrates research on the two types of networks and investigates how the knowledge network of a firm influences work-related interactions among its inventors. To this end, we associate inventors with specific knowledge elements in the firm's knowledge network and examine how this association affects the inventors' popularity and activity in a work-related advice network. Empirically, we combine survey data on 135 inventors working in a German high-tech firm with information derived from the firm's 1031 patents. Results from multilevel exponential random graph models (ERGM) show that different dimensions of knowledge derived from the firm's knowledge network shape the transfer of advice among inventors in unique ways. Thus, our study demonstrates how structural features of the firm's knowledge stock influence interpersonal interactions among its inventors thereby affecting the intra-organizational diffusion of knowledge and the recombinant possibilities of the firm.

Keywords: corporate R&D, advice network, knowledge network, patent, exponential random graph model, multilevel

1. Introduction

While traditionally, researchers have represented organizational knowledge as an aggregation of knowledge elements used by firms for inventive activities (e.g., Ahuja and Katila, 2001; Fleming, 2001; Quintana-García and Benavides-Velasco, 2008), recent studies have drawn attention to the structure of the firm's knowledge stock as a determinant of innovation (Dibiaggio et al., 2014; Guan and Liu, 2016; Wang et al., 2014; Yayavaram and Ahuja, 2008). In its structural representation, firm knowledge is a collection of links between knowledge elements (Dibiaggio et al., 2014) that can be conceptualized as a network (Guan and Liu, 2016; Wang et al., 2014). In this "knowledge network"[1], knowledge elements embody discrete pieces of knowledge and links between them indicate whether and how the firm has combined these elements in the process of knowledge creation and invention. Knowledge networks hence capture commonalities in the subject matters of different knowledge elements (Carnabuci and Bruggeman, 2009; Yayavaram and Ahuja, 2008).

The properties of knowledge networks have been shown to influence the usefulness of innovations that firms generate (Yayavaram and Ahuja, 2008) and affect firms' and inventors' tendency to engage in exploitative and exploratory innovation (Guan and Liu, 2016; Wang et al., 2014). While these findings confirm that knowledge networks matter for innovation outcomes, scholars have been at odds concerning their relationship with social networks as an important component of the innovation process (e.g., Carnabuci and Operti, 2013; Singh, 2005). Yayavaram and Ahuja (2008) have suggested that the structure of a firm's knowledge network is reflected in the social ties among its employees – that is, the two networks are supposed to be isomorphic. In contrast, Guan and Liu (2016) and Wang et al.

[1] In line with Guan and Liu (2016) and Wang et al. (2014) our use of the term "knowledge network" differs from its use in other studies (e.g., Hansen, 2002; Owen-Smith and Powell, 2004) that investigate social knowledge networks. Whereas social knowledge networks capture knowledge transfer among individuals or collectives, the knowledge networks focused upon in this study represent "the combination and consequent affiliation of knowledge elements in the process of creating new knowledge" (Phelps et al., 2012: 1156).

(2014) have demonstrated that a firm's knowledge network and its social network possess distinct structural features and influence innovation differently. They have concluded that knowledge networks and social networks are not isomorphic but rather decoupled. Aiming to dissolve this tension and provide a more detailed understanding of the different networks that determine innovation in organizations, this study addresses the question of how a firm's knowledge network relates to the social network among its inventors and thereby affects the social process of innovation generation in corporate R&D.

We argue that while the knowledge network and the social network may be decoupled in the sense that they have unique structural features (Guan and Liu, 2016; Wang et al., 2014), they are not independent from each other. Corporate inventors creating the social network are embedded in their firm's knowledge network by possessing specific knowledge elements that reflect their individual knowledge (Wang et al., 2014). We assume that this embeddedness in the knowledge network affects the inventors' work-related social ties, particularly the transfer of advice as part of their day-to-day work. In other words, inventors' knowledge relative to the overall knowledge of the firm is supposed to drive their popularity as advisors, that is, the extent to which they get addressed for advice by their colleagues, as well as their activity as advice seekers, that is, the extent to which they ask colleagues for advice. We follow Wang et al. (2014) and conceptualize knowledge as a multidimensional, complex structure reflected by the firm's knowledge network and the inventors' embeddedness in it. We investigate (1) inventors' knowledge diversity, (2) uniqueness of knowledge, (3) combinatorial potential and (4) combinatorial opportunities offered by knowledge elements, as well as (5) knowledge proximity among inventors as distinct knowledge dimensions determining the transfer of work-related advice.

To analyze the influence of the firm's knowledge network on the inventors' social network we follow a multilevel network approach (Zappa and Lomi, 2015) integrating three distinct networks into one multilevel framework. Drawing on data collected in a German high-tech firm in the electrics and electronics industry, we examine the structure of the firm's knowledge network at the macro level determining the structure of the social network among its inventors as the outcome variable at the micro level. We link the social network to the knowledge network using an affiliation network that connects each inventor to single knowledge elements within the knowledge network, thereby reflecting the inventors' embeddedness in the knowledge network of the firm. To empirically construct the multilevel network, we combine data from different sources. While the social network is derived from survey data on 135 corporate inventors, we draw on all of the firm's patents – more precisely the co-assignment of technology classes to these patents – to construct its knowledge network and to derive information on the technological knowledge elements that the inventors possess. Analytically, we apply newly developed exponential random graph models (ERGMs) for multilevel networks (Wang et al., 2013) that allow accounting for cross-level influences of network structure at one level on the emergence of ties at another level. ERGMs thus enable us to investigate how properties of the firm's knowledge network affect the presence or absence of work-related advice ties in the social network, explicitly taking into account that ties in a (multilevel) network do not occur independent of each other.

Our study contributes to existing research first, by extending our understanding of the firm's knowledge network as a factor influencing the social process of innovation generation in corporate R&D. Most prior studies have treated firm knowledge as an aggregation of knowledge elements (e.g., Ahuja and Katila, 2001). By taking into account the structural properties of firm knowledge and embedding corporate inventors within this knowledge network, we are able to provide a more precise understanding of the role it plays for innovation. In addition, to the best of our knowledge there are only two studies that have integrated knowledge networks and social networks into a single analytical framework (Guan and Liu, 2016; Wang et al., 2014). Both studies have examined the separate influence of the two networks on innovation outcomes and call for future research investigating the influence of the knowledge network on the innovation process. Following their call, we demonstrate that the knowledge network and the social network are closely related as the structure of firm knowledge influences patterns of informal interactions among inventors thereby affecting intra-organizational knowledge diffusion and the overall innovation process (Singh, 2005).

Second, we add to research on the determinants of social networks as a central component of corporate R&D's function to generate new knowledge by recombining existing knowledge (Fleming, 2001; Kogut and Zander, 1992; Nerkar and Paruchuri, 2005). Social networks are the main channels for inventors to transfer recombination-related knowledge (Allen, 1977; Hansen, 1999; Singh, 2005). They influence inventors' productivity (Harhoff et al., 2013; Tortoriello, 2015; Tortoriello and Krackhardt, 2010) as well as the way that firms innovate (Carnabuci and Operti, 2013). In short, effective social networks are crucial in corporate R&D and understanding the drivers of tie creation in these networks is essential to reach this effectiveness. While scholars have demonstrated that factors such as formal organizational structure (Brennecke and Rank, 2016; Caimo and Lomi, 2015), status (Agneessens and Wittek, 2012; Lazega et al., 2012), spatial proximity (Kabo et al., 2014), as well as network endogenous processes (Rank et al., 2010) determine the structure of social networks, knowledge has attracted limited attention as a driver of interpersonal exchange. This seems surprising because one of the main goals of seeking advice from colleagues is complementing what one knows with other knowledge elements. To fill this gap, we investigate how different knowledge dimensions that account for the relation of individual to firm knowledge influence the work-related transfer of advice among corporate inventors.

2. Theoretical framework

2.1. The firm's knowledge network and the inventors' embeddedness in it

The knowledge network of a firm is a structural representation of its cumulative stock of rules, routines, practices, or documents and as such is the result of collective efforts of past and present employees (Wang et al., 2014). Reflecting the firm's inventive history, it is more than the sum of its current inventors' individual knowledge stocks. The basic building blocks or "nodes" of a knowledge network are knowledge elements, in our study pieces of technological knowledge that are the fundamental components of an invention (Fleming and Sorenson, 2004). Knowledge elements are often embodied in discrete artifacts such as patents, products, or scientific publications (Phelps et al., 2012). Connections or "ties" between knowledge elements result from their combination in the process of knowledge creation and invention (Carnabuci and Bruggeman, 2009; Fleming and Sorenson, 2004). The printing press, for instance, can be seen as a combination of knowledge elements from areas such as press, metallurgy, ink and others (Diamond, 1997). Ties in the knowledge network thus indicate the degree of relatedness in the subject matters of single knowledge elements, with elements that have been combined in inventions more often being more closely related (Fleming, 2001). The position of each knowledge element in the knowledge network reflects its combinatorial history within the firm (Carnabuci and Bruggeman, 2009). It mirrors the firm's idiosyncratic beliefs about which knowledge elements should be considered jointly and, conversely, which knowledge elements are unrelated or do not work well together, for instance to create scientific or commercial benefits (D'Este, 2005; Dibiaggio et al., 2014). In our multilevel framework, the knowledge network of the firm represents the macro level supposed to influence the structure of advice transfer between inventors at the micro level.

