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How to Build a Network that Facilitates Firm-level Innovation: An Integration of Structural and Managerial Perspectives

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ABSTRACT In this paper, we examine to what extent the firm's propensity to be embedded in a network with advantageous structural attributes is driven by its capabilities for network management. Specifically, we discern network management practices on two organizational levels (relationship management (RM) and portfolio management (PM)) and explore their effects on three dimensions of local network structure (network centrality (NC), knowledge complementarity (KC), and tie strength (TS)). To test our hypotheses, we collect sociometric survey data from the largest inter-firm network in the German energy industry. The results indicate that intra-firm processes for network management indeed are key enablers of structural network advantages. Further, we demonstrate that RM and PM exert distinct effects: PM helps the firm improve NC, RM leads to increased TS, and KC results from an additive effect of the two capabilities. In all, our work contributes to theory on strategic networks by providing an integrated perspective on how network structure and network management benefit innovation performance.

Keywords: strategic networks, network structure, network management, organizational capabilities, innovation

INTRODUCTION

A growing number of management scholars attribute organizational performance, especially innovation, to the firm's network of strategic relationships. The strategic network perspective assumes that the structural attributes of the firm's local network position, i.e., the pattern of network ties in which the firm is embedded (Burt, 1992), determine the quantity and quality of the external knowledge that the firm can acquire (Gulati et al.,

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2000). In line with this assumption, research produced extensive evidence for the significant influence of local network structure on firms' innovation performance (see Phelps et al., 2012 for an overview).

However, most strategic network literature has one serious limitation: network structures have been considered as static and exogeneous (Stuart and Sorenson, 2007). Hence, firms 'are treated as being randomly assigned particular network positions or ego network structures' (Phelps et al., 2012, p. 1154). Recently, this 'structuralist' assumption of exogeneity has been challenged. Scholars argue that firms should rather be perceived as strategic agents that purposefully engage in shaping their local networks (Rowley and Baum, 2008a). Performance advantages would thus stem 'not merely from opportunity structures embedded in networks but also from the distribution of ability and motivation among firms' (Madhavan et al., 2008, p. 457).

Rather independent of the 'structuralist heritage' of network theory (Gulati et al., 2011), a second theoretical viewpoint has emerged recently: the 'managerial perspective' on strategic networks (Faems et al., 2012). This perspective centres around the organizational capability of 'network management', i.e., the processes by which firms initiate, nurture, and restructure their relations with external partners (Khanna, 1998). Putting the focus on internal management practices, the managerial perspective addresses exactly the firm-level factors that the more traditional 'structural perspective' on strategic networks misses out on (Rowley and Baum, 2008b).

Surprisingly, however, though the managerial perspective puts forth potentially complementary explanations to the structural perspective, both streams ignore each other for the most part. For instance, Wang and Rajagopalan (2015) argue that the neglect of network structure is the major reason that the causal mechanisms that link network management to firm performance are still unclear. The structural perspective, in turn, is criticized for leaving unanswered the question of *how* firms achieve structural network advantages (Rowley and Baum, 2008a). In all, there is lack of research on 'the interaction between […] network management and structural […] network characteristics (e.g., network centrality, network density) in influencing innovation performance' (Faems et al., 2012, p. 262).

Our paper addresses this research gap aiming to integrate both perspectives on strategic networks. Specifically, we seek to answer two central research questions: (1) Does network management help the firm strategically shape local network structures, i.e., are firms with highly developed network management capabilities more likely to build a network with advantageous structural attributes? (2) Do firms require network management capabilities on different levels for obtaining different types of network advantages, and if yes, in what way?

As baseline logic, we suggest that the development of structural network advantages is afflicted with constraining forces. The nature of those constraining forces depends on the specific network attribute the firm tries to improve (Koka and Prescott, 2008). Internal processes for network management help overcome those constraints (Ozcan and Eisenhardt, 2009). Based on this reasoning, we develop a set of hypotheses that link network management capabilities on two levels (dyadic-relational and portfolio) to three key attributes of local network structure (centrality, knowledge complementarity, and tie strength) that should affect innovation.

We test the hypotheses analysing data from the largest inter-firm network in the German energy industry and make three contributions to extant theory. First, we enrich the prevalent understanding on the origins of strategic networks by demonstrating that indeed network management is a strong determinant of network structure. Second, our results indicate that in large part, network management capabilities do not drive innovation by themselves but by operating on the firm's network advantages. By this, we help clarify the mechanisms by which network management links to strategic outcomes. Third, disentangling the effects of portfolio and relationship management, we show that the two serve distinct but overlapping functions. On this basis, we posit that the two capabilities are much less intertwined than previously assumed and represent largely independent approaches for successful networking.

THEORETICAL BACKGROUND

Local Network Structure and Innovation Performance

In the main, our considerations are based on the strategic network perspective (Gulati et al., 2000). The strategic network perspective emerged as scholars began to apply social network theories to explain the performance effects of inter-firm relations (Lavie, 2007). The core assumption is that local network structure, i.e., the content and arrangement of the network ties of a social actor (Burt, 1992), determines the quantity and quality of external resource access. In the innovation context, especially intangible assets in the form of information and knowledge are considered as key resources obtained from networks (Sammarra and Biggiero, 2008).

We start our theory development by defining the structural network attributes that are relevant in explaining innovation. In the literature, there are three broad streams, each focusing on a different architectural element of network structure (Ahuja et al., 2012). The first one treats structure as a matter of topology and assesses the overall pattern of network ties (e.g., Ahuja, 2000). The second stream focuses on the resources embedded in the network and examines the characteristics of the firm's partners (e.g., Sampson, 2007). The third stream focuses on the relational attributes of network ties as conduits to channel knowledge (e.g., Tiwana, 2008).

Recently, scholars called for consolidating those three conceptual traditions. Most prominently, Gulati et al. (2011) argue that the divide between the streams has led to 'incomplete theoretical and empirical treatment' of performance effects (p. 208). Advocating a more comprehensive conceptualization of network structure, they suggest that outcome differentials are the result of three distinct resource advantages: reach, richness, and receptivity. Reach describes the quantity of knowledge that a firm can acquire by virtue of its network ties, richness covers the potential value of this knowledge, and receptivity stands for the network's capacity for knowledge transfer. Regarding the performance effects of strategic networks, Gulati et al. (2011) recommend that theoretical models should consider all three mechanisms simultaneously.

The distinction between reach, richness, and receptivity resonates well with other approaches toward a more holistic perspective on network structure. For instance, Phelps et al. (2012) highlight the 'volume' and 'content' of knowledge in the network, and the 'bandwidth' of knowledge transfer as the key drivers of innovation. Other studies develop their theoretical frameworks along similar lines (e.g., Andrevski et al., 2016; Gilsing et al., 2008; Koka and Prescott, 2002). Therefore, in building our research model, we follow the suggestion by Gulati et al. (2011) and include structural attributes linked to each of the three mechanisms. Namely, we select network centrality, knowledge complementarity, and tie strength because (a) those structural attributes have been highly prominent in previous research, and (b) they distinctively relate to the reach, richness, and receptivity of the firm's local network.

First, to capture reach, the bulk of strategic network studies employed positional network attributes, in particular, centrality (e.g., Ahuja, 2000; Soh et al., 2004). Following Gulati et al. (2011), reach refers to 'the extent to which the organization's network of ties connects it to distant and diverse partners' (p. 211). The larger the distance and diversity, the larger is the amount of non-redundant knowledge accessible (Koka and Prescott, 2002). By this, the likelihood of receiving new insights and thus, opportunities for learning and innovation increase (Powell et al., 1996). Centrality, in turn, denotes 'the extent to which the focal actor occupies a strategic position in the network by virtue of being involved in many significant ties' (Gnyawali and Madhavan, 2001, p. 435). Centrality relates to distance as generally, central actors are 'connected to a large number of firms by a short average path' (Schilling and Phelps, 2007, p. 1115). Also, centrality is linked to diversity, as '[b]eing highly central implies a higher chance of being faced with different kinds of knowledge and information' (Gilsing et al., 2008, p. 1728). Therefore, we follow previous research and employ network centrality (hereafter 'NC') to operationalize differences in the reach of firms' local network structure.

Second, richness is typically depicted by the qualities of the firm's partners (e.g., Sampson, 2007). While reach captures the quantity but 'says little about the quality' of external knowledge (Soh et al., 2004, p. 909), richness reflects the potential value of partners' expertise. Network theory posits that such value is ultimately a result of resource combinations (e.g., Lavie, 2007). Hence, to assess network richness, 'one must take into account possible synergies that can emerge by combining […] internal resources with those available via external ties to partners' (Gulati et al., 2011 p. 214). In other words, richness results from a 'good match' (Fang, 2011) and 'additive fit' (Mindruta et al., 2016) between partners' knowledge bases.

In the literature, there are two viewpoints on what constitutes a 'good match'. One perspective highlights knowledge similarity as key quality. Those works argue that firms with similar knowledge may pool their expertise to profit from efficiency-based synergies (Harrison et al., 2001). Still, the similarity perspective is criticized as it neglects value-based synergies that occur 'when two firms have nonoverlapping or different knowledge bases that might be combined and integrated to create value that did not exist in either firm before' (Fang, 2011, p. 159). In the innovation context, such value-based synergies are of particular importance so that 'economies of fitness' should outweigh 'economies of sameness' (Bauer and Matzler, 2014). Thus, we follow the second perspective and focus on knowledge complementarity (hereafter 'KC') to represent the richness of the firm's network. We define KC as the extent to which partners 'bring in unique and valuable strengths' (Sarkar et al., 2001a, p. 361) and 'eliminate deficiencies in each other's portfolio of [knowledge] resources' (Lambe et al., 2002, p. 144).

Third, receptivity is defined as the extent to which the network facilitates resource flows (Gulati et al., 2011). As innovation-related knowledge includes tacit elements that cannot be easily codified, firms often experience transfer problems so that the realized value of external knowledge may be significantly smaller than the potential value (Tiwana, 2008). Accounting for this, the concept of receptivity explains why firms with similar knowledge access extract dissimilar benefits (McEvily and Marcus, 2005). Following Gulati et al. (2011), the receptivity of the firm's network 'depends first and foremost on the quality of its ties to partners' (p. 215). Past works represent receptivity by relational network attributes, in particular, tie strength (e.g., Tiwana, 2008). Tie strength (hereafter 'TS') is defined as the level of repeated and intensive interaction between firms (Capaldo, 2007). Strong ties help the firm 'nurture interorganizational trust, resolve organizational problems, overcome interorganizational conflict, and commit to making specific investments that are essential for value creation in networks' (Gulati et al., 2011, p. 216). We thus include TS as third structural attribute into our theoretical model.

