European Management Journal 41 (2023) 263–273

Contents lists available at ScienceDirect

European Management Journal

journal homepage: www.elsevier.com/locate/emj

Which collaborations allow firms to become gatekeepers? A longitudinal analysis of a large-scale collaboration network

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ARTICLE INFO

Keywords:
Gatekeeper position
Collaboration types
Collaboration network
Knowledge
Longitudinal data

ABSTRACT

Having a gatekeeper position in a collaborative network offers firms great potential to gain competitive advantages. However, it is not well understood what kind of collaborations are associated with such a position. Conceptually grounded in social network theory, this study draws on the resource-based view and the relational factors view to investigate which types of collaboration characterize firms that are in a gatekeeper position, which ultimately could improve firm performance in subsequent periods. The empirical analysis utilizes a unique longitudinal data set to examine dynamic network formation. We used a data crawling approach to reconstruct collaboration networks among the 500 largest companies in Germany over nine years and matched these networks with performance data. The results indicate that firms in gatekeeper positions often engage in medium-intensity collaborations and less likely weak-intensity collaborations. Strong-intensity collaborations are not related to the likelihood of being a gatekeeper. Our study further reveals that a firm's knowledge base is an important moderator and that this knowledge base can increase the benefits of having a gatekeeper position in terms of firm performance.

1. Introduction

Over the past few years, it has become increasingly common for firms to aim to position themselves in their collaboration networks such that they can gain competitive advantages, which eventually improve firm performance. A gatekeeper position—that is, a position from which a firm connects partners in a collaboration network who would not otherwise be connected with each other—can offer substantial benefits for a firm in terms of, for example, differentiation from the competition through new services and products enabled by internalizing novel information (Klimas et al., 2021; Piezunka & Dahlander, 2015). Despite the well-known advantages of a gatekeeper position, however, it is rather unclear which types of collaboration characterize firms that are in such a position.

Extant research has mostly focused on the outcomes of a gatekeeper position. Multiple studies have empirically shown the beneficial effects of a gatekeeper position on firms' innovation and financial performance (Gilsing et al., 2008; Soda, 2011; Tan et al., 2015; Zaheer & Bell, 2005). In addition, some studies have focused on the individual or team level (e.g., Carnabuci & Dioszegi, 2015; Hinz & Spann, 2008; Ter Wal et al., 2017; Weiler & Hinz, 2019; Zaheer & Soda, 2009), also indicating mostly positive effects of gatekeeper positions on various performance outcomes. In contrast, only a few studies have investigated the development of social networks (Weiler et al., 2021) and especially the antecedents of a gatekeeper position. One such study is Sytch et al.'s (2011) study, which shows that the number of existing relationships with other organizations, an increasing dependence of firms, and the opportunity to build new relationships increase the likelihood of new bridging ties that constitute a gatekeeper position (see Table 1 for a comparison of this study with extant empirical literature regarding the outcomes and antecedents of a gatekeeper position at the firm level).

However, little research investigates the factors pertaining to the nature of the network relationships in terms of how they can help firms attain a gatekeeper position. Firms' positions in their networks are related to the types of collaboration they choose, as not all types of collaboration are equally suitable for every network position (Michelfelder & Kratzer, 2013; Perry-Smith & Shalley, 2003). In this context, the finding that firms engage in diverse types of collaboration with partners

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https://doi.org/10.1016/j.emj.2021.09.008
Received 11 May 2020; Received in revised form 9 September 2021; Accepted 16 September 2021
Available online 15 October 2021