Corporate inventors as nodes in the micro-level advice network are embedded in their firm's knowledge network because they have acquired certain knowledge through their education and work experience. Thus, they are connected to specific knowledge elements that have a distinct position in the firm's knowledge network. Importantly, an inventor's embeddedness in the firm's knowledge network and the position of his or her knowledge elements in the network are not determined solely by the individual inventor. Instead, they depend on the collective efforts of generations of past and current inventors of the firm who have shaped the structure of the knowledge network and the distribution of knowledge elements among inventors. The knowledge network hence confronts inventors with an external reality (Berger and Luckmann, 1966), which as a member of the organization they need to understand at least in parts to participate in knowledge production and innovation (Wang et al., 2014). As schematically depicted in Figure 1, not all inventors possess the same knowledge elements; instead, they vary in their knowledge.

--- Insert Figure 1 about here ---

While some inventors possess a high number of diverse knowledge elements, others possess only a few. Moreover, some knowledge elements within the knowledge stock of the firm are held by several inventors while others are only held by one or two specialists. Some knowledge elements may not be held by any of its current inventors, highlighting that the firm's knowledge network persists over time independent of the inventors who create it. Finally, the knowledge elements that the inventors possess differ in their position in the knowledge network, for instance by being connected to varying numbers of other knowledge elements. Below, we draw on these variations in inventors' embeddedness in the knowledge network to conceptualize different knowledge dimensions that account for the relation of individual to firm knowledge.

2.2. The social network among inventors as part of the innovation process

It has long been acknowledged that knowledge creation and innovation are inherently social processes (Berger and Luckmann, 1966; Mead, 1934). According to the Schumpeterian view of innovation, new ideas are generated by recombining existing ones (Fleming, 2001; Schumpeter, 1934). Similarly, new knowledge can be seen as the outcome of linking existing knowledge elements (Carnabuci and Bruggeman, 2009). Facilitating the diffusion of the typically sticky and tacit knowledge that is of high importance in corporate R&D (Hansen, 1999; Szulanski, 1996) and enabling the recombination of ideas, social networks are a crucial component of the innovation process (Carnabuci and Operti, 2013; Singh, 2005) and have been shown to influence inventor productivity in terms of new patents filed (Harhoff et al., 2013; Tortoriello, 2015; Tortoriello and Krackhardt, 2010). They provide the "social infrastructure" for innovation (Aalbers and Dolfsma, 2015) and allow inventors to handle the growing "burden of knowledge" (Crescenzi et al., 2016; Jones, 2009) by complementing their own knowledge with elements from other people's knowledge stock, thereby increasing the chances of having innovative ideas (e.g., Burt, 2004; Fleming et al., 2007; Ibarra, 1993).

Following prior research on social networks as part of the innovation process (e.g., Ibarra, 1993; Rodan and Galunic, 2004), we focus on the informal transfer of work-related advice, in our case among corporate inventors. Networks such as advice transfer have repeatedly been linked to enhanced innovative performance (e.g., Obstfeld, 2005; Sparrowe et al., 2001). For instance, individuals' actively seeking advice from colleagues show higher levels of creativity (Baer, 2010; Burt, 2004). Likewise, being a popular advisor for colleagues positively influences the advisor's performance providing him or her with opportunities to think through work-related aspects more thoroughly by verbalizing them (Shah et al., 2015).

We conceptualize advice seeking as a choice process (Borgatti and Cross, 2003) in which the decision to turn to a colleague for work-related input is informed by characteristics of the advice-seeker and the advisor, the relationship between them, as well as by other individuals the advice-seeker might turn to. The knowledge network of the firm is assumed to influence this process as corporate inventors habitually engage in local search activities, for instance by considering knowledge elements present within the firm (March, 1991; Nerkar and Paruchuri, 2005). Following this logic, we expect inventors to seek advice from colleagues whom they perceive to be linked to knowledge elements beneficial for their own task success – given their own set of knowledge elements. In line with the idea of temporal local search (Nerkar, 2003), we assume that knowledge elements used or added more recently are more relevant for the inventors' advice seeking behavior in this process, because they reflect the state-of-the-art in a given field and are more salient to the firm and its inventors. Furthermore, we acknowledge that task dependencies embodied in the formal structure of the firm form the backbone of informal interactions among colleagues (Kleinbaum et al., 2013; McEvily et al., 2014) and that social preferences of individuals determine advice seeking activities (McPherson et al., 2001). Thus, after holding constant known drivers of advice tie creation such as formal organizational structure (Brennecke and Rank, 2016; Caimo and Lomi, 2015), person characteristics (Lazega et al., 2012; Lomi et al., 2014) or network endogenous processes (Rank et al., 2010), we expect inventors to choose advisors based on their own and the advisors' embeddedness in the firm's knowledge network. More precisely, different dimensions of knowledge are thought to affect the tendency of colleagues to address them for work-related advice – that is, they should influence inventors' popularity in the advice network. Likewise, the different knowledge dimensions are supposed to influence inventors' network activity, that is, their tendency to seek advice from others.

In the following, we discuss how the different dimensions of knowledge may shape the work-related transfer of advice. As will become clear, the literature allows for more precise predictions regarding the effect of some of the knowledge dimensions on advice transfer, while for others competing arguments impede the derivation of directed hypotheses. Therefore, we formulate broader research questions for all five knowledge dimensions to guide our subsequent empirical analysis on the influence of the firm's knowledge network on inventors’ popularity as advisors and activity as advice-seekers. While Research Questions 1, 3, and 4 concerning knowledge diversity, combinatorial potential, and combinatorial opportunities refer to directed (i.e., positive or negative) relationships, Research Questions 2 and 5 on of knowledge uniqueness and proximity account for competing mechanisms and are thus formulated more openly.

2.3. Dimensions of knowledge as drivers of social networks

2.3.1. Diversity of knowledge

Knowledge diversity as a dimension of knowledge derived from an inventor’s embeddedness in the firm’s knowledge network refers to the variety in knowledge elements possessed by the inventor (e.g., Fleming et al., 2007). Based on their education and career, most inventors develop highly specialized, narrow knowledge (Melero and Palomeras, 2015). They are connected to few knowledge elements within the firm’s knowledge network. Some inventors, however, typically hold a larger set of different knowledge elements. Their knowledge is distributed among different areas and they can be said to be generalist inventors with diverse expertise and knowledge (Melero and Palomeras, 2015). Boh et al. (2014) have demonstrated that inventors with diverse knowledge approach the innovation process in a specific way. Compared to inventors with narrow knowledge, they are more open-minded and not overly burdened with existing viewpoints leading them to suggest new perspectives and different ways of how to approach a given problem. Moreover, they are better able to relate knowledge from different areas and make more informed choices with respect to knowledge recombination (Gruber et al., 2013). In terms of Melero and Palomeras (2015: 155) they play a “knowledge bridging” function when interacting with others.

Building on this characterization, we argue that whether or not inventors possess diverse knowledge will influence their position in the work-related advice network. For instance, their ability to suggest a new angle on a given problem should make inventors linked to a high number of knowledge elements in the firm's knowledge network popular sources for advice from the perspective of their colleagues. In addition, they might be popular advisors because their broad knowledge makes it easier to find a common language and communicate with them (Melero and Palomeras, 2015). At the same time, possessing diverse knowledge provides inventors with a solid foundation for their innovative work. In contrast to inventors with narrow knowledge, inventors with diverse knowledge might depend less on other people's knowledge elements to innovate and therefore be less active seeking advice from colleagues. Based on these considerations we pose the following research question:

> *Research Question 1: Will knowledge diversity positively influence inventors' popularity as advisors and negatively influence their activity seeking advice from colleagues?*

2.3.2. Uniqueness of knowledge

Uniqueness as a dimension of knowledge refers to corporate inventors being knowledgeable in an area that their colleagues are not familiar with. Particularly, inventors possessing unique knowledge are connected to knowledge elements within the firm's knowledge network that none or few of their colleagues are connected to as well, which might influence their popularity or activity in the advice network for different reasons. On the one hand, theories of social networks have long emphasized the idea that access to unique knowledge sources can be of value for individuals and organizations (Burt, 1992; Granovetter, 1973). Possessing an exclusive knowledge-based resource, inventors with unique knowledge elements might be preoccupied with its exploitation and thus less actively seek new input from colleagues. Similarly, they might be popular advisors for their colleagues who also want to gain access to the exclusive resource. In line with this reasoning Schulz (2001) has provided empirical evidence showing that the uniqueness of a subunit's knowledge positively affects the amount knowledge this unit supplies to other subunits.

On the other hand, uniqueness might be a sign for a knowledge element to be of little importance or use to the firm's innovative activities (Kuhn, 1996; Yayavaram and Ahuja, 2008). Other inventors might thus not be interested to exploit this knowledge further, which could negatively influence the possessing inventors' popularity in the advice network. At the same time, this lack of interest might spur the inventors' activity seeking advice from colleagues. In order to profit from the unique knowledge that they possess, inventors might strive to informally connect with others to promote the recombination and thus exploitation of their knowledge elements. Given the competitive nature of the above arguments we ask:

Research Question 2: How will uniqueness of knowledge influence inventors' popularity as advisors and their activity seeking advice from colleagues?

2.3.3. Combinatorial potential of knowledge

Combinatorial potential is a knowledge dimension derived from the position of an inventor's knowledge elements within the firm's knowledge network. Thus, while diversity and uniqueness of knowledge depend on an inventor's embeddedness in the knowledge network relative to the embeddedness of his or her colleagues, combinatorial potential draws on the links between knowledge elements, which typically vary depending on the elements' combinatorial history (Carnabuci and Bruggeman, 2009).