Network Management and Local Network Structure

While the literature provides much insight on the performance effects of strategic networks, much less research examines how local network structures originate (Fang et al., 2015). Most basically, scholars acknowledge that 'networks do not evolve by themselves' (Ozcan and Eisenhardt, 2009, p. 246): it is the firms who shape network structures by the intentional formation and dissolution of ties (Rowley and Baum, 2008a). Thereby, it is at least implicitly assumed that firms behave strategically, seeking to maximize network advantages and trying to navigate their way into valuable structural positions (Stuart and Sorenson, 2007).

In line with the structuralist heritage of network theory, past studies explain network advantages by differences in opportunity (Koka et al., 2006). Those works argue that based on rather stable firm-level characteristics (e.g., firm size) and, in particular, past network structure, some firms are endowed with greater maneuvering space. Still, others have questioned this focus on opportunity differentials, arguing that enacting network opportunities is not an easy task (Rowley and Baum, 2008b). Expanding and reshaping the firm's network should be viewed as a process of organizational change that entails various obstacles and constraints (Kim et al., 2006). To deal with those constraints, the firm would require adequate skills (Madhavan et al., 2008).

We argue that the emerging 'managerial perspective' on strategic networks (Faems et al., 2012) is well-suited to represent the role of firm-level skills in explaining network-level outcomes. The managerial perspective has its origin in the capability-based view of strategic management and is centred around the idea that firms differ in their proficiency for inter-firm networking (Hite and Hesterly, 2001). The core concept is 'network management', defined as a set of identifiable intra-firm processes to initiate, nurture, and restructure network ties (Khanna, 1998). Network management is seen as a valuable organizational capability and as key driver of competitive heterogeneity (Sarkar et al., 2009). In what follows, we extend this notion and contend that firms engaging in deliberate network management are more likely to overcome the constraining forces that interfere with strategic network action. Hence, those capable firms should be better able to shape their network in a goal-oriented manner (Kim et al., 2006).

To this end, we follow past research and distinguish between network management processes on two levels of organization: 1) *individual relationships* to external partners; and 2) the firm's *overall portfolio* of network ties (Wang and Rajagopalan, 2015). For each level, distinct bundles of managerial practices exist, namely *relationship management* and *portfolio management* (Kale and Singh, 2009). Relationship management (hereafter 'RM') describes the extent to which the firm engages in practices to cultivate individual network ties (Schilke and Goerzen, 2010). RM encompasses practices of coordination, communication, and bonding (Schreiner et al., 2009). Elaborated RM processes help overcome 'problems of cooperation' (Gulati et al., 2005, p. 419) and 'relational imperfections' (Sarkar et al., 2009, p. 587). RM thus benefits the firm as the collaborative interaction in its network ties is optimized (Gulati and Singh, 1998). Portfolio management (hereafter 'PM') describes processes that address the firm's network in its entirety (Hoffmann, 2007). The notion of PM posits that the network portfolio is more than the sum of the single ties (Sarkar et al., 2009). A lack of PM thus may result in what Granovetter (1992, p. 33) calls 'dyadic atomization', a neglect of interdependences between network relationships. Sophisticated PM practices enable the firm to identify synergies between partners and configure a network of ties that collectively meet the firm's strategic needs (Kale and Singh, 2009). Essentially, PM encompasses processes for searching potential partners, coordinating interdependences, and monitoring the firm's network and its performance (Walter et al., 2006).

In the following, we argue that both RM and PM help firms improve the structural attributes of their local networks. More specifically, we suggest that these two types of network management actuate unique mechanisms and affect network structure in distinct ways. In doing so, we draw on the argument that in the development of either of the three network attributes outlined, the firm must overcome a distinct set of constraining forces (Koka and Prescott, 2008). Depending on the nature of the constraints, either RM, PM, or both will help the firm improve towards the desired structural attribute. By this logic, we develop a comprehensive model that integrates the reasoning of the structural and the managerial perspective on strategic networks. Figure 1 depicts the research model; Table I summarizes the variables and underlying mechanisms.

HYPOTHESIS DEVELOPMENT

Network Management and Network Centrality

We argue that it is mainly the PM capabilities that enable the firm to hold a central position in the network. First, NC is constrained by the firm's awareness of the network environment in which it is embedded (Gulati et al., 2011). When firms lack information on the network environment, they miss out on opportunities for establishing new ties and rather rely on past partners (Powell et al., 1996). This hinders them to migrate from the periphery to the core of inter-firm networks. In turn, with more complete information,

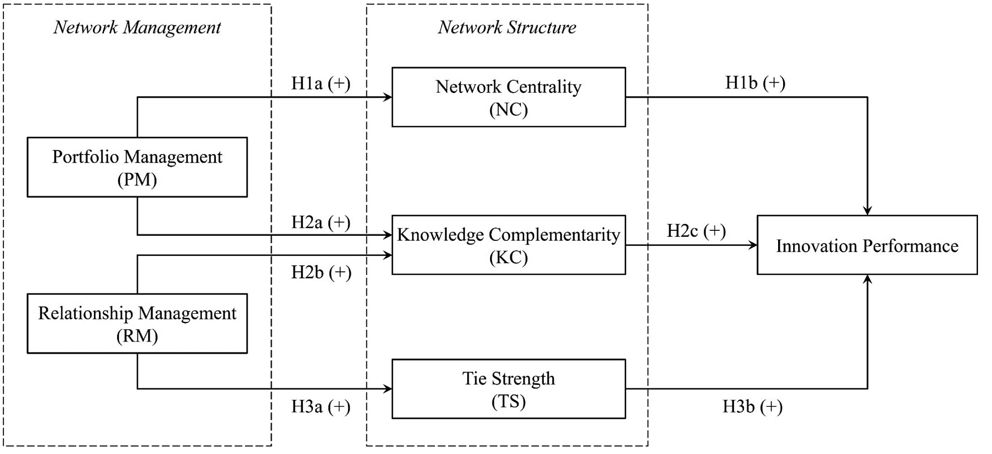

Figure 1. Research model

Table I. Summary of the theoretical framework

Network attribute	*Resource advantage*	*Constraining forces*	*Associated management capabilities*
Network Centrality (NC)	Reach, i.e., larger range and diversity of the knowledge resources accessible from network partners	• Lack of information on the network environment and limited awareness of partnering opportunities • Network complexity due to interdependences and potential conflicts between partners	Portfolio Management (PM)
Knowledge Complementarity (KC)	Richness, i.e., higher potential value of the knowledge resources accessible from network partners	• Scarcity of valuable partners and competition for partnering opportunities • Difficulties to attract valuable partners and maintain a mutually beneficial relationship	Portfolio Management (PM), Relationship Management (RM)
Tie Strength (TS)	Receptivity, i.e., greater capacity of the network for facilitating high-bandwidth knowledge transfer	• High resource and time commitment over the process of strong formation • Fragile nature of inter-firm ties and risk of relationship failure	Relationship Management (RM)

the firm can locate valuable positions before others do (Rowley and Baum, 2008b). Experimental studies support this notion by demonstrating that actors who possess more information on their network environment are significantly more likely to improve in NC than firms who lack such information (van Liere et al., 2008).

Superior PM should lead to a better awareness of network structure. Managerial attention on the portfolio level results in 'a high alertness to environmental information'

(Schilke and Goerzen, 2010, p. 1197). For instance, Ozcan and Eisenhardt (2009) found that firms engaging in PM develop sophisticated practices for scanning and visualizing network information. Similarly, Duysters and Lokshin (2011) argue that by focusing on portfolio issues, firms establish a 'radar function' (p. 582) for network opportunities. By planning, coordinating, and monitoring their overall portfolio of ties, the firm will thus expand its 'network horizon' (van Liere et al., 2008, p. 602) and become more able to navigate into a central position.

Second, complexity is another constraining force associated with NC. With growing NC, firms find themselves in a 'tangled web' (Parise and Casher, 2003, p. 26) of interdependences as some partners will have contradicting interests or even engage in adversities (Schilke and Goerzen, 2010). Dealing with potential conflicts might soon exceed the firm's action capacity and result in it getting caught up in attending to existing ties at the cost of pursuing new ones (Rowley and Baum, 2008b). Hence, complexity sets a limit on the firm's ability to improve NC (Duysters and Lokshin, 2011). We argue that PM enables the firm to handle complexity more effectively. For one, PM will help the firm configure its network in a way that prevents a good share of negative interdependences. Fang et al. (2015), for instance, found that by taking a portfolio-oriented approach, new ventures obtained crucial insights on potential partners, namely on 'what they do, what they need, and what their interests are' (p. 198). Based on such information, the firm can minimize potential conflicts already on the stage of partner selection (Kale and Singh, 2009). Further, firms with strong PM will regularly monitor their networks for conflicts (Degener et al., 2018). Hence, they are more likely to anticipate tensions in advance and engage in activities to resolve adversities between partners (Parise and Casher, 2003).

In sum, we argue that the more complex the information needs and interdependences, the more the firm must 'move beyond the dyadic concerns' (Rowley and Baum, 2008b, p. 642) and allocate attention to portfolio issues (Duysters and Lokshin, 2011). All else being equal, firms with more sophisticated PM should obtain higher levels of NC. We propose:

Hypothesis 1a: Portfolio management has a positive effect on network centrality.

By this effect, PM helps the firm set up a major success driver of innovation. High levels of NC will endow the firm with benefits of reach, that is, access to a broader and more diverse range of knowledge (Gulati et al., 2011). By such reach, the likelihood of receiving new insights that provide solutions to technological or market-related problems increases (Dong et al., 2017). As a result, learning and knowledge creation are fostered (Ahuja, 2000). We thus propose:

Hypothesis 1b: Network centrality has a positive effect on innovation performance.