A knowledge element's combinatorial potential reflects its suitability for recombining it with other knowledge elements. Knowledge elements with high combinatorial potential have a central position within the firm's knowledge network – in other words, they have been combined with many other knowledge elements in the firm's past (Guan and Liu, 2016; Wang et al., 2014). Knowledge elements with a low centrality in the knowledge network have low combinatorial potential for different reasons. The fact that a knowledge element has not been combined extensively before suggests low levels of inventors' belief in the value of the knowledge element (Kuhn, 1996; Yayavaram and Ahuja, 2008). Moreover, it indicates that little experience exists within the firm in combining the element with others, which means that substantial efforts would be required to do so. Finally, not all knowledge elements can be combined with each other. A peripheral position in the knowledge network can be a sign that a knowledge element is not suited for extensive recombination (Wang et al., 2014).

Guan and Liu (2016) and Wang et al. (2014) have drawn on the concept of combinatorial potential to argue that organizations and inventors whose knowledge elements are not well connected – thus having low combinatorial potential – need to invest greater efforts into exploring possibilities to combine their knowledge elements with existing or new knowledge. One means to do this might be by relying on informal advice seeking. Inventors might turn to colleagues possessing knowledge elements with high combinatorial potential to benefit from the inventive possibilities that they offer. Similarly, because search is often triggered by shortcomings or crises (Cyert and March, 1963; Kim, 1998), inventors might be more active seeking work-related advice from their colleagues if their own knowledge elements offer low combinatorial potential. This way, they might discover novel inventive possibilities. In line with these assumptions, we ask:

> *Research Question 3: Will the combinatorial potential of corporate inventors' knowledge elements positively influence the inventors' popularity as advisors and negatively influence their activity seeking advice from colleagues?*

2.3.4. Combinatorial opportunities of knowledge

Just like combinatorial potential, combinatorial opportunities as knowledge dimension concerns the position of knowledge elements within the firm's knowledge network. According to Wang et al. (2014) knowledge elements connected to other knowledge elements that have themselves not be combined in an invention – that is, knowledge elements that bridge structural holes in the knowledge network – offer opportunities for recombination that have not yet been exploited. Since the knowledge elements that they connect are likely to be thematically related, they have a higher potential to be combined in a future invention than random other knowledge elements. By contrast, knowledge elements with few structural holes in their immediate environment leave fewer combinatorial opportunities untapped; their inventive capacity may have been largely depleted (Kim and Kogut, 1996).

Wang et al. (2014) have demonstrated that inventors possessing knowledge elements with high combinatorial opportunities are more likely to take advantage of their current knowledge and conduct exploitative innovation. Conversely, inventors lacking combinatorial opportunities in their knowledge elements have a stronger motivation to seek for new knowledge and engage in explorative innovation. Extending this reasoning to interpersonal networks as the social infrastructure enabling innovation, we argue that the combinatorial opportunities of knowledge elements may influence inventors' advice seeking behavior. Similar to what we proposed for combinatorial potential, inventors might seek advice from colleagues possessing knowledge elements with high combinatorial opportunities to extend their capacity for innovation. Based on this logic, inventors with knowledge elements high in combinatorial opportunities would be particularly popular advisors. Likewise, inventors might try to compensate a lack of opportunities inherent in their own knowledge elements by actively seeking work-related advice and thus explore new opportunities. By contrast, if their knowledge elements offer significant combinatorial opportunities, inventors might be less active seeking advice and instead focus on the exploitation of the resources that they already possess. In line with these arguments we raise the following question:

> *Research Question 4: Will the combinatorial opportunities of corporate inventors' knowledge elements positively influence the inventors' popularity as advisors and negatively influence their activity seeking advice from colleagues?*

2.3.5. Knowledge proximity

Knowledge proximity (Boschma, 2005; Crescenzi et al., 2016)[2] as a dimension of knowledge refers to similarity in inventors' embeddedness in the knowledge network and might influence the transfer of advice in opposing ways. On the one hand, corporate inventors

[2] The concept proximity which is widely used in the innovation literature is tightly related to the sociological concept of homophily (Boschma & Frenken, 2012; McPherson, Smith-Lovin, & Cook, 2001).

might actively seek advice from colleagues possessing dissimilar elements from the firm's knowledge stock to complement their own knowledge. Particularly, accessing heterogeneous knowledge decreases the risk of inventive lock-in (e.g., Sydow et al., 2009) and is beneficial for innovative performance (e.g., Burt, 2004; Tortoriello and Krackhardt, 2010). In line with this reasoning, Crescenzi et al. (2016) have provided evidence that inventors strive towards cognitive diversity by co-patenting with others possessing dissimilar knowledge.

On the other hand, proximity between individuals has repeatedly been shown to be one of the most important drivers of tie creation (e.g., Kleinbaum et al., 2013; McPherson et al., 2001). Being connected to similar knowledge elements within the firm's knowledge network might facilitate interactions among inventors as it provides them with a shared language and a common understanding of the world that surrounds them. In addition, similar others seem more approachable and show a higher responsiveness to advice requests. Thus, the costs for approaching them are smaller, and communication and the exchange of ideas is more efficient (Ertug and Gargiulo, 2012). Likewise, shared knowledge makes it easier to learn from each other (Nooteboom, 2000) and can be a precondition to absorb and process new knowledge (Boschma and ter Wal, 2007). Thus, instrumental and affective motives might cause inventors to interact with colleagues possessing proximate knowledge. Based on these opposing arguments we ask:

Research Question 5: How will knowledge proximity influence the transfer of advice among corporate inventors?

Figure 2 provides an overview of the research questions outlined in the previous sections and links them to our multilevel framework.

--- Insert Figure 2 about here ---

3. Data and method

3.1. Empirical context and data

To investigate the influence of the different knowledge dimensions on advice transfer among inventors we use data gathered as part of a larger study in the R&D department of a German high-tech firm within the patent intensive electrics and electronics industry (Hall, 2004). The R&D department of the firm consist of seven divisions at different locations in Germany. The firm's management considers R&D to be the key success factor of the firm and patents are the most important means the company employs to protect its innovations. Inventors are strongly encouraged to create patentable inventions. The vast majority of patents are filed by inventors belonging to the same division as they typically work on common projects and tasks related to the focus of the division. However, occasionally inventors from different divisions collaborate on an invention. Moreover, interpersonal exchange of knowledge and advice – even across divisional boundaries – is an important characteristic of the inventors' day-to-day work. To facilitate the department-wide detection of individual expertise, the firm employs a computer based knowledge management system.

In this study, we consider all inventors within the firm that have filed at least one patent in the time between 2009 and 2013. These 178 inventors were invited to participate in an online survey conducted to find out about the work-related advice network in the end of 2013. Of the 178 inventors 135 (76 percent) filled in the survey.[3]

In line with previous research (e.g., Wang et al., 2014; Yayavaram and Ahuja, 2008), we draw on patent data – specifically on the co-assignment of technology classes to patents – to construct the firm's knowledge network and derive information on the different dimensions of knowledge. We retrieved patent data from the EPO Worldwide Patent

[3] To check for a potential non-response bias, we compare respondents and non-respondents with regards to their number of patents (derived from PATSTAT), status, age, and tenure (proved by the firm's HR-department) using *t*-tests. The results revealed no significant differences between respondents and non-respondents.

Statistical Database (PATSTAT) that includes information on the patents' technology classes according to the International Patent Classification (IPC). Technology classes are commonly considered to be valid proxies for knowledge elements (e.g., Carnabuci and Bruggeman, 2009; Melero and Palomeras, 2015; Yayavaram and Ahuja, 2008). Following prior studies (e.g., Dibiaggio et al., 2014; Guan and Liu, 2016) we used the four-digit version of the IPC code that includes a section, class, and subclass and has been shown to sufficiently capture the knowledge features of a patent (Guan and Liu, 2015).

3.2. Variables and measures

For our empirical analysis, we estimate a model for the probability of advice ties as a function of the different knowledge dimensions derived from the knowledge network and the inventors' embeddedness in it as well as inventor-specific control variables and network endogenous effects. In the following, we explain the different elements of our model and highlight why it is important to account for network endogeneity in order to avoid spurious modelling results.

3.2.1. The advice network

The presence of advice ties among inventors is the dependent variable in our analysis. For each advice tie, there is a sender and a receiver. The sender of a tie is the inventor seeking advice from a colleague with inventors seeking a lot of advice being particularly active. By contrast the receiver of a tie acts as advisor for a colleague with a high number of received ties reflecting inventor popularity. Using a roster method for ties to colleagues belonging to the same division and a name generator for colleagues belonging to different divisions (for a similar approach see Oh et al., 2004), we asked the inventors to name colleagues within the R&D department of their firm to whom they turned to regularly for work-related advice, for instance with respect to current R&D projects they were working on. Ties were recorded dichotomously and arranged in a 135x135 binary adjacency matrix $\mathbf{x}$ =

$\{x_{ij}\}$, in which cell x_{ij} corresponds to i's relation to inventor j. If i turned to j to seek advice, cell x_{ij} was coded as 1 and 0 otherwise.

3.2.2. The knowledge network and the different dimensions of knowledge

To construct the knowledge network, we relied on the technology classes assigned to all 1,031 patents[4] that the firm has applied for since its foundation in the midst of the 20th century – overall, 118 different technology classes. These 118 technology classes are the nodes representing the knowledge elements in the firm's knowledge network. Two knowledge elements are connected by a tie in this network if they have been applied to the same patent (for a similar approach see for instance Boschma et al., 2015; Wang et al., 2014). We link the inventors to the firm's knowledge network – more precisely to single knowledge elements – drawing on their patenting activities in the last five years prior to our survey (i.e., 2009 to 2013) based on the patents' application date. Using a 5-year window allows us to account for the tendency of temporal local search mentioned above (Nerkar, 2003). Moreover, it is in line with recommendations by Benner and Waldfogel (2008) as well as existing research on inventors and their patents (Lee, 2010; Wang et al., 2014). During this period, the 135 inventors who participated in the survey were listed on 229 patents filed by the firm under investigation. Overall, 54 distinct knowledge elements were assigned to these patents. Examples include knowledge elements from the area of physics such as "measurement of volume and volume flow" and "image data processing and generation" or knowledge elements from the area of electricity such as "transmission of digital information". Following prior studies, we assume inventors to possess a knowledge element as long as they have filed at least one patent related to it (Melero and Palomeras, 2015; Wang et al., 2014). In others words, inventors are connected to a knowledge element in the knowledge network if this element is assigned to one of their patents.

[4] We only take into account one member of a patent family to avoid double counting inventions.

We draw on the inventors' connection to the knowledge network and on the structure of the knowledge network itself to derive information on the different knowledge dimensions. To capture *knowledge diversity* we consider the number of knowledge elements an inventor possesses (for a similar approach see Boh et al., 2014; Fleming et al., 2007; Wang et al., 2014). To account for *uniqueness of knowledge*, we count the number of inventors in our sample connected to a knowledge element giving us a measure of how widespread a knowledge element is. To obtain a measure of uniqueness, we invert this count for the inclusion in our model. We followed Wang et al. (2014) to derive information on the combinatorial potential and combinatorial opportunities of each knowledge element from its position in the knowledge network. We calculate *combinatorial potential* as the weighted degree centrality (Freeman, 1979) of a knowledge element within the knowledge network, reflecting how often and with how many other knowledge elements it has been combined in the past. A high degree centrality reflects high combinatorial potential. *Combinatorial opportunities* of knowledge elements is calculated using Burt's (1992) constraint measure for each knowledge element within the knowledge network. Following Fleming and Waguespack (2007), we use the negative of constraint as a measure of structural holes reflecting the extent to which knowledge elements related to a focal knowledge element are disconnected, thus indicating that the focal knowledge element has high combinatorial opportunities. Finally, to capture *knowledge proximity*, we take into account to what extent two inventors are linked to the same knowledge elements.[5] Table 1 summarizes and explains the measurement of the different knowledge dimensions.

--- Insert Table 1 about here ---

[5] Following suggestions by Snijders et al. (2006), knowledge proximity is included in our models by using a so called "alternating effect" where different weights are assigned to inventors sharing several knowledge elements as compared to inventors sharing only one or two knowledge elements.

In our empirical model specified below, we include the different knowledge dimensions by capturing their cross-level influence on inventors' popularity as advisors and their activity seeking advice from their colleagues. Since knowledge proximity is measured at the level of the dyad, by definition no distinction is made between activity and popularity.

3.2.3. Inventor-specific control variables

We control for the influence of the inventors' position within the formal organizational structure as well as relevant person characteristics. Regarding the formal structure, we first take into account the inventors' *hierarchical status* within the firm as a reflection of the organization's vertical structuring. Hierarchical status has been shown to be an important predictor of advice ties (Agneessens and Wittek, 2012; Lazega et al., 2012) and we capture it as a binary variable distinguishing between individuals with leadership authority (1) and employees (0). Second, we account for inventors belonging to the *same division* as they are more likely to work on common tasks and hence to create informal work-related advice ties (Brennecke and Rank, 2016; Caimo and Lomi, 2015). Belonging to the same division is a dyadic attribute relating to pairs of inventors. With respect to other person characteristics, we account for the inventors' *tenure in the firm* and their *number of patents* which may well be assumed to influence their popularity and activity in the advice network. We measure tenure in years and the number of patents as a count of all of the inventors' patent applications between 2009 and 2013. Finally, we control for past collaborations between the inventors considering whether they have had a *joint invention* in the five years prior to our survey as a dyadic attribute.

In our empirical model, we include each control variable by capturing its influence on inventors' popularity and activity. In addition, we control for homophily effects, that is, the tendency of similar inventors to transfer advice (McPherson et al., 2001). The dyadic attributes are incorporated as entrainment patterns, capturing the tendency for advice to be transferred between inventors belonging to the same division or having a joint patent.

3.2.4. Network endogenous effects

Prior research on advice networks has shown that they are characterized by complex endogenous dependencies, as the creation of advice ties is determined by individuals' own patterns of interactions as well as by interactions among their potential partners (Lomi et al., 2014; Rank et al., 2010). To account for this tendency of social networks to self-organize into meaningful structural patterns (Robins et al., 2005) we include network endogenous effects. These effects represent theoretical claims on the processes that drive the emergence of network patterns and are thus more than statistical ameliorations (Contractor et al., 2006; Lomi et al., 2014). Omitting network endogenous effects could lead to invalid findings on the effects that are of theoretical interest, as results may actually be attributable to structural mechanisms driving the emergence of ties (Robins et al., 2007; Snijders, 2011). In order to isolate the influence of the different knowledge dimensions on inventors' popularity and activity in the advice network, we consider for the following network endogenous effects.

Controlling for the simplest form of dependence that exists at the dyadic level, we account for the overall tendency of corporate inventors to create advice ties (*arc*) and to reciprocate them (*reciprocity*). Since dyadic dependencies alone are unlikely to sufficiently capture network endogenous effects (Lomi et al., 2014; Robins et al., 2009; Snijders, 2011), we additionally take into account differences in the inventors' tendency to be nominated as advisors (*popularity spread*) and to seek advice (*activity spread*).[6] These effects control for the in- and outdegree distribution of the advice network and reflect the finding that ties in social networks are seldom distributed evenly (Robins et al., 2009). Finally, we include

[6] The popularity two-star included in the model describes the tendency for corporate inventors to be nominated as advisor by two colleagues and is redundant with respect to the popularity spread. It was included because it led to a significant improvement of the goodness of fit by capturing the skewness of the indegree-distribution.

effects to capture clustering, specifically tendencies towards *transitive closure* and *cyclic closure* (Robins et al., 2009). In general, closure is the tendency for ties to be created between individuals who share common ties (Davis, 1970; Rank et al., 2010). Transitive closure involves ties from *i* to *j*, from *j* to *k*, and from *i* to *k* and in work-related advice networks reflects tendencies for hierarchical differences among individuals as there is only one individual in a triad that two others turn to (Rank et al., 2010). By contrast, cyclic closure captures cycles of ties connecting individual (i.e., *i* seeks advice from *j*, *j* seeks advice from *k*, and *k* seeks advice from *i*) and indicates tendencies for generalized exchange (Molm et al., 2007; Rank et al., 2010). Table 2 summarizes the cross-level patterns referring to the different knowledge dimensions, the patterns referring to inventor-specific control variables, and the network endogenous patterns represented in the empirical model specification that we discuss in the following.

--- Insert Table 2 about here ---

3.3. Exponential random graph models

We analyze our data applying exponential random graph models (ERGMs, for an introduction see Lusher et al., 2013) for multilevel networks (Wang et al., 2013). ERGMs have been developed to account for dependencies in network structures described above and enable us to explicitly model the choice process of advice tie creation. The models describe the patterns characterizing an observed network by modelling a stochastic process in which the presence of a particular tie is influenced by the presence or absence of other ties or exogenous attributes. In contrast to other statistical approaches in the family of network analysis, ERGMs do not operate at the dyadic level but their outcome variable is the overall structure of a network. The models treat the whole network as a single observation, thus freeing it from any independence assumptions. As social ties imply dependence, we consider this as a major strength of our modeling approach, which is of theoretical as well as empirical importance for the analysis of our research question.

While originally developed for the examination of single-level networks, ERGMs have recently been adapted for the analysis of multilevel networks (Wang et al., 2013; Wang et al., 2016). Multilevel ERGMs enable us to account for complex cross-level dependencies, such as the influence of the firm's knowledge network on its inventors' popularity and activity in the advice network. Stated formally, multilevel ERGMs express the probability of the overall network structure in terms of parameters associated with specific effects or local patterns within the network. They focus on the interaction between three networks – in our case the firm's knowledge network at the macro level, the micro-level advice network, and the affiliation network linking corporate inventors to knowledge elements. At the same time, they allow taking into account inventor attributes as exogenous predictors of the network structure. Multilevel ERGMs have the general form:

$$\Pr(M = m | Y = y) = \left(\frac{1}{\kappa}\right) \exp\left(\sum_Q \theta_Q \, Z_Q(m, y)\right) \qquad (1)$$

where (i) $M = [A,X,B]$ denotes the multilevel network variable, and $m = [a,x,b]$ denotes the corresponding realizations. M is composed of a macro-level network A (in our case the knowledge network), a micro-level network B (the interpersonal advice network), and an affiliation network X (the connection of the inventors to the knowledge elements); (ii) Y is an array of actor attributes with realizations y; (iii) $Z_Q(m, y)$ is a network statistic counting the number of network patterns of type Q for a particular network realization m and given the vector of actor attributes y; (iv) θ_Q is the parameter corresponding to the statistic $Z_Q(m, y)$; and (v) κ is a normalizing constant included to ensure that (1) is a proper probability distribution. The summation is taken over all network patterns Q included in a given model. The above equation describes a probability distribution of multilevel networks with u nodes at one level and v nodes at the other. The probability of observing any particular network m in this distribution (including the one that is actually observed) is dependent both on the statistics Z_Q(m, y) and the corresponding parameter values θ_Q for all effects in the model.