Network Management and Knowledge Complementarity

Complementarity in the firm's network is mainly constrained by the factor market for partners, i.e., 'the set of potential collaborator firms that […] possess required strategic resources' (Sarkar et al., 2009, p. 587). To improve towards KC, the firm must strategically search for specific expertise profiles. As suitable partners are scarce, the searching firm is confronted with a 'small numbers' problem (Sarkar et al., 2001b). For one, the small numbers problem will lead to a low hit rate in the firm's efforts to locate the 'right' partners (Hite and Hesterly, 2001). Further, the firm will have to compete for partnering opportunities. Even when the firm is able to recognize valuable targets, it might still get trapped in a situation of supply-side scarcity in which potential partners are already 'used up' by their ties to other firms (Sarkar et al., 2009).

We argue that PM can be instrumental in overcoming this scarcity constraint. First, firms that engage in PM will possess a more complete network horizon (van Liere et al., 2008) and more timely information about partnering opportunities (Degener et al., 2018). Especially when complementary partners are scarce, this should help the firm realize first-mover advantages (Sarkar et al., 2001b). Second, PM will help firms take a more resource-driven approach in extending their networks (Fang et al., 2015). Those firms possess a clearer picture of the value added by each tie and a better overview of the expertise of potential partners (Parise and Casher, 2003). In contrast to other firms which tend to 'congeal around the existing network structure' (Rowley and Baum, 2008b, p. 647), firms with strong PM will be more likely to solidify ties to complementary partners while avoiding ties to less valuable partners. In sum, we posit:

Hypothesis 2a: Portfolio management has a positive effect on knowledge complementarity.

Further, we suggest that RM contributes to KC. Beyond scarcity, another feature of the market for network partners is its 'two-sided voluntary nature' (Mindruta et al., 2016, p. 208). Inter-firm partnerships are created based on mutual agreements (Kale and Singh, 2009). To establish a network tie, the firm needs to convince potential partners to collaborate (Gulati et al., 2005). To do so, it is important to persuade the opposite party of a win-win situation. Especially if a potential partner has strong expertise, the firm may have difficulties to spark and keep up the target's interest (Hite and Hesterly, 2001). Yet, due to the small numbers problem, the firm cannot afford to miss out on or lose the 'right' partners if it wants to ensure high levels of KC.

Park and Ungson (2001) and Schreiner et al. (2009) argue that there are two major reasons for failing to establish and maintain a relationship with a key partner: 1) lack of mutual value prospects; and 2) insufficient management of joint action. Concerning the former, firms with strong RM should be more likely to empathize the needs of key partners (Kale and Singh, 2009). Thus, they should find effective ways to correspond to those needs, reconcile them with the own goals, and inspire 'feelings of mutuality' (Sarkar et al., 2009, p. 587). Concerning the latter, firms with well-elaborated RM should be more able to detect bilateral coordination problems early (Gulati et al., 2005). Moreover, RM should enable firms to better communicate those issues with its partners so that appropriate solutions can be developed jointly (Kale et al., 2000). In all, we suggest that effective RM practices are conducive to KC. Hence, we suggest:

Hypothesis 2b: Relationship management has a positive effect on knowledge complementarity.

By facilitating improvement in KC, PM and RM help foster the firm's potential for superior innovation outcomes. High levels of KC result in richness-based advantages (Gulati et al., 2011). That is to say, the expertise of the firm and its partners are mutually supportive, and their combinatory value is super-additive (King et al., 2008). This creates learning opportunities, encourages creativity, and fuels the firm's innovative efforts (Fang, 2011). We propose:

Hypothesis 2c: Knowledge complementarity has a positive effect on innovation performance.

By assuming positive effects of PM and RM, a further question arises: Is there an interactive effect of the two? We believe that two competing propositions are plausible. First, there might be a positive interaction. Thus, both PM *and* RM would be necessary for high KC. This perspective coincides with the notion that to connect with valuable partners, firms must know how 'to identify and locate relevant partners' but 'also need the skills to establish ties to those partners' (Gulati et al., 2011, p. 213). Second, PM and RM may exert independent, additive effects. This proposition involves 'twin predictions' (Mehra et al., 2001, p. 127) in that there are two alternative ways towards KC: a) by opportunity recognition due to PM; b) by more effective preservation of key partners due to RM. This perspective coincides with the notion of 'equifinal' approaches for network building (Koka et al., 2006) and reflects Rowley and Baum's (2008a) distinction between 'networking strategy' and 'partnering strategy'. In our empirical study, we explore both the possibility of interactive and additive effects.

Network Management and Tie Strength

Finally, we argue that the main constraining force on TS results from the amount of time and effort firms devote during the relationship lifecycle (Kale and Singh, 2009). Strong ties only form over time (Mariotti and Delbridge, 2012). As inter-firm interactions are fragile in nature, various incidents and conflicts between partners may cause an instant failure of the relationship (Park and Ungson, 2001). Firms willing to cultivate strong ties must dedicate considerable managerial effort to prevent such relationship failure. This will drain costly resources so that a firm's capacity for developing strong ties is fundamentally limited (Gulati and Singh, 1998).

RM is likely to have a positive influence on TS. First, RM should allow firms to pass more smoothly through the process of strong tie development. When the firm engages in intense communication with its partners and installs appropriate mechanisms for governing dyadic relationships, it should anticipate critical incidents at a higher probability (Sarkar et al., 2009). Second, RM helps keep the costs of maintaining strong ties in check (Gulati et al., 2005). The more a firm engages in RM, the more it will develop effective rules and codes of conduct (Schreiner et al., 2009). This 'relational capital' leads to increased efficiency in joint operations and lowers the need to safeguard against opportunism (Kale et al., 2000). Hence, firms with sophisticated RM can administer high levels of TS more effectively and efficiently. We suggest:

Hypothesis 3a: Relationship management has a positive effect on tie strength.

Finally, we expect TS to impact innovation performance. Higher levels of TS entail receptivity-based benefits in the form of mutual understanding and trust (McEvily and Marcus, 2005). Particularly when knowledge is tacit, this should increase the effectiveness of knowledge transfer (Tiwana, 2008) and boost new knowledge creation (Capaldo, 2007). We propose:

Hypothesis 3b: Tie strength has a positive effect on innovation performance.

Alternative Specifications of Effect Directionality and Causal Sequencing

Our model suggests a clear causal chain: from network management over network structure to innovation. While our argumentation is well-grounded, we acknowledge that alternative specifications for effect directionality may be plausible. Regarding network structure and innovation, recent studies have discussed reverse causality and provided substantial evidence for the effect direction proposed above (e.g., Degener et al., 2018; Dong et al., 2017; Matous and Todo, 2017). Referring to those works, there are strong reasons to assume that the effect from network structure to innovation, and not the reverse, will predominate. Regarding network structure and network management, a reverse effect could be postulated based on capability development literature. The main argument would be that network structure relates to the firm's 'accumulated collaborative experience' (Phelps et al., 2012, p. 1135). For instance, only firms that occupy a central network position should be aware of the actual challenges associated with high NC (Madhavan et al., 2008). This problem exposure may stimulate learning effects and drive the development of corresponding management capabilities (Kim et al., 2006).

We cannot dismiss that collaborative experience could induce mechanisms of capability development. Research indicates, however, that experience is neither sufficient nor necessary to establish network management capabilities. Regarding sufficiency, network studies found that many firms 'fail to capitalize on the lessons associated with their prior experience' (Kale et al., 2001, p. 465). This is because capability development requires deliberate investment of scarce resources (Zollo et al., 2002). Mere exposure to network issues only results in repeated 'ad-hoc problem-solving' (Winter, 2003, p. 993) instead of constant improvements in management practices. Thus, collaborative experience is only 'a crude approximation' (Kale et al., 2002, p. 750) of the mechanisms that lead to the development of network management capabilities. Regarding necessity, the literature shows that peripheral firms without significant collaborative experience may still engage in network management and implement appropriate managerial practices. For instance, a substantial share of past research discussed network management in the context of new ventures (e.g., Fang et al., 2015; Ozcan and Eisenhardt, 2009; Walter et al., 2006). Adding to this, studies on network management explicitly outline that firms can 'jumpstart' capability development 'by for instance gathering best practices and going to externally organized trainings' (Heimeriks and Duysters, 2007, p. 40).

Beyond collaborative experience, behavioural theories on capability development might even imply detrimental effects of network structure on network management. Those theories assume a 'satisficing logic' (Winter, 2000, p. 983): if the end result at which a capability aims is already reached, the firm will invest less efforts into building the capability. Capability development is the domain of firms that perceive room for improvement, not of those 'enamored with the resources they currently possess, […] that cherish the status quo' (Teece, 2014, p. 332). In this vein, network management capability should depend foremost on firms' inclination toward 'network entrepreneurship' (Rowley and Baum, 2008a, p. xix), i.e., their strategic intent to improve their current network position (Koka et al., 2006). As firms in strong positions tend to settle for and stabilize current structures (Hoffmann, 2007), it is reasonable to assume that a substantial share of them may fail to nurture their internal processes for network management.

In line with the notion of firms as strategic network agents (Rowley and Baum, 2008a) and the reasons presented, we posit that network management should precede network structure rather than the reverse. Nonetheless, we acknowledge that beyond a certain point it will be difficult to fully disentangle the relation between the two. Both by the logic of strategic network and capability literatures, it seems reasonable to expect some form of coevolutionary dynamic (e.g., Zollo et al., 2002): network management helps the firm improve network structure, which in turn yields networking experiences that help further refine managerial practices. In our analysis, we thus take measures to account for endogeneity issues arising from reciprocal effects (Phelps et al., 2012). We will also include robustness checks to further assess effect directionality.

METHODOLOGY

Sample and Data Collection

In our empirical approach, we followed previous studies (e.g., Fonti et al., 2017; Rank and Strenge, 2018; Wincent et al., 2010) and focused on a bounded network environment. Based on this 'whole network' design (Marsden, 2005), we were able to obtain a complete census of ties among a predefined set of firms. An alternative method, the egocentric design, would not allow for such a comprehensive mapping of network structure. Further, the focus on a single inter-firm network enabled us to gather survey data instead of solely relying on archival data. Doing so, we were able to obtain information on tie characteristics and data on internal practices of network management. For this reason, we preferred the analysis of a bounded network to an exploration of the overall industry network (e.g., Schilling and Phelps, 2007).