The objective of using ERGMs is to investigate which patterns characterize an observed network and based on that draw conclusions on the choice processes that determine the creation of ties. The patterns included in the model are determined by the theory-based dependence assumptions regarding tie creation and the exogenous attributes – such as the knowledge dimensions derived from the knowledge network and the inventor-specific control variables – discussed above. To estimate our model, we apply Markov chain Monte Carlo maximum likelihood (MCMCML) estimations as recommended by several authors (e.g., Snijders et al., 2006; van Duijn et al., 2009) using the multilevel PNet software (Wang et al., 2013). Since we are interested in the drivers of advice tie creation, we treat the knowledge network and the affiliation network as exogenously given and fix them in the estimation. Theoretically, we thus assume that the structure of the firm's knowledge network and the inventors' embeddedness in it may have an effect on the advice network but that advice transfer does not influence the knowledge network and the inventors' possession of knowledge elements. Empirically, we do not model the structure of the firm's knowledge network and the inventors' embeddedness in it as these two components of the multilevel network precede the observed advice network in time and hence cannot depend on it. In essence, we predict the advice network from the rest of the multilevel network.

4. Results

4.1. Descriptive results

Table 3 provides descriptive measures and correlations for the variables in our study. The advice network has a density of 3 percent; in other words, three percent of all 18,090 possible ties between the 135 inventors are actually present within the observed network. While 55 percent of all advice ties were within-division ties, 45 percent of advice seeking requests were directed to members of other divisions. Moreover, while half of the knowledge elements were exclusively held by members of a single division, the other half was shared by members of at least two different divisions. Figure 3 visualizes (a) the knowledge network of the firm, (b) the advice network among its inventors, and (c) the affiliation network of inventors possessing knowledge elements as the three components of the multilevel network under investigation. Figure 4 highlights how the three components fit together: The firm's knowledge network and the individual-level advice network are linked by the affiliation network and form one multilevel network that is the object of our analysis.

--- Insert Table 3 about here ---

--- Insert Figure 3 about here ---

--- Insert Figure 4 about here ---

4.2. Results of the exponential random graph model

Table 4 contains the results of our model estimation. Conditional on all other patterns in the model, a positive (negative) parameter indicates that a pattern is observed more (less) often in the network than we would expect if ties emerged randomly. Similar to a logistic regression, the size of the parameter estimates can be interpreted in terms of (conditional) log odds. For every increase of a variable by one unit, the conditional odds of observing an advice tie increase by a factor that can be obtained by calculating the exponential function of the parameter value (Hunter et al., 2008; Robins and Daraganova, 2013).

With respect to Research Question 1 that addresses the influence of knowledge diversity on the transfer of work-related advice among inventors, we find that the *knowledge diversity popularity* effect is positive (exp(0.125) = 1.133). Having diverse knowledge as indicated by possessing a high number of knowledge elements leads to corporate inventors being particularly sought-after as advisors by their colleagues. Conversely, the *knowledge diversity activity* effect is negative (exp(-0.110) = 0.896), indicating that corporate inventors with diverse knowledge generally seek less work-related advice from their colleagues. Concerning Research Question 2, our results show that the *uniqueness popularity* effect is negative (exp(-0.601) = 0.548) indicating that inventors possessing unique knowledge are unpopular advisors for their colleagues. At the same time, we obtain a positive *uniqueness activity* effect (exp(0.967) = 2.631) indicating that corporate inventors possessing rare knowledge elements much more actively seek advice from their colleagues.

Regarding Research Questions 3 and 4 relating to the structural features of the firm's knowledge network, we find that combinatorial potential of knowledge elements has a negative effect on receiving advice requests (*combinatorial potential popularity*, (exp(-0.209) = 0.811)) and a positive effect on seeking advice (*combinatorial potential activity*, (exp(0.170) = 1.185)). Conversely, we find that the more combinatorial opportunities inventors' knowledge elements offer, the more others turn to them for advice (*combinatorial opportunities popularity*, (exp(0.282) = 1.326)) and the less the inventors rely on interpersonal advice seeking (*combinatorial opportunities activity*, (exp(-0.222) = 0.801)). Finally, with respect to Research Question 5 addressing *knowledge proximity*, we find that inventors embedded similarly in the firm's knowledge network by possessing the same knowledge elements are almost twice as likely to be connected by an advice tie (exp(0.676) = 1.966). Thus, similarity in knowledge fosters advice tie creation.

We included the remaining patterns as control variables to account for exogenous influences on advice transfer among the inventors and for network endogenous processes. With respect to the exogenous inventor attributes, we find a negative *hierarchical status popularity* effect (exp(-0.399) = 0.671) indicating that high status inventors are nominated as advisors less often than expected if ties were created randomly. Moreover, inventors with the same status (*hierarchical status homophily*, (exp(0.697) = 2.008)) and a similar number of years spend at the firm (*tenure homophily*, (exp(-0.015) = 0.985)) are more likely to seek advice from each other.[7] The number of patents is negatively related to receiving advice requests by colleagues (*patents popularity*, (exp(-0.112) = 0.894)) and positively related to seeking advice (*patents activity*, (exp(0.069) = 1.071)). Finally, inventors belonging to the same division and those who have jointly patented in the past are more likely to be connected by an advice tie as indicated by the positive *entrainment by division* (exp(0.492) = 1.636) and *entrainment with co-invention* (exp(0.964) = 2.622) effects. The remaining exogenous effects are insignificant.

Concerning the network endogenous control variables, the negative *arc* effect (exp(-3.903 = 0.020) indicates that it is rare for inventors to create advice ties outside of the other, more complex patterns included in the model. The positive *reciprocity* effect shows that conditional on the presence of an advice tie from one inventor to the other, the odds of reciprocation are more than twenty times (exp(3.100) = 22.198) the odds of no reciprocation. The negative *popularity spread* (exp(-0.307) = 0.736) and *activity spread* (exp(-0.275) = 0.760) effects indicate that the network is decentralized. Hence, each inventor roughly was nominated by and nominated the same number of colleagues. The positive *popularity two-star* effect (exp(0.013) = 1.013), included mainly to improve the model fit, highlights that inventors are likely to be nominated as advisors by more than one colleague. Finally, the tendencies for *transitive closure* (exp(1.391) = 4.019) and against *cyclic closure* (exp(-0.537) = 0.584) point towards hierarchical differences among inventors in the sense that there is only one inventor in a triad that two others turn to for knowledge (Rank et al., 2010).

--- Insert Table 4 about here ---

[7] For binary attributes such as status a positive parameter indicates homophily. For continuous attributes such as tenure the homophily parameter captures the difference in size between values of a continuous attribute. A negative value indicates a small difference, suggesting that actors are similar, thus indicating homophily.

4.3. Goodness of fit

After estimating the model, we assessed the goodness of fit based on the procedure suggested by Hunter et al. (2008) simulating a high number of graphs from the fitted model and comparing the characteristics of the simulated graphs to the characteristics of the observed network. We built on a sample of 5,000 graphs out of 500 million simulated networks. Drawing on the criteria suggested by Robins et al. (2009) the results revealed that our model yields a very good fit. The goodness of fit statistics of all effects included in the model were below the threshold value of 0.1. Moreover, all of the almost 100 graph statistics that were not explicitly modeled but included in the goodness of fit analysis reached values below the recommended threshold of 2. In sum, the observed network can be reproduced adequately based on the model.

5. Discussion and Conclusions

Knowledge is a valuable asset and an important source of competitive advantage for firms (Grant, 1996). In this study, we conceptualize the firm's knowledge stock as a network and investigate several research questions on how the structural features of this knowledge network influence a social network among the firm's inventors. Taking a multilevel network approach, our results show that different dimensions of knowledge derived from the inventors' embeddedness in the knowledge network determine their popularity and activity within a work-related advice network.

We find that inventors possessing a diverse set of elements from the firm's knowledge stock are popular advisors for their colleagues while at the same time they less actively seek advice. The qualities going along with high knowledge diversity, such as being open-minded and having expertise in a variety of areas (Boh et al., 2014) seem to make these inventors attractive sources for work-related advice. Moreover, due to having diverse knowledge they are less in need for advice. These findings add to a broader literature on the role of generalist inventors in corporate R&D. While this literature has focused on how generalists influence innovation outcomes (Boh et al., 2014; Lettl et al., 2009; Melero and Palomeras, 2015) our results contribute to a better understanding of their role in the innovation process which heavily relies on social networks (Nerkar and Paruchuri, 2005). We highlight how knowledge diversity informs the choice process of advice tie creation leading to inventors with diverse knowledge and inventors with narrow knowledge occupying different positions in work-related social networks. This difference influences how knowledge diffuses within the organization and thus affects knowledge creation and recombinant possibilities.

Concerning uniqueness of knowledge, we find that inventors with widespread rather than unique knowledge elements are more popular as advisors for their colleagues. It seems that inventors do not consider unique knowledge elements to be valuable resources. Rather, these knowledge elements might have the air of being too exotic to be useful. Moreover, the lack of experience in working with the knowledge elements within the firm might discourage inventors to allocate further attention to them (Wang et al., 2014). This could also be one reason why inventors possessing knowledge elements that none or few of their colleagues possess as well are more active seeking advice from colleagues. In order to stay involved in the process of recombining knowledge to generate innovation, inventors with unique knowledge elements show an increased tendency to seek advice from colleagues who might help them to exploit the unique resource they possess and to gain new knowledge. In sum, our findings concerning uniqueness of knowledge show that the question of how many colleagues are connected to elements from the firm's knowledge network plays a critical role for the transfer of advice in knowledge-intensive organizations. From a practical viewpoint, inventors' tendency to avoid seeking advice from colleagues with unique knowledge may lead to missed recombinant possibilities, with potential negative consequences for the firm.

We further find that possessing knowledge elements with a high degree centrality and thus high combinatorial potential according to our above definition is positively related to seeking advice and negatively related to receiving advice requests. In light of these findings, it seems that knowledge elements that have already been combined extensively in the past and that the inventors are thus familiar with are no longer perceived to offer many possibilities for recombination (Carnabuci and Bruggeman, 2009; Wang et al., 2014). Therefore, inventors possessing such knowledge elements try to extend their knowledge by seeking advice from colleagues. At the same time, this feature of their knowledge elements makes them less attractive as advisors for their colleagues. All in all, these findings indicate that inventors rely on their knowledge elements' degree centrality as an inverse measure for the future inventive possibilities they bring about.

By contrast, the possession of knowledge elements that offer high levels of combinatorial opportunities leads inventors to rely less on advice seeking while a lack of combinatorial opportunities increases advice seeking. Thus, it seems that inventors try to substitute the lacking opportunities provided by their knowledge elements by exploring their colleagues' knowledge using interpersonal ties. This finding complements findings by Wang et al. (2014) who show that researchers whose knowledge elements lack combinatorial opportunities more heavily engage in explorative innovation. In addition, we find that the more combinatorial opportunities their knowledge elements provide, the more others turn to inventors for work-related advice. Colleagues thus try to benefit from these opportunities by asking for knowledge and advice and potentially initiate joint inventions in the future. Overall, our findings concerning combinatorial potential and opportunities confirm that inventors' popularity and activity in the advice network depend on the position of their knowledge elements within the firm's knowledge network. They illustrate that structural features of the firm's knowledge stock have a direct influence on interpersonal interactions and can thereby influence the diffusion of knowledge and thus recombinant possibilities within the firm (Singh, 2005).

Finally, drawing on the literature on proximity (e.g., Boschma, 2005) and homophily (McPherson et al., 2001) we complement existing studies on the importance of similarity as a driver of social networks (e.g., Kleinbaum et al., 2013). We highlight that being embedded similarly in the firm's knowledge network, just like sharing similar demographic attributes, increases the chance of advice transfer among inventors in corporate R&D. This result contradicts a finding by Crescenzi et al. (2016) who show that inventors co-patent with others possessing dissimilar knowledge and thereby highlights the differences between social networks derived from formal collaboration and more informal work-related advice networks. While formal collaboration on patents is likely to be influenced by organizational staffing decisions, advice seeking can occur independent of such formal requirements. This finding also has implications for knowledge diffusion and possibilities for recombination in organizations. On the one hand, knowledge proximity facilitates communication, exchange, and learning among inventors. On the other hand, it increases the risk of technological lock-in (e.g., Sydow et al., 2009) by restricting inventors' interpersonal exchange to others possessing a similar knowledge stock and may thus be detrimental for the generation of innovation in the context of knowledge-intensive work. Innovation managers might want to make inventors aware of how their interpersonal networking behavior is influenced by their own and their colleagues' knowledge. This way, they might motivate them to consciously consider and if necessary adapt their advice ties to the requirements of their tasks.

Integrating research on social and knowledge-based search (e.g., Guan and Liu, 2016; Yayavaram and Ahuja, 2008) in corporate R&D, our findings highlight that while the firm's knowledge network and the social network among its inventors might be decoupled (Guan and Liu, 2016; Wang et al., 2014), they are at the same time closely related. The way that firm knowledge is structured and distributed among inventors critically influences interpersonal interactions and guides individual search behavior. In other words, social search and knowledge-based search are tightly intertwined as inventors account for properties of their own and their colleagues' knowledge elements when creating social network ties aimed at obtaining work-related advice. Since social networks can be seen as an important component of the search process underlying recombinant invention (Nerkar and Paruchuri, 2005) and have been argued to be the main channels for inventors to transfer recombination-related knowledge (Hansen, 1999; Singh, 2005), this finding can be linked to the innovation process in corporate R&D. Particularly, the choice of advisors based on knowledge influences recombinant possibilities and thus has an important bearing on the firm's innovative potential.

Our study further highlights the multilevel nature of inventors' network embeddedness (Brass et al., 2004; Kilduff and Brass, 2010; Wang et al., 2014) and extends research on the determinants of social networks in knowledge-intensive settings. While prior studies have shown that these networks are the primary means in organizations through which inventors seek knowledge for recombination (Allen, 1977; Singh, 2005) and have linked networks to innovation outcomes (Harhoff et al., 2013; Tortoriello, 2015; Tortoriello and Krackhardt, 2010), the determinants of tie creation have attracted comparatively little attention. We build on the assumption that advice seeking is a choice process that is informed by characteristics of the advice-seeker and the advisor, the relationship between them, as well as by other network actors (Borgatti and Cross, 2003). Accounting for the influence of known drivers of interpersonal tie creation, the results of our empirical model show that depending on their knowledge relative to the overall knowledge stock of the firm, corporate inventors approach advice seeking – and hence the innovation process – in different ways. Moreover, different dimensions of knowledge influence their choice of advisors and thereby the structure of work-related advice transfer in unique ways.

The fact that knowledge has not been investigated before as a driver of work-related social networks points to another contribution of our study. As Borgatti and Carboni (2007) have pointed out, accurately measuring knowledge in organization studies is difficult. We show that technology classes assigned to patents are a useful, objective, and easily observable proxy to capture knowledge of a firm and its inventors. As demonstrated in this study, they allow for a conceptualization of knowledge as a multidimensional, complex structure, which reflects that knowledge can be more than a mere attribute of the individual inventors. This conceptualization is important because, as our results demonstrate, different knowledge dimensions fulfil different roles in structuring the transfer of advice. Of course, drawing on patents to measure knowledge also has its limitations. It means that we capture corporate inventors' technological and codified knowledge only. Even though past research has shown that firms' propensity to patent correlates with measures incorporating tacit knowledge (Brouwer and Kleinknecht, 1999) it would be a fruitful avenue for future research to directly compare and contrast tacit and codified knowledge as determinants of interpersonal interactions. Likewise, investigating the role of non-technical knowledge as a driver of social networks is an avenue worth pursuing.

Another limitation of our study is that we were only able to capture advice seeking at one point in time and could not account for its evolution. In other words, due to the temporal structure of our data, we had to concentrate on how the knowledge network of the firm influences the social network among corporate inventors. Yet, it is not realistic to assume that this relationship is strictly one-sided. Rather, the social network and the knowledge network are likely to be mutually dependent. Interpersonal interactions among inventors lead to new patentable inventions (e.g., Harhoff et al., 2013; Tortoriello, 2015) which then modify and extend the knowledge network of the firm and in turn lead to changes in the advice network. To fully disentangle these interdependencies, future longitudinal studies should investigate the co-evolution of social networks and knowledge networks within firms. A second temporal aspect opening up opportunities for future research relates to recency effects in remembering and accessing knowledge briefly mentioned above. As highlighted by Katila (2002) and Nerkar (2003) drawing on recent knowledge or using established knowledge can both benefit innovation outcomes. Uncovering the drivers for varying tendencies to concentrate on new or re-use old knowledge elements in the innovation process can shed further light on firm-level and individual-level approaches to innovation.

Finally, we build on the assumption that inventors have at least a broad overview of the knowledge network of their firm and of the knowledge elements possessed by their colleagues. Doing so, we follow Wang et al. (2014: 488) who state that to be able to participate in knowledge production, an inventor "needs to grasp at least part of a firm's knowledge stock, and must have some understanding of potential and realized connections among its knowledge elements." However, we acknowledge that in larger firms, with a higher number of corporate inventors it will become more difficult for the inventors to maintain this overview.