Specifically, we selected the largest network of utilities in the German energy industry as our empirical setting. This context is well-suited as innovation and collaboration between utilities continuously grow in importance. The energy sector is in a nascent period of change (Eklund and Kapoor, 2019). The main driver is the rise of decentralized electricity generation in distributed small-scale systems which threatens the 'centralized model' of incumbent utilities (Frei et al., 2018). In the past, the German energy market has been split between four multinationals (the 'Big Four') and several hundred large (>1000 employees), medium (100–1000 employees), and small (<100 employees) local providers (Richter, 2013). Until recently, those firms accounted for nearly all electricity generation and sales. In the wake of renewable energy legislations (especially in 2000 and

2012), however, market shares eroded as private persons, independent project developers, and large institutional investors entered the industry.

In the light of those threats, utilities need to explore new value propositions. On the technology side, decentralization requires the combination of renewables, storage systems, and 'smart' digital devices (Dellermann et al., 2017). On the business side, utilities must transition from commodity sellers to energy service providers, from pricing electricity usage to providing equipment and consulting. As Richter (2013, p. 1232) puts it: 'The main problem is to develop a product or service that offers sufficient value to the customer to be attractive, but also generates sufficient value to the utility to be profitable'. The innovative challenge is aggravated by the fact that most utilities are semi-public companies. Because of this, they often struggle in justifying high-risk investments and are unable to allocate sufficient attention toward emerging opportunities (Eklund and Kapoor, 2019). To mitigate those constraints, especially small and medium firms rely on partnerships with other utilities to bundle resources and 'foster the accumulation of know-how and innovation capabilities' (Richter, 2013, p. 1234). Hence, strategic networks are a driving force of innovation in the sector (Kolloch and Reck, 2017).

The bounded network that we investigated has its origin in a multi-partner alliance formed in the early 1970s between a handful of medium-sized utilities located mainly in South Germany. Since then, the network grew continuously, especially in the early 1990s when many formerly state-controlled utilities from East Germany joined as new members, and the early 2000s after a substantial regulatory liberalization and the disbanding of regional monopolies. At the time of our study, the network comprised 84 members (5 large, 31 medium, and 48 small utilities). In a study by Raynor and Ahmed (2013) that examined 25,000 companies over a 40-year period, the network ranked among the 'Miracle Workers', i.e., organizations that consistently outperformed their industry in profitability.

One major mission of the network is to stimulate exchange on innovative topics. To this end, the network provides a broad range of platforms for collaboration, such as innovation circles, workshops, and joint R&D projects. Thereby, all collaboration is voluntary so that nested within the network boundaries, member firms are free to form and resolve ties of knowledge transfer. As an example, a group of three members collaborated to design a 'smart home & solar package' that combines rooftop photovoltaics, storage devices, and a smartphone app as user interface. Making the prototype openly available as 'white-label solution', the group attracted further members to join the piloting process. Currently, 20 member firms are invested in the developed product-service bundle, now successfully launched into the market.

Data collection was done in Spring 2016. We pursued a key informant approach by online survey. To this end, we obtained contact information for at least two informants for all 84 member firms: the CEO and one further senior manager responsible for innovation or related functions (e.g., R&D, Marketing). The questionnaire was pre-tested with 26 industry experts; our study was actively promoted by the network's management board. In all, we obtained 147 completed questionnaires. Data came from 74 member firms, resulting in a firm-level response rate of 88.1 per cent. This is comparable to other bounded-network studies (Fonti et al., 2017; Rank and Strenge, 2018), so that our data allows for an adequately complete depiction of network structure. We tested for non-respondent bias by comparing observable attributes of respondents and non-respondents (e.g., firm size, network tenure). There were no significant differences.

Research Variables and Construct Measurement

For all non-network variables, we collected data based on item scales with seven-point Likert ratings (1 = 'completely disagree' to 7 = 'completely agree'). The outcome variable *innovation performance* was measured by three items that asked respondents to rate their firm's innovation achievements in relation to competitors in the industry (Yli-Renko et al., 2001). Especially in industries lacking rich patent or objective financial data, it is appropriate to rely on managers' evaluations of firm-level innovation (Zhang and Li, 2010). To further validate the approach, we triangulated our measure by two observable indicators of firms' innovation performance.

First, between 2016 and 2018 we analysed announcements of innovation outcomes in the quarterly newsletter published by the network board. In this period, the newsletter issues comprised a total of 845 individual articles. One of the authors and an independent rater manually coded the articles for reports on member firms' innovation activity. Both raters possess practical experience in the utility context. Examples for innovations reported in the newsletter are a comparison-shopping engine for smart home devices, a cloud-based sharing application for solar electricity, and the piloting of green hydrogen generation, among others. Agreement between raters was substantial (Cohen's Kappa = 0.86), controversial announcements were discussed to reach a decision. The measure 'newsletter announcements' was computed as the number of coded articles for each firm. Rank correlations with the self-report measure were significant (Spearman's $\rho = 0.42$, $p < 0.001$; Kendall's $\tau = 0.31$, $p < 0.001$).

Second, we computed the measure 'award nominations'. To identify relevant innovation awards, we first searched national newspapers in the 'Genios Deutsche Wirtschaftsdatenbank' press archive (GBI, 2019) for articles published between 2016 and 2018 that included the term 'innovation award'. By this, we derived a shortlist of potential awards. We then consulted the award homepages and removed awards for which eligibility was limited to a specific region, firm size, firm age, or any industry other than energy. The cleansed shortlist was discussed with industry experts and further entries were added based on the feedback. In all, we included eight industry-specific[1] and six industry-spanning awards.[2] For each firm, we counted the nominations earned between 2016 and 2018. The correlations with the self-reports were significant (Spearman's $\rho = 0.27$, $p < 0.05$; Kendall's $\tau = 0.22$, $p < 0.05$).

The variables *PM* and *RM* are measured based on scales developed by Sarkar et al. (2009) and Schreiner et al. (2009). In order not to overburden respondents, especially as network questionnaires are time-consuming (Marsden, 2005), we consolidated the single first-order constructs and compared them with similar scales in the literature (e.g., Kale et al., 2000; Schilke and Goerzen, 2010; Walter et al., 2006). As a result, we derived two six-item measures that indicate firm-level practices for PM and RM.

To depict network structure and elicit each firm's network ties, we used sociometric techniques (Marsden, 2005). In a roster-based approach, we presented to the respondents a list of all 84 member firms and asked them to assign network ties by the following question:

> Please select the firms from which your company received innovation-related knowledge within the last three years. This knowledge receipt may stem from formal exchange during joint R&D projects, discussions in innovation circles, or informal exchange on the personal level, among others. Please include as many firms as you consider to be relevant knowledge sources.

Roster-based approaches are widely seen as advantageous since they help capturing weak ties that are often forgotten by respondents in free recall methods (Rank and Strenge, 2018). We arranged the reported ties in a 74 × 74 adjacency matrix. Each cell x_{ij} indicates if there is a network tie from member *i* to member *j*. Note that the ties in the network can be asymmetric, as oftentimes, in dyadic relationships one actor is primarily knowledge receiver and the other is knowledge provider (Sammarra and Biggiero, 2008). Consequently, the resulting network is directed so that the existence of tie x_{ij} does not prescribe the existence of tie x_{ji}. In all, the respondents assigned 553 ties between the firms in the network.

We used the adjacency matrix to calculate the *centrality* scores for each firm. There are different operationalizations of NC. First, degree centrality (NC_{Degree}) denotes the number of the firm's direct ties (Wincent et al., 2010). It is a basic but valid measure of network reach. Second, closeness centrality ($NC_{Closeness}$) computes the average path length between the firm and all other network members (Soh et al., 2004). The assumption behind this measure is that by a short average path, information reaches the firm more quickly and with less risk of distortion (Schilling and Phelps, 2007). Third, betweenness centrality ($NC_{Betweenness}$) is defined 'as the fraction of shortest paths between other companies that pass through the focal firm' (Gilsing et al., 2008, p. 1723). $NC_{Betweenness}$ is a measure of 'bridging position advantages' (Rowley and Baum, 2008b, p. 464), i.e., the extent to which the firm controls the information flow between disconnected groups. Finally, eigenvector centrality ($NC_{Eigenvector}$) captures 'the degree to which a firm collaborates with other central organizations' (Dong et al., 2017, p. 528). Here, ties to partners who are well-connected themselves are assessed as more valuable. As all four measures capture important facets of reach, we follow past works (e.g., Schilling and Phelps, 2007; Soh et al., 2004) and sequentially include each one in our empirical model for sensitivity testing.

Regarding *KC*, we considered two alternative measurement approaches. First, previous studies operationalized KC as the extent to which partners' expertise in relevant technology fields differs (e.g., Gilsing et al., 2008; Mindruta et al., 2016). In the energy industry, renewables, storage systems, and ICT are examples for complementary technologies (Eklund and Kapoor, 2019). Second, KC has been operationalized as knowledge in different functional areas (Fang, 2011). For instance, network scholars outline that firms with strong technological expertise should find knowledge complements in partners with strong marketing capabilities (King et al., 2008; Lavie, 2007) or managerial know-how (Sammarra and Biggiero, 2008). We decided for the latter approach as the innovative contribution of utilities is mainly architectural: they orchestrate component technologies developed by equipment manufacturers to set up systems that meet customer needs, legal standards, and organizational requirements (Schilling and Esmundo, 2009). Hence, innovation is more a business model than a technological challenge (Richter, 2013). While expertise from different technology fields is combined for innovation in the energy sector, we argue that for utilities it is the combination of technological, market, managerial, and regulatory knowledge that matters more in their innovation efforts.

To obtain our KC measure, we asked every respondent to rate their firms' proficiency in each of those four knowledge domains. To this end, we aggregated two items for each dimension, one representing the skills of the firm's employees and one representing the institutionalized knowledge residing within firm-internal structures and processes (Subramaniam and Youndt, 2005). For each pair of firms connected by a network tie, we then calculated a complementarity score as the Pearson correlation on the two firms' knowledge profiles. For presentation clarity, we reversed this scale so that the maximum value would be +1, the minimum −1. A high value indicates that the relative strengths of one firm lie in the knowledge areas in which the other has relative weaknesses (Gilsing et al., 2008). To derive the indicator for the overall KC of the firm's network, we calculated the average complementarity score across all ties of the firm.

Finally, to measure *TS*, we obtained information on knowledge exchange intensity within each dyad of collaborating firms (Wincent et al., 2010). Thereby, the respondents rated the intensity of knowledge inflows from each of their contacts on a scale from 1 (no exchange) to 7 (highly intensive exchange). As innovation-related knowledge is multifaceted, we asked the respondents to provide information on the inflow intensity for the four knowledge contents discussed above (technological, market, managerial, regulation). The intensity score reflects the interaction time spent in any reported tie and is thus a valid measure of TS on the inter-firm level (Capaldo, 2007). In line with past works, we calculated the average intensity of the firm's network ties to arrive at the overall TS indicator score (e.g., Wincent et al., 2010).

Several control variables were included into our analysis. First, the firm's internal knowledge base is likely to affect innovation (Subramaniam and Youndt, 2005). Hence, besides using firm-internal technological, market, managerial, and regulation knowledge to compute KC scores on the dyadic level, we employed these four knowledge components as firm-level controls. Second, *firm size* may lead to slack resources which support networking and innovation. We thus used the logged number of full-time employees as control variable. Third, we include firms' *network tenure* in terms of membership years. This control variable serves to reflect the role of collaboration history and structural determinism in explaining our outcome variables (Kim et al., 2006). Fourth, firms' strategic orientation, such as *diversification* and *expansion*, may affect the propensity for collaboration and innovation. We measured diversification by computing Blau's Index (Blau, 1977) for the firms' sales across the market sectors electricity, gas, and heat. Expansion was measured as the mean annual investment-to-sales ratio of each firm based on its net increment of real and immaterial assets in the 2013–2015 period.

Adequacy of Measures

Although the inclusion of network measures should reduce common method variance, we utilized both procedural and statistical remedies to prevent bias resulting from single instrument data collection (Podsakoff et al., 2003). First, procedural steps included ensuring respondent anonymity and reducing evaluation apprehension. Second, we conducted Harman's one-factor test. Six factors explained 69.6 per cent of the variance, 30.9 per cent was the largest variance explained by one factor. Thus, we are confident that common method bias is not a problem.

For 62 firms, we received data from more than one respondent. Despite the information benefits, utilizing multiple respondents per firm might entail some issues. First, there might be a selection problem resulting in varying degrees of informant knowledge on the topic of investigation. While we are confident that our informant selection ensured high levels of expertise, different professional backgrounds of respondents may yield different perspectives (Kumar et al., 1993). We therefore conducted *t*-tests to compare the responses of CEOs and innovation managers. The results did not differ significantly among the two groups.

Furthermore, there is a potential issue of disagreement between informants (Kumar et al., 1993). We followed Schilke and Goerzen (2010) to assess inter-rater reliability by the percentage of item ratings in which respondents from the same firm differ by one point or less on the Likert-scale (90.8 per cent of ratings). For the network measures, we computed the mean percentage agreement following Tsai and Ghoshal (1998). We divided the number of ties assigned by the firm's respondents by the number of all ties reported for the firm. The average agreement was 73.1 per cent in our study which is well acceptable. For the Likert scale ratings of knowledge inflow intensity, inter-rater reliability was 76.9 per cent (as described above). Based on the high degree of agreement, we aggregated the responses of the individual respondents in the further analysis.

RESULTS

We tested the hypotheses by structural equation modelling (SEM). Among the two common SEM approaches – covariance-based SEM (CB-SEM) and partial-least-squares SEM (PLS-SEM) – we chose PLS-SEM based on two reasons. First, PLS-SEM places less restrictions on the distribution of residuals, which is advantageous owing to scale differences between network and Likert-scale variables (Hair et al., 2019). Second, network data usually violate the independence of observations assumption on which many statistical tests are based, including CB-SEM. For example, the closeness centrality of one firm in our sample fundamentally depends on how well-connected other firms in the network are. Bootstrapped methods, such as PLS-SEM, are robust against varying and unknowable amounts of observation interdependence. Hence, such methods are particularly useful for estimating research models that are based on network data (Krackhardt, 1988).

Measurement Model Assessment

In the assessment of our measurement model, we first examined reflective indicator loadings (see Table II). All loadings are significant ($p < 0.001$) and above the proposed threshold of 0.707 respectively 0.600 (Hair et al., 2019). For internal consistency, all Cronbach's α, composite reliability, and Jöreskog ρ_c are well above the required thresholds (see Table II and III). For convergent validity, average variance extracted (*AVE*) ranges between 0.61 and 0.89, exceeding the common standard of 0.50. Finally, to assess discriminant validity we employed the hetero-trait-monotrait ratio (*HTMT*) following

Table II. Construct specifications and item statistics

Construct	*Item*	*Load*	*Mean*	*SD*
Innovation Performance ($CR = 0.87$, $\rho_c = 0.77$, AVE = 0.69)	We develop and introduce new product/service offerings in the market.	0.852	4.27	1.38
	We regularly improve existing product/service bundles.	0.817	4.36	1.35
	Our product/service offering is based on novel technologies.	0.817	4.17	1.33
Portfolio Management ($CR = 0.90$, $\rho_c = 0.88$; AVE = 0.61)	We actively search for new potential knowledge exchange partners.	0.742	4.27	1.32
	We evaluate interdependencies, conflicts, and synergies between our partners to coordinate our relationship portfolio holistically.	0.805	3.62	1.49
	We develop goals for modifying and using our network based on our company's business strategy.	0.787	4.06	1.31
	We evaluate our benefit from the network portfolio to derive action plans for its modification.	0.802	3.84	1.26
	We observe, document, and assess the development of our network and its environment.	0.769	3.70	1.39
	We present ourself as attractive partners by publishing success stories and referrals.	0.782	4.31	1.25
Relationship Management ($CR = 0.91$, $\rho_c = 0.89$, AVE = 0.63)	We communicate intensively with our partners to keep informed about their situation and needs.	0.821	4.58	1.15
	In the case of conflicts, we discuss the issue intensely with our partner and develop solution approaches mutually.	0.812	4.41	1.15
	We bring together key persons of both organizations, e.g., via social events.	0.809	3.97	1.26
	We regularly monitor the state and development of our relationships concerning goals, potentials, and surroundings of our partners.	0.847	3.90	1.30
	We assign internal responsibles with corresponding competerncies to each exchange relation.	0.673	4.29	1.36
	We conjointly develop and act on firm-spanning processes and standards of collaboration.	0.781	3.90	1.24
Technological Knowledge ($CR = 0.94$, $\rho_c = 0.88$, AVE = 0.89)	Concerning technologies and scientific insights, our employees possess superior knowledge and skills compared to the rest of our industry.	0.949	4.62	1.02
	Our technological knowledge is reflected by internal standards, procedures, and intellectual property.	0.942	4.35	1.04
Market Knowledge ($CR = 0.90$, $\rho_c = 0.87$, AVE = 0.82)	Our employees possess a high degree of knowledge about customers and understand their preferences and needs.	0.941	4.66	1.06
	We possess a sophisticated repertoire of methods to gain a better in-depth understanding of our customers.	0.869	4.30	1.05

Table II. *Continued*

Construct	*Item*	*Load*	*Mean*	*SD*
Managerial Knowledge ($CR = 0.91$, $\rho_c = 0.94$, AVE = 0.83)	Our management personnel has profound knowledge on leadership, operative, and strategic management.	0.867	4.17	1.09
	We have guidelines for management and leadership culture which may be both implicit (e.g., success stories, 'unwritten laws') or explicit (e.g., rules, leadership development programmes).	0.952	4.42	1.20
Regulation Knowledge ($CR = 0.93$, $\rho_c = 0.84$, AVE = 0.86)	Our employees are up to speed concerning legal issues, regulation, and political developments.	0.929	4.72	1.08
	We have systematic methods to interprete our regulatory environment.	0.928	4.43	1.06

CR = composite reliability; ρ_c = Jöreskog's ρ; AVE = average variance extracted; SD = standard deviation.

Table III. Descriptive statistics and correlations

	Variable	*Mean*	*SD*	α	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*	*13*	*14*	*15*	*16*
1.	Innovation Performance	4.27	1.13	0.77																
2.	PM	3.97	1.05	0.87	0.45*															
3.	RM	4.17	0.99	0.88	0.14	0.33*														
4.	NC_{Degree}	7.47	5.66	–	0.49*	0.49*	0.09													
5.	$NC_{Closeness}$	0.34	0.05	–	0.44*	0.48*	0.02	0.83*												
6.	$NC_{Betweenness}$	1.77	2.14	–	0.40*	0.29*	0.16	0.71*	0.59*											
7.	$NC_{Eigenvector}$	0.80	0.60	–	0.45*	0.45*	0.10	0.94*	0.79*	0.59*										
8.	KC	0.03	0.36	–	0.42*	0.38*	0.40*	0.14	0.16	0.20	0.11									
9.	TS	3.17	0.83	–	0.06	0.08	0.44*	−0.17	−0.15	−0.15	−0.11	0.27*								
10.	Technological Knowledge	4.48	0.98	0.88	0.27*	0.21	0.27*	0.14	0.21	0.19	0.13	0.18	0.10							
11.	Market Knowledge	4.48	0.97	0.78	0.38*	0.08	0.20	0.07	0.05	0.19	0.02	0.12	0.11	0.25*						
12.	Managerial Knowledge	4.30	1.05	0.80	0.18	0.12	0.08	0.21	0.25*	0.36*	0.11	0.26*	0.04	0.28*	0.29*					
13.	Regulation Knowledge	4.57	1.00	0.84	0.37*	0.30*	0.21	0.08	0.16	0.21	0.05	0.32*	0.26*	0.34*	0.31*	0.54*				
14.	Firm Size	246.57	484.86	–	0.08	−0.05	−0.09	0.14	0.15	0.24*	0.14	−0.07	−0.13	0.23*	0.03	0.15	0.19			
15.	Network Tenure	14.49	9.71	–	−0.16	−0.03	−0.15	−0.12	−0.08	−0.14	−0.08	−0.13	−0.03	0.14	−0.07	−0.01	−0.06	−0.02		
16.	Diversification	0.40	0.18	–	0.09	0.26*	0.13	−0.05	−0.09	0.05	−0.14	0.18	0.01	0.13	0.11	0.27*	0.47*	0.20	−0.07	
17.	Expansion	0.08	0.05	–	0.04	−0.09	−0.11	−0.03	0.03	−0.06	−0.01	−0.06	0.03	−0.17	−0.18	−0.29*	−0.09	−0.19	−0.03	−0.28*

N = 74.
PM, Portfolio Management; RM, Relationship Management; NC, Network Centrality; KC, Knowledge Complementarity; TS, Tie Strength.
*p < 0.05.