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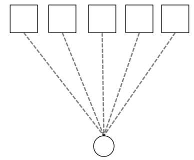
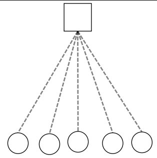
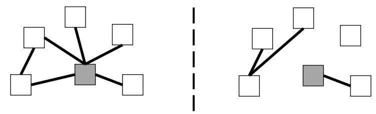
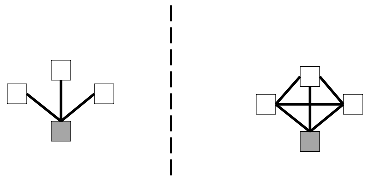
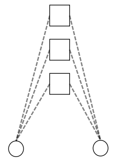
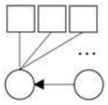
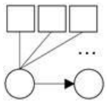
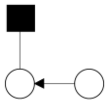
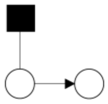
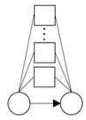
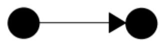
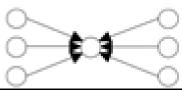
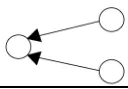
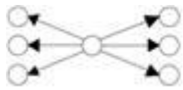
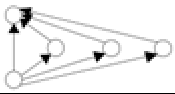
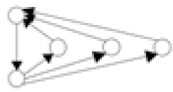
Table 1
Conceptualization of the knowledge dimensions

Variable	Measurement Level	Definition	Visualization	Formula
Knowledge diversity	Inventor	Number of knowledge elements *k* an inventor *i* is connected to in the affiliation network *X*. The larger the number of knowledge elements, the broader the inventor's knowledge.		$d_i = \sum_k \mathrm{x}_{ik}$
Uniqueness of knowledge	Knowledge element	Number of inventors *i* linked to a knowledge element *k* in the affiliation network *X*. The fewer inventors possess a knowledge element, the more unique it is.		$u_j = (-1)\sum_i x_{ik}$
Combinatorial potential	Knowledge element	Degree centrality of a knowledge element *k* within the knowledge network *A*. A high average degree centrality reflects high combinatorial potential.	 *high potential* *low potential*	$cp_k = \sum_k a_{kl}$
Combinatorial opportunities	Knowledge element	Structural holes a knowledge element *k* bridges within the knowledge network *A*. A high average structural holes measure reflects high combinatorial opportunities.	 *high opportunities* *low opportunities*	$co_j = (-1)\sum_k c_{kl}$ with $c_{kl} = \left(p_{kl} + \sum_q p_{kq}p_{ql}\right)^2$ and p being the proportional strength of individual ties
Knowledge proximity	Dyad of inventors	Two inventors *i* and *j* being connected to the same knowledge elements with *a* being the overall number of knowledge elements and P_{ij} representing the number of shared knowledge elements of two inventors. λ is a dampening factor (Snijders et al., 2006).		$\sum_{ij}\sum_{k=1}^{a-2}(-1)^{k-1} * \frac{\binom{P_{ij}}{k}}{\lambda^{k-1}}$

Note: □ = knowledge element; ○ = corporate inventor, ■ = focal knowledge element

Table 2
Network patterns included in the ERGM

Pattern	Visualization	Interpretation
Cross-level patterns relating to the knowledge dimensions		
Knowledge diversity popularity		Tendency for corporate inventors with many knowledge elements to be sought-after for advice by colleagues
Knowledge diversity activity		Tendency for corporate inventors with many knowledge elements to seek advice from colleagues
[Knowledge attribute] popularity		Influence of an attribute assigned to a knowledge element on corporate inventors to be sought-after for advice by colleagues
[Knowledge attribute] activity		Influence of an attribute assigned to a knowledge element on corporate inventors' tendency to seek advice from colleagues
Knowledge proximity		Tendency for corporate inventors connected to the same knowledge elements to establish advice ties
Patterns relating to inventor-specific control variables		
[Inventor attribute] popularity		Tendency for inventors with a high value on an assigned attribute to be popular as advisor
[Inventor attribute] activity		Tendency for corporate inventors with a high value on an assigned attribute to seek advice
[Inventor attribute] homophily		Tendency for corporate inventors with a similar values on an assigned attribute to transfer advice
Entrainment with dyadic attribute		Tendency for advice ties to co-occur between inventors connected by a tie in another network
Patterns relating to network endogenous effects		
Arc		Baseline propensity to form advice ties
Reciprocity		Tendency towards reciprocity
Popularity spread		Tendency for variation in the degree to which corporate inventors are nominated as advisors
Popularity two-star		Tendency for corporate inventors to be nominated as advisor by two colleagues
Activity spread		Tendency for variation in the degree to which corporate inventors nominate others
Transitive closure		Tendency for triadic closure, indicative of transitivity
Cyclic closure		Tendency for cyclic closure, indicative of a prevailing generalized exchange

Note: □ = knowledge element; ○ = corporate inventor, ■ = knowledge element with attribute; ● = inventor with attribute.

Table 3
Descriptive statistics and correlations

	Variables	Mean	S.D.	Min	Max	1	2	3	4	5	6	7	8
1.	Outgoing advice ties	4.06	3.26	0	16								
2.	Incoming advice ties	4.06	3.83	0	25	0.44**							
3.	Number of knowledge elements (knowledge diversity)	2.81	2.28	1	11	0.27**	0.31**						
4.	Average uniqueness of knowledge elements	-25.40	13.36	-48	-1	-0.13	-0.10	0.28**					
5.	Average combinatorial potential of knowledge elements	118.57	62.17	0	228	0.16	0.10	-0.19*	-0.93**				
6.	Average combinatorial opportunities of knowledge elements	-0.22	0.18	-1	-.09	0.17*	0.13	-0.12	-0.64**	0.69**			
7.	Hierarchical status	-	-	0	1	0.28**	0.18*	0.41**	0.19*	-0.14	-0.07		
8.	Tenure in firm	11.73	8.33	1	39	0.06	0.06	0.22*	0.10	-0.03	0.06	0.24**	
9.	Number of patents	2.83	2.69	1	14	0.39**	0.20*	0.72**	0.10	-0.05	0.00	0.29**	0.16

Note: N = 135, * $p<0.05$, ** $p<0.01$.

Table 4

Maximum likelihood estimates of the multilevel ERGM for advice ties

Pattern	**Parameter**	**Standard Error**
Effects relating to the knowledge dimensions		
Knowledge diversity popularity	0.125**	0.036
Knowledge diversity activity	-0.110**	0.040
Uniqueness popularity	-0.602†	0.336
Uniqueness activity	0.967**	0.353
Combinatorial potential popularity	-0.209**	0.065
Combinatorial potential activity	0.170*	0.071
Combinatorial opportunities popularity	0.282*	0.139
Combinatorial opportunities activity	-0.222†	0.135
Knowledge proximity	0.676**	0.086
Effects relating to inventor-specific control variables		
Hierarchical status popularity	-0.399**	0.114
Hierarchical status activity	-0.025	0.117
Hierarchical status homophily	0.697**	0.138
Tenure popularity	-0.001	0.006
Tenure activity	-0.002	0.006
Tenure homophily	-0.015*	0.006
Patents popularity	-0.112**	0.024
Patents activity	0.069**	0.023
Patents homophily	0.022	0.017
Entrainment with division	0.492**	0.069
Entrainment with co-invention	0.964**	0.118
Network endogenous effects		
Arc	-3.903**	0.315
Reciprocity	3.100**	0.229
Popularity spread	-0.307*	0.141
Popularity two-star	0.013**	0.005
Activity spread	-0.275*	0.138
Transitive closure	1.391**	0.083
Cyclic closure	-0.537**	0.077

†*p* < 0.10; **p* < 0.05; ***p* < 0.01.

Figure 1
Schematic depiction of the inventors' embeddedness in the knowledge network