Henseler et al. (2015). The maximum *HTMT* observed between constructs was 0.66, well below the threshold of 0.85 that would indicate validity issues.

Structural Model Assessment

To evaluate the structural model, we ran the non-parametric bootstrapping method to examine 5,000 subsamples in SmartPLS 3.2.3 (Ringle et al., 2015). Table IV summarizes the results. For innovation performance, column (1) depicts the model with control variables only, (2) depicts the direct effects model adding network management, columns (3a-d) depict the hypothesized models by the centrality measure employed, and (4a-d) depict the curvilinear effects models evaluated in the robustness checks. For the network attributes, (1) depicts the hypothesized model, and (2) includes the interaction term of PM and RM to test for moderation effects.

We evaluated the structural models following Hair et al. (2019). First, we assessed potential collinearity issues using variance inflation factors (*VIF*). All *VIF*s were below the threshold of 3. Second, we evaluated predictive power (R^2) and accuracy (Q^2) for all outcome variables. The observed values were adequately large. Third, we compared the increment of predictive power between models based on the Bayesian Information Criterion (*BIC*). *BIC* values factor in both predictive power and model complexity; models that minimize the *BIC* for a certain target construct should be preferred. Finally, we assessed the overall model fit. For our hypothesized model, standardized root mean square residual (*SRMR*) was 0.071 indicating good fitness levels.

Regarding the research hypotheses, H1a predicts a positive impact of PM on NC. For all four centrality measures, the effect is significant. We evaluated effect sizes based on Cohen's f^2 (Cohen, 1988): $f^2_{PM\_to\_Degree} = 0.49$; $f^2_{PM\_to\_Closeness} = 0.48$; $f^2_{PM\_to\_Betweenness} = 0.10$; $f^2_{PM\_to\_Eigenvector} = 0.40$. While there are strong effects on NC_{Degree}, $NC_{Closeness}$, and $NC_{Eigenvector}$, the effect on $NC_{Betweenness}$ is substantially weaker. This finding indicates that bridging advantages may be less 'manageable' from the firm's perspective. For instance, one incalculable factor is that in contrast to the other centrality types, betweenness of the focal firm can deteriorate simply due to other firms forming additional ties between isolated groups. In other words, once the firm 'has established a position between unconnected partners, others may follow' (Rowley and Baum, 2008b, p. 650), reducing $NC_{Betweenness}$. Despite the weaker effect, however, the likelihood of the firm moving into bridging positions still increases significantly with PM. In sum, H1a thus receives strong support. H1b is supported as well. All NC measures have significant path coefficients with f^2 ranging between 0.06 and 0.17 (weak to moderate effects). In line with past network research, we thus find that NC fosters innovation.

H2a and H2b suggest positive effects of PM and RM on KC; the path coefficients are significant. The f^2-value is 0.06 for PM and 0.09 for RM, indicating weak positive effects. Both hypotheses receive support. For H2c, KC has a significant effect on innovation. f^2 values across (3a-d) range between 0.14 and 0.17 (weak to moderate). Hence, H2c is supported. Regarding a potential interaction of PM and RM, the corresponding path coefficient is not significant. The effects of PM and RM on KC are thus independent and additive (Mehra et al., 2001). Both capabilities may serve as viable pathways for the firm to foster KC.

Table IV. PLS-SEM results

	Innovation Performance										NC_{Degree}		$NC_{Closeness}$		$NC_{Betweenness}$		$NC_{Eigenvector}$		*KC*		*TS*	
Variable	*(1)*	*(2)*	*(3a)*	*(3b)*	*(3c)*	*(3d)*	*(4a)*	*(4b)*	*(4c)*	*(4d)*	*(1)*	*(2)*	*(1)*	*(2)*	*(1)*	*(2)*	*(1)*	*(2)*	*(1)*	*(2)*	*(1)*	*(2)*
Technological Knowledge	0.16	0.10	0.11	0.09	0.11	0.11	0.10	0.15	0.10	0.11	0.00	0.01	0.09	0.08	0.00	0.01	0.00	−0.01	−0.03	−0.03	−0.01	0.00
Market Knowledge	0.28*	0.30**	0.29**	0.31**	0.29**	0.30**	0.32**	0.30**	0.25*	0.31**	0.03	0.04	0.02	0.00	0.09	0.11	0.01	0.02	0.00	−0.00	−0.03	−0.04
Managerial Knowledge	−0.06	−0.04	0.20†	−0.17†	−0.17†	−0.15	−0.23*	−0.19	−0.23*	−0.17	0.29**	0.29**	0.29**	0.29**	0.38***	0.38***	0.15	0.15	0.16	0.16	−0.10	−0.10
Regulation Knowledge	0.29†	0.20	0.24	0.20	0.20	0.21	0.21	0.19	0.26†	0.19	−0.20	−0.21	−0.06	−0.07	−0.14	−0.14	−0.10	−0.11	0.12	0.13	0.33*	0.34*
Firm Size (log)	0.01	0.07	0.02	0.04	0.03	0.01	0.02	0.01	0.02	0.02	0.22	0.22	0.20	0.21	0.27†	0.28†	0.23	0.24	−0.06	0.07	−0.11	−0.12
Network Tenure	−0.16	−0.14	−0.13	−0.15	−0.14	−0.15	−0.11	−0.12	−0.12	−0.14	−0.11	−0.10	−0.07	−0.06	−0.15†	−0.14†	−0.08	−0.08	0.12	0.12	−0.09	−0.10
Diversification	−0.07	−0.13	−0.06	−0.07	−0.11	−0.04	−0.06	−0.04	−0.15	−0.04	−0.21†	−0.20	−0.30**	−0.28**	−0.12	−0.11	−0.32*	−0.31*	0.02	0.02	−0.13	−0.13
Expansion	0.11	0.13	0.08	0.08	0.09	0.10	0.08	0.10	0.11	0.09	0.08	0.08	0.12	0.12	0.11	0.11	0.04	0.04	0.04	0.04	0.00	0.01
PM		0.42***	0.13	0.19	0.29*	0.16	0.12	0.15	0.21†	0.16	0.60***	0.60***	0.59***	0.58***	0.29**	0.29**	0.57***	0.57***	0.23*	0.23*	−0.13	−0.13
RM		−0.06	−0.15	−0.11	−0.19	−0.15	−0.13	−0.13	−0.12	−0.11	−0.03	−0.02	−0.13	−0.10	0.12	0.12	−0.01	0.01	0.29*	0.28*	0.45***	0.44***
NC_{Degree}			0.36***				0.52***															
$NC_{Closeness}$				0.25*				0.44**														
$NC_{Betweenness}$					0.21†				0.57**													
$NC_{Eigenvector}$						0.31**				0.42**												
KC			0.33**	0.33**	0.31**	0.33**	0.29*	0.25*	0.31*	0.29*												
TS			−0.01	−0.05	−0.01	−0.04	−0.04	−0.05	−0.08	−0.08												
NC^2_{Degree}							−0.12															
$NC^2_{Closeness}$								0.10														
$NC^2_{Betweenness}$									−0.22*													
$NC^2_{Eigenvector}$										−0.06												
KC^2							−0.07	−0.06	−0.00	−0.04												

Table IV. *Continued*

	Innovation Performance										NC_{Degree}		$NC_{Closeness}$		$NC_{Betweenness}$		$NC_{Eigenvector}$		*KC*		*TS*	
Variable	*(1)*	*(2)*	*(3a)*	*(3b)*	*(3c)*	*(3d)*	*(4a)*	*(4b)*	*(4c)*	*(4d)*	*(1)*	*(2)*	*(1)*	*(2)*	*(1)*	*(2)*	*(1)*	*(2)*	*(1)*	*(2)*	*(1)*	*(2)*
TS^2							0.06	0.08	0.08	0.07												
PM × RM												0.05		0.10		0.08		0.06		−0.02		−0.06
R^2	0.28	0.43	0.57	0.53	0.53	0.56	0.60	0.58	0.58	0.57	0.40	0.40	0.43	0.44	0.31	0.31	0.36	0.36	0.30	0.30	0.29	0.29
Stone-Geisser's Q^2	0.10	0.19	0.28	0.25	0.25	0.27	0.30	0.25	0.28	0.28	0.21	0.19	0.22	0.22	0.14	0.14	0.15	0.13	0.02	0.00	0.08	0.06
BIC	13.32	5.39	−3.38	3.22	4.16	−1.00	4.91	8.32	7.79	9.36	8.41	12.35	4.87	7.87	19.20	22.75	13.54	17.39	20.05	24.25	21.41	25.30

N = 74.
PM, Portfolio Management; RM, Relationship Management; NC, Network Centrality; KC, Knowledge Complementarity; TS, Tie Strength.
***$p < 0.001$; **$p < 0.01$; *$p < 0.05$; $^{\dagger}p < 0.10$.

Finally, we found that RM significantly impacts TS ($f^2 = 0.23$; moderate effect). The firm's capability for managing individual relationships indeed seems to increase the effectiveness (in terms of overcoming critical relational incidents) and efficiency (in terms of reducing relational costs) of strong tie formation (Mariotti and Delbridge, 2012). H3a is thus supported. In contrast, there is no significant effect of TS on innovation so that H3b is rejected. An explanation for this could be that at least in our context, TS may induce detrimental effects that diminish the hypothesized benefits. Literature contends that strong ties have downsides, e.g., locking firms into established relationships at the expense of novel ideas from new partners (Phelps et al., 2012). Those shortcomings of TS come to pass especially in contexts characterized by impactful environmental change (e.g., Rowley et al., 2000). As the energy sector is exactly in such a state of change, it seems plausible that while NC and KC impact innovation, TS is not as valuable.