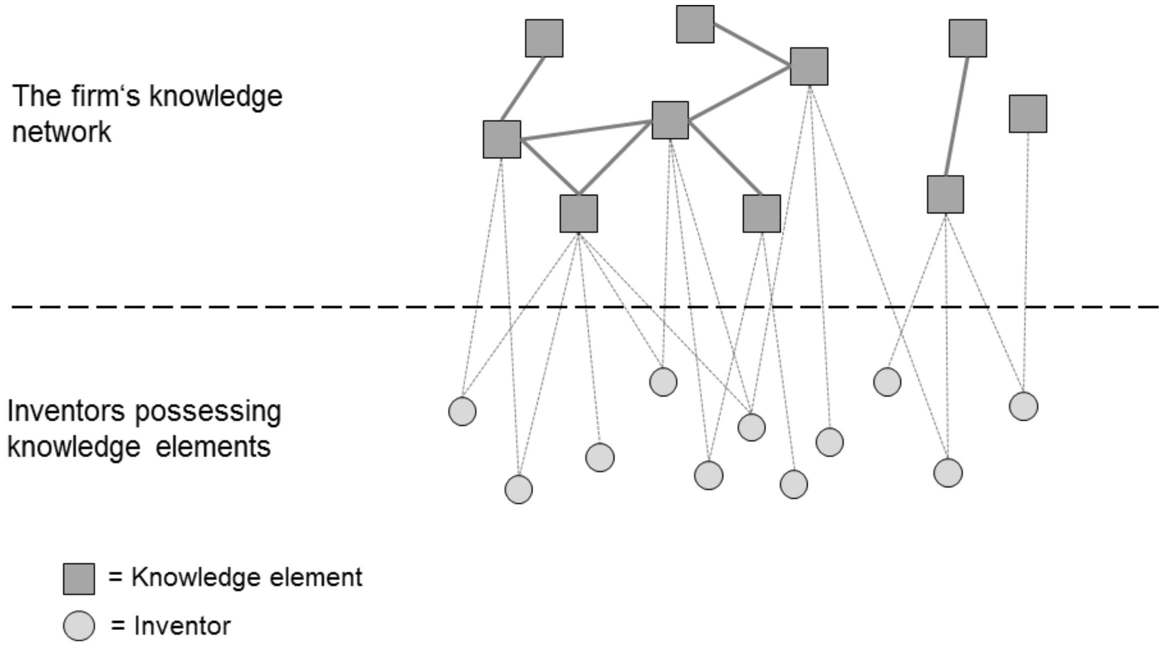


Figure 2
Overview of research questions and their link to the multilevel network

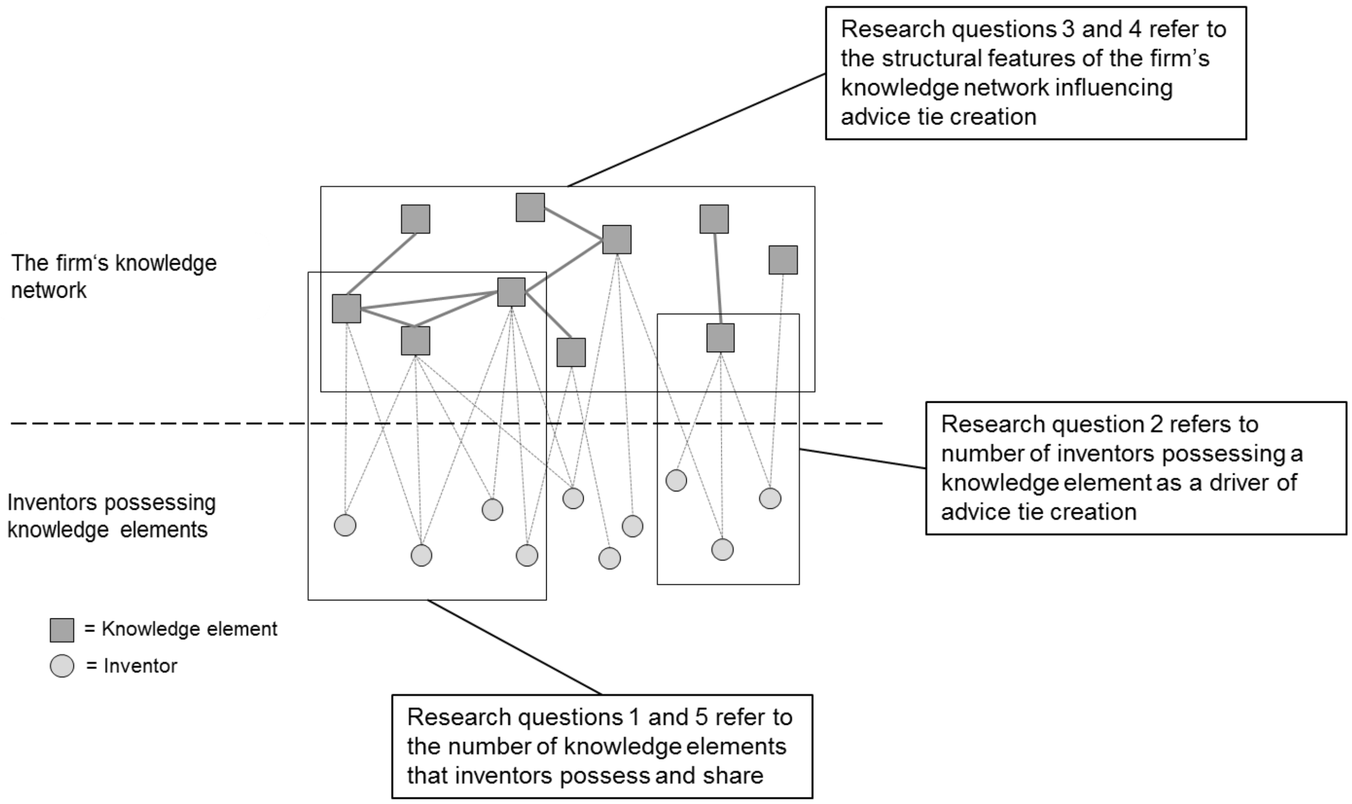
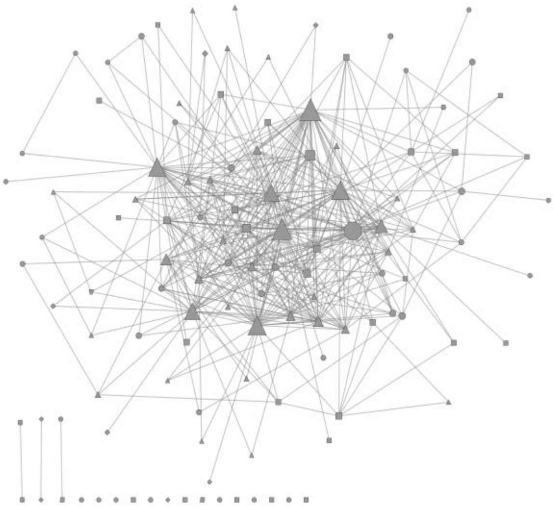


Figure 3

Visualizations of the observed networks

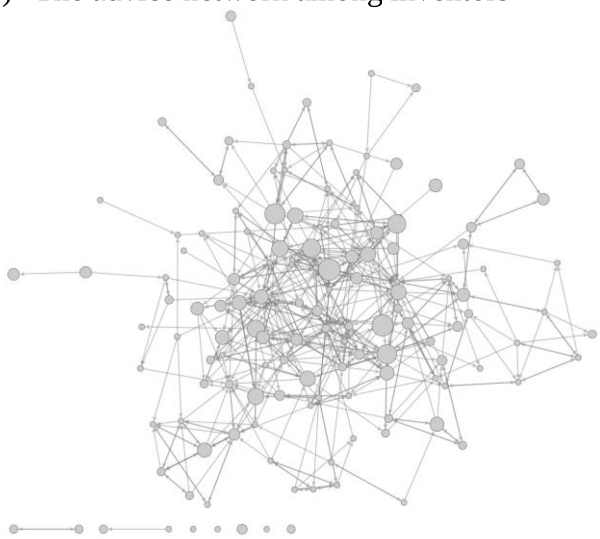
a) The firm’s knowledge network



Notes. M = 118 knowledge elements; the size of the knowledge elements reflects the number of the firm’s patents they have been assigned to; the shapes represents the broad knowledge area according to the main IPC sections.

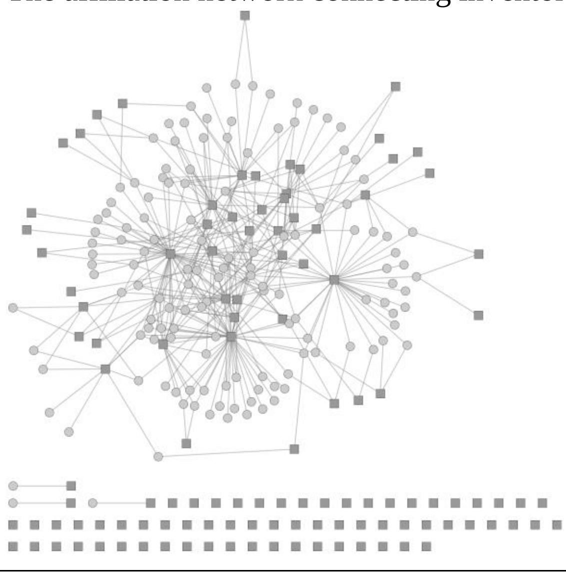
= physics
= electricity
= performing operations; transporting
= textiles; paper
= mechanical engineering; lighting; heating; weapons; blasting
= fixed constructions
= human necessities
= chemistry; metallurgy

b) The advice network among inventors



Notes. N = 135, the size of the inventors reflects the number of patents they have.

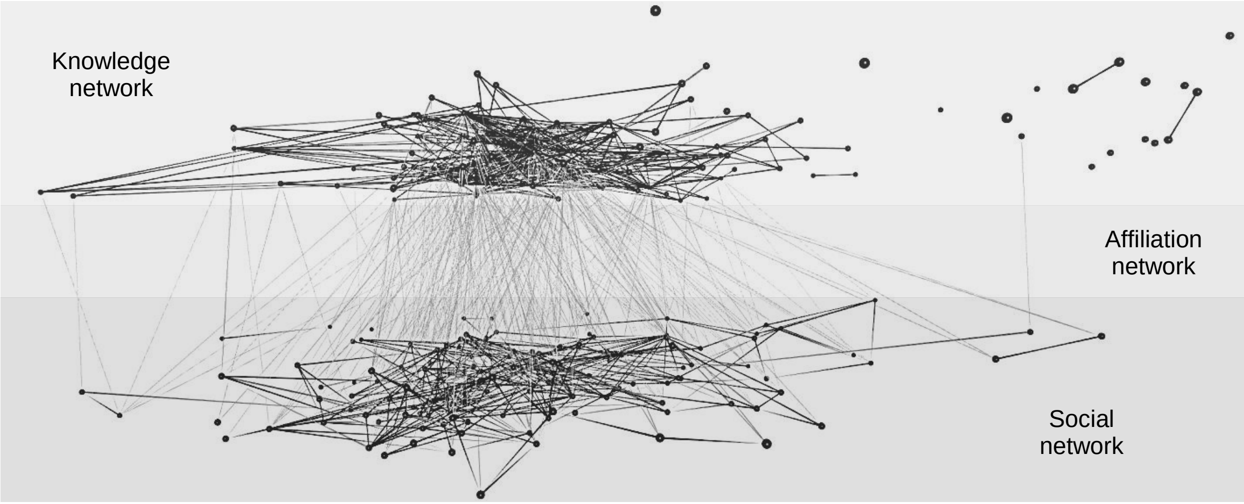
c) The affiliation network connecting inventors to knowledge elements



Notes. N = 135 inventors and M = 118 knowledge elements

= Knowledge element
= Inventor

Figure 4
The observed multilevel network



Note: The visualization was created using code based on Brailly et al. (2016).