Together, our results indicate that by fostering NC and KC, PM and RM are important indirect antecedents of innovation. To substantiate this notion, we followed Nitzl et al. (2016) and computed the specific indirect effects (*SIE*) as the product term (a × b) of the path coefficients from the respective management capability to the network attribute (a) and from the network attribute to innovation performance (b). The indirect effect of PM over NC is positive and significant (NC_{Degree}: *SIE* = 0.22, $p < 0.01$; $NC_{Closeness}$: *SIE* = 0.15, $p < 0.10$; $NC_{Betweenness}$: *SIE* = 0.06, $p < 0.10$; $NC_{Eigenvector}$: *SIE* = 0.18, $p < 0.05$) as are the indirect effects of PM (*SIE* = 0.07, $p < 0.10$) and RM (*SIE* = 0.09, $p < 0.10$) over KC. To evaluate the 'mediated portion' (Nitzl et al., 2016, p. 1858), i.e., the extent to which the process chain over network structure explains the total effect of network management on innovation, we calculated the variance accounted for (*VAF*) as *specific indirect effect* / (*total indirect effect* + *direct effect*). For PM over NC, *VAFs* are 52% (NC_{Degree}), 36% ($NC_{Closeness}$) 14% ($NC_{Betweenness}$), and 42 per cent ($NC_{Eigenvector}$); for PM over KC, *VAF* is 18%. Jointly, the combined *VAFs* of NC and KC reach up to 70 per cent indicating that the indirect effect explains the main part of PM's contribution to firm-level innovation. For RM, there is no meaningful *VAF* as the direct effect on innovation is negative (though not significant). Nitzl et al. (2016) denote this as 'competitive partial mediation': despite the negative direct effect, RM contributes to innovation performance by the positive effect on KC. This implies that at least in our research setting, the only benefit of RM regarding innovation lies in enabling KC.

Robustness Checks

We conducted several robustness checks. First, we tested for non-linear effects (Hair et al., 2019). Scholars have argued that besides the negative side-effects of TS discussed above, beyond a certain point also NC and KC may become detrimental (e.g., Dong et al., 2017; Sampson, 2007). Hence, the relation between network structure and innovation might be more accurately captured by inverse U-shaped effects. Accounting for this, we tested a series of models that include the squared terms of the network variables (4a-d). Except for $NC_{Betweenness}$, none of the quadratic effects was significant. Further, the *BIC* values indicate that the gains in predictive power in the curvilinear models are too small to justify growing model complexity.

Second, Phelps et al. (2012) outline that particularly in network research, endogeneity may be an issue due to potential reverse or reciprocal effects. Following the guidelines of Hair et al. (2019), we checked for endogeneity by applying Park and Gupta's (2012) Gaussian copula approach. This approach encompasses three steps: (1) calculation of a Gaussian normal cumulative distribution function for each independent variable; (2) computation of the copulas as the inverse of the distribution functions; (3) inclusion of the copulas in the model and estimation of their significance. The smallest *p*-values were for the copulas of $NC_{Betweenness}$ and $NC_{Eigenvector}$ at 0.12 and 0.13; *p*-values for all other copulas were above 0.25 so that none of them had a significant effect on a dependent variable. Thus, endogeneity is unlikely an issue.

Third, we tested alternative specifications for effect directions, following previous applications of SEM in network research (e.g., Kale et al., 2000; McEvily and Marcus, 2005). We sequentially reversed one or several of the hypothesized effects in the model, re-ran the analysis, and assessed model fit. While CB-SEM has for long relied on tests of fit to compare structural models, similar approaches for PLS-SEM have only been validated recently (Hair et al., 2019). At present, literature recommends the exact fit criteria d_{ULS} and d_G alongside *SRMR* as benchmark indices (Henseler et al., 2016). None of the possible alteration models surpassed the fit of the hypothesized model. As an example, the fully reversed model including NC_{Degree} performs clearly worse ($SRMR = 0.086$; $d_{ULS} = 3.44$; $d_G = 2.25$) than the original model ($SRMR = 0.071$; $d_{ULS} = 2.35$; $d_G = 2.11$). Hence, the tests support our specifications of effect directionality.

Fourth, we tested an alternative measure of KC that weighs in both the difference and magnitude of partners' knowledge. The rationale behind this approach is that firms may profit more from partners with high overall levels of innovation-related expertise than from partners with less knowledge magnitude (e.g., Lavie, 2007). Alongside the Pearson coefficient employed for our original measure, we computed partners' knowledge level as the mean of the Likert ratings on the four domains of firm-internal knowledge. For each reported tie, we created a composite complementarity score as the product term of the two measures. As both indicators use different scales, we followed previous network research and standardized the indicator scores beforehand to a value range from 0 to 1 (e.g., Gilsing et al., 2008; Nohria and Gulati, 1997). Again, we calculated the average complementarity score across all ties of the firm. Including this alternative measure had no major impact on our results. The effects of PM ($\beta = 0.23$; $p < 0.05$) and RM ($\beta = 0.30$; $p < 0.01$) on KC remained significant, as did the effect of KC on innovation performance ($\beta = 0.23$ to 0.28; $p < 0.05$) and all other significant effects from the original analysis.

Finally, we examined if our results hold true when we use the triangulation measures for innovation – 'newsletter announcements' and 'award nominations'. As both outcome variables display highly skewed distributions (newsletter: $skew = 1.6$, $kurtosis = 5.2$; awards: $skew = 1.8$, $kurtosis = 5.4$), PLS-SEM is likely to produce unreliable results (Goodhue et al., 2012). As an alternative, literature recommends the use of Poisson or negative binomial regression (e.g., Dong et al., 2017). Because both target variables are over-dispersed (newsletter: $mean = 2.7$, $SD = 3.8$; awards: $mean = 0.4$, $SD = 0.8$), negative binomial regression was the appropriate choice in our case. Table V reports the regression results for both alternative measures. For the newsletter announcements, there are significant positive effects of the NC measures and KC. For the award nominations, the effects of

Table V. Negative binomial regression results for alternative measures of innovation performance

	Newsletter Announcements				*Award Nominations*			
Variable	*(1)*	*(2)*	*(3)*	*(4)*	*(1)*	*(2)*	*(3)*	*(4)*
Technological Knowledge	0.01 (0.14)	−0.04 (0.15)	0.00 (0.14)	−0.00 (0.14)	0.44 (0.31)	0.37 (0.29)	0.40 (0.30)	0.43 (0.31)
Market Knowledge	−0.25* (0.13)	−0.23† (0.13)	−0.26* (0.13)	−0.23† (0.13)	−0.20 (0.41)	−0.16 (0.23)	−0.19 (0.24)	−0.18 (0.25)
Managerial Knowledge	0.16 (0.15)	0.19 (0.15)	0.15 (0.15)	0.24 (0.15)	0.46† (0.27)	0.45† (0.27)	0.44† (0.27)	0.53† (0.28)
Regulation Knowledge	0.06 (0.16)	0.03 (0.16)	−0.04 (0.16)	0.01 (0.16)	−0.26 (0.28)	−0.25 (0.28)	−0.35 (0.29)	−0.30 (0.28)
Firm Size (log)	1.37*** (0.24)	1.44*** (0.25)	1.41*** (0.25)	1.38*** (0.25)	1.11* (0.46)	1.12* (0.45)	1.13* (0.44)	1.12* (0.46)
Network Tenure	−0.04* (0.02)	−0.04** (0.01)	−0.03* (0.01)	−0.04** (0.01)	−0.03 (0.03)	−0.03 (0.03)	−0.03 (0.03)	−0.03 (0.03)
Diversification	−0.43 (0.83)	−1.02 (0.78)	−1.21 (0.74)	−0.68 (0.80)	−0.00 (1.40)	−0.18 (1.36)	−0.35 (1.31)	0.21 (1.45)
Expansion	0.00 (2.97)	0.30 (3.00)	−0.41 (3.05)	0.66 (2.96	6.30 (5.06)	6.00 (4.92)	5.21 (5.12)	6.81 (5.07)
PM	0.04 (0.14)	0.09 (0.14)	0.20 (0.12)	0.09 (0.13)	0.06 (0.25)	0.06 (0.25)	0.19 (0.22)	0.12 (0.23)
RM	0.19 (0.15)	0.23 (0.16)	0.12 (0.16)	0.18 (0.15)	−0.26 (0.28)	−0.28 (0.29)	−0.36 (0.29)	−0.27 (0.28)
NC_{Degree}	0.07*** (0.02)				0.07† (0.04)			
$NC_{Closeness}$		8.42* (3.31)				11.13† (6.33)		
$NC_{Betweenness}$			0.15** (0.06)				0.15† (0.09)	
$NC_{Eigenvector}$				0.54** (0.17)				0.51† (0.28)
KC	0.64* (0.32)	0.65† (0.34)	0.56† (0.33)	0.68* (0.33)	0.25 (0.66)	0.36 (0.66)	0.25 (0.63)	0.27 (0.65)
TS	0.10 (0.16)	−0.13 (0.17)	0.01 (0.17)	−0.14 (0.15)	0.10 (0.30)	0.11 (0.30)	0.18 (0.32)	0.05 (0.29)
Intercept	−2.50* (1.21)	−5.19*** (1.50)	−2.31† (1.26)	−2.76* (1.22)	−5.62* (2.38)	−8.70** (2.90)	−4.95* (2.38)	−5.90* (2.39)
Chi^2	80.89	79.49	79.88	80.82	58.13	57.79	58.61	58.08
AIC	280.17	282.48	282.09	280.79	132.79	132.45	133.27	132.74

N = 74.
PM, Portfolio Management; RM, Relationship Management; NC, Network Centrality; KC, Knowledge Complementarity; TS, Tie Strength.
Standard errors are in parentheses.
***$p < 0.001$; **$p < 0.01$; *$p < 0.05$; $^{\dagger}p < 0.10$.

the NC measures are significant; KC has no significant effect. In sum, we consider the results adequately robust across different innovation indicators.

DISCUSSION

Theoretical Implications

Although strategic network researchers have demonstrated that the structural characteristics of the firm's local network have a strong influence on innovation performance, less attention has been paid to the question of how firms actually build networks that facilitate innovation. Past research has been criticized for treating firms as 'empty vessels with no strategic interests' (Phelps et al., 2012, p. 1149) and thus for neglecting their efforts to shape the network structures surrounding them (Rowley and Baum, 2008b). In this paper, we intend to fill this research void and answer calls for 'bringing the firm back into network studies' (Madhavan et al., 2008, p. 497). To this end, we integrate two previously separate streams of literature: (1) the structural perspective that links innovation performance to network characteristics; (2) the managerial perspective that examines firm-level processes and practices for inter-firm networking.

From the theoretical perspective, we argue that networks with specific structural attributes provide the firm with resource advantages. Obtaining an advantageous structural position is, however, a challenging task, as in this endeavour firms must overcome several constraining forces. To this end, firms need specific capabilities for network management. Further, we argue that each of the advantageous network attributes is associated with a distinct set of constraining forces. Depending on the nature of those constraints, firms need network management capabilities on different levels to obtain different types of network advantages. In all, we provide strong empirical support for this rationale. In essence, we demonstrate that network management plays a key role in the creation of network advantages, namely, higher levels of NC, KC, and TS. As two of those attributes (NC and KC) foster innovation performance, we contend that network management processes are important indirect antecedents of firm-level innovation.

With respect to strategic network literature, we contribute to existing research by explaining the origins of structural network advantages. Recently, a growing number of network scholars has begun to criticize the purely structuralist explanations that dominate large parts of network evolution literature (e.g., Hite and Hesterly, 2001; Rowley and Baum, 2008a; Stuart and Sorenson, 2007). Those scholars refute the wide-spread assumption that network advantages mainly stem from a better 'starting position' of some firms in that future relationships are shaped by existing network structures. Instead, they highlight network agency, i.e., the firm's strategic intent to navigate into valuable structural positions (Koka et al., 2006; Rank and Strenge, 2018).

By our study, we move beyond the notion of mere strategic intent: factoring in that 'not all network actors are capable of pursuing network strategies' (Doreian, 2008, p. 266), we add firm-level capability to the discussion. As our results demonstrate, firms differ considerably in the extent to which they have implemented processes for network management. Further, it was evident that differences in network management capability yield differences in local network structure. Within the bounded network environment under study, firms that engaged in network management were able to obtain more central positions (NC), compile more valuable partners (KC), and cultivate stronger collaborative relationships (TS). In contrast, factors that relate to inherent differences in network opportunity between firms, such as firm size and network tenure (e.g., Fund et al., 2008), had no or very little effect on the network attributes obtained.

Together, those findings indicate that network advantages are the result of capability rather than of opportunity differentials. To a substantial degree, network structure appears to be 'subject to managerial design' (Lorenzoni and Lipparini, 1999, p. 333), with network management processes acting as key enablers. Network structures thus are not just the result of firms acting on external circumstances they cannot control. Instead, firms can actively increase their chances of success if they invest into building adequate internal skills and managerial practices. In all, this strong role of network management implies that without an explicit incorporation of firm-level capabilities, theories of how strategic networks originate are incomplete.

Further, our paper contributes to the literature on network management capabilities. In the current state, it remains largely unclear how exactly network management helps the firm create value as 'we often do not know why certain capabilities lead to certain outcomes' (Wang and Rajagopalan, 2015, p. 248). Past research assigned network management to the role of a first-order dynamic capability (e.g., Schilke and Goerzen, 2010; Schreiner et al., 2009; Zollo et al., 2002), arguing that network management fosters firms' 'ability to develop and utilize inter-organizational relationships' (Walter et al., 2006, p. 541). However, as studies only investigated direct effects of network management, they did not show whether performance improvements are indeed due to changes in the firm's network. Further, one could argue that in the prevalent approach network management is actually treated as a 'dual-purpose' capability (Helfat and Winter, 2011) that blends two distinct mechanisms: (1) operational benefits, i.e., helping the firm 'utilize' its network resources and generate outcomes from network ties; (2) dynamic benefits, i.e., helping the firm 'develop' its local network to create new resource advantages.

By extracting the effect of network management over network structure, we were able to single out the latter of the two mechanisms and assess its causal importance. We demonstrate that PM helps increase the reach (NC), PM and RM affect the richness (KC) of the firm's local network. Both were found to give firms an edge over competitors in the innovation game. RM further impacts network receptivity (TS) that did not foster innovation performance in our empirical setting but may be a valuable success driver in other industry contexts (e.g., Rowley et al., 2000; Tiwana, 2008). Decomposing direct and indirect effects of network management, we find that with a 'mediated portion' of up to 70% there is a strong partial mediation of PM over NC and KC (80% is regarded as the threshold for full mediation (Nitzl et al., 2016)). RM contributes to innovation solely by its positive effect on KC. Leaving aside this indirect effect, RM even exerts a slightly negative effect innovation performance (though not significant).

Those findings open the 'black box' and provide some important insight on the nature of network management as an organizational capability. The predominance of the indirect effects indicates that in essence, the value of intra-firm network management processes lies in improving the firm's 'means', that is structural network advantages, to the 'ends', that is superior innovation outcomes. Therefore, it is not primarily network management that drives innovation performance; rather, network management should be thought of as an antecedent of the external resources that the firm can access via its network. Taken together, our study thus substantiates and clarifies the notion of network management as a first-order dynamic capability, with the purpose to create and expand the firm's resource base to innovate and respond to environmental changes (Helfat and Winter, 2011; Teece, 2014). Thereby, we extend prevalent perspectives as we demonstrate how exactly network management operates on network resources and highlight the role of network structure as an intervening variable.

Finally, our research helps disentangle the performance effects of network management practices on the relationship level and the portfolio level (Wassmer, 2010). To this end, we demonstrate that while each of the two types of network management help the firm construct a network that facilitates innovation, both have idiosyncratic effects with PM impacting NC and KC, and RM impacting KC and TS. Moreover, our results suggest that both capabilities are largely independent from one another, as indicated by the lack of significant interactive effects.

As an implication, there apparently is no one definite strategy on 'how to network smart' (Stuart and Sorenson, 2007, p. 219). Instead, the effectiveness of network management practices depends on the specific structural attributes that the firm wants to improve. Thereby, the operating ranges of PM and RM are distinct but partially overlapping. Put differently, the two capabilities perform clearly separate functions (as indicated by their solitary effects on NC and TS) but to some extent, they produce equifinal outcomes (as indicated by their additive effect on KC). This insight contrasts extant viewpoints that consider PM and RM as integral parts of an overarching capability bundle: to network successfully, firms would require a basic proficiency in both of them (Kale and Singh, 2009; Sarkar et al., 2009; Schilke and Goerzen, 2010). Instead, our findings suggest that in the main, PM and RM are not intertwined and ultimately represent alternative approaches for effecting change to the firm's network.

Practical Implications

Our research provides two-fold insight for management practitioners. On the one hand, we offer implications on how firms can actively 'make a difference' in their network environment (Rowley and Baum, 2008a, p. xix). Namely, we demonstrate the effectiveness of specific developable managerial practices. Previous works attributed network advantages usually to opportunity differentials between firms such as their size, reputation, or past network structures. This perspective, however, is not helpful for practical applications as it mainly describes a 'Matthew effect' (i.e., the rich will get richer) instead of delivering 'workable [...] managerial prescriptions at the level of the specific firm' (Madhavan et al., 2008, p. 497). In contrast, our work is particularly helpful to firms that do not have the advantage of a superior starting position as it shows which capabilities those firms should acquire to get able to network effectively.

On the other hand, it is important to keep in mind that significant firm-specific investments are necessary to build organizational capabilities (Zollo et al., 2002). Thus, a key strategic decision for the firm is to choose *which* types of capabilities to develop (Wang and Rajagopalan, 2015). To this end, we demonstrate that both PM and RM are viable options for improving innovation performance (though PM has a stronger empirical effect). This implies that the firm can choose between a 'networking strategy' and a 'partnering strategy' (Rowley and Baum, 2008a, p. xix) to build a local network that facilitates innovation: (a) by configuring the overall pattern of net-work ties (high-level PM); and b) by nurturing individual ties to key partners (high-level RM).

Limitations and Further Research

Our work has several limitations that point at promising avenues for future research. First, our unit of analysis was at the firm level which bears some caveats. Particularly, we had to condense relational data to obtain firm-level indicators and dealt with average scores for KC and TS. Though this approach is common in network research, the conversion still 'might filter away certain specific circumstances or cases that might be worthwhile to explore in detail' (Heimeriks and Duysters, 2007, p. 42).

Second, our data collection relied on cross-sectional self-reports. We took several precautions to prevent and control for informant biases; distortions, however, may remain. Also, the possibility of reverse causality or reciprocal effects cannot fully be ruled out – even though we checked for endogeneity, tested models with alternative effect directions, and used time-lagged triangulation measures for innovation. In the light of those shortcomings, we suggest that future studies should employ longitudinal designs and rely on analytical procedures that are able to reconstruct processes of network structure emergence over time, e.g., exponential random graph models (e.g., Matous and Todo, 2017; Rank and Strenge, 2018). Doing so, network research may strive toward an understanding of potential coevolutionary dynamics between firm-level capabilities, network structure, and innovation that were beyond the scope of our study.

Finally, regarding the empirical context, our research was conducted in one single bounded network in the energy sector. By this approach, the effects of sectoral specifics could not be controlled for. Future works should conduct network studies in other innovation- and collaboration-intensive industry sectors such as software or medical engineering and test the generalizability of our findings. In sum, however, we believe that our study makes a valuable contribution to research on strategic networks, network management, and innovation. We hope that our work stimulates further academic discussion and helps companies become more effective network actors and more successful innovators.

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NOTES

[1] Greentec Awards, Deutscher Nachhaltigkeitspreis, Energy Awards, Energy Efficiency Awards, Energy App Award, VKU Innovationspreis, LEW Innovationspreis Intelligente Energie, Innovationspreis Klima und Umwelt.

[2] Deutschland Land der Ideen, Innovationspreis der deutschen Wirtschaft, Top 100 Innovatoren, Deutscher Innovationspreis, German Innovation Awards, Deutscher Zukunftspreis.

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