to gain access to complementary resources is well established (Belderbos et al., 2004; Piezunka & Dahlander, 2015), showing that collaboration can range from weak intensity (e.g., participation in associations) to strong intensity (e.g., participation in joint ventures). Business practice confirms this finding; for example, our data show that electronics company Siemens AG is in a gatekeeper position in its network and the company relies on a multitude of medium-intensity collaborations in many different forms. Among these are consortia (e.g., an interdisciplinary consortium in the area of regional mobility together with public transportation companies such as Deutsche Bahn, consulting firms, and Alcatel from the communication sector, in which Siemens acts as a systems integrator) and joint research projects (e.g., a project in the health care sector together with partners from a multitude of different industries including Lufthansa Systems, SAP, and T-Systems). In addition, Siemens also maintains a few strong- and some weak-intensity collaborations, participating in, for example, the "CEO of the future" initiative together with insurance firm Allianz, pharma company Bayer, and partners from the media. Although some studies in extant research offer hints as to which types of collaboration might be more successful in accessing new knowledge and new parts of the network (Michelfelder & Kratzer, 2013; Tortoriello et al., 2012; Zardini et al., 2020) and under which conditions firms might be more likely to become gatekeepers (Sorenson & Stuart, 2008; Sytch et al., 2011), no studies explain how different types of collaboration influence firms' ability to gain gatekeeper positions.

Against this backdrop, our research questions are as follows: *Which types of collaboration are associated with gatekeeper positions of firms? And how can firms profit from this position, contingent on their own knowledge base?* Using a unique data set of large-scale, quantitative longitudinal data from the 500 largest companies in Germany, we investigate how three types of collaboration—weak-, medium-, and strong-intensity collaboration—are related to being in a gatekeeper position. We also examine firms' knowledge base as a contingency factor that determines how successful firms are in transforming their gatekeeper position into firm performance, as extant research shows that after firms gain new knowledge, they still face the difficult task of combining this information with their existing knowledge (Katila & Ahuja, 2002; Piezunka & Dahlander, 2015).

By addressing the research questions, this study contributes to the body of research in multiple ways. First, this study is among the first to examine which types of collaboration characterize firms being gatekeepers in a collaboration network and to explain why not all categories of collaboration intensity may be suitable for this specific position. Second, we extend the application of the resource-based view (RBV; Barney, 1991) and the relational factors view (RFV; Dwyer et al., 1987; Morgan & Hunt, 1994) to gatekeeper positions and derive the theoretical mechanism for our hypotheses, which is strongly rooted in these theories. Third, this study contributes to the literature on successful knowledge transfer in collaboration networks (Katila & Ahuja, 2002; Massaro et al., 2019; Tsai, 2001) by providing an explanation why not all firms that hold similar positions in a social network (in this context, those in gatekeeper positions) are equally successful in benefiting from these positions to improve firm performance.

2. Theoretical development and hypotheses

2.1. Conceptual grounding

To develop a theoretical reasoning for explaining the effects of various types of collaboration, we combine insights from social network theory (SNT; Ahuja, 2000; Burt, 1992) with the RBV (Barney, 1991) and the RFV (Dwyer et al., 1987; Morgan & Hunt, 1994). Whereas SNT provides the conceptual groundings, the RBV and RFV provide the basis for us to derive one theoretical mechanism that jointly provides the

Table 1
Literature review and comparison.

Source	Antecedents of GK Pos.	Outcomes of GK Pos.	Data Source	Main Results
Gilsing et al. (2008)	–	Explorative innovation performance (number of explorative patents)	Network data about 85 companies in the chemical, automotive, and pharmaceutical industries over a 12-year period	Exploration success of a gatekeeper position depends on two other forms of embeddedness: There is a negative interaction effect between technological distance and betweenness centrality [GK pos.] and a positive interaction effect between betweenness centrality [GK pos.] and network density.
Soda (2011)	–	Innovation performance	Joint venture data in the automotive industry about 232 companies over four years	Bridge ties in a firm's network [GK pos.] are highly supportive of a firm's innovation performance, particularly in comparison to the relatively low effect of a firm's network density.
Sytch et al. (2011)	Current local ties × current bridging ties (H1) Bridging ties by dependent firms (H2) Opportunity for bridging (H3)	–	Network data from the global computer industry with 7962 unique participating firms over a 15-year period	The number of existing relationships with other organizations, an increasing dependence of firms, and the opportunity to build new relationships increase the likelihood of new bridging ties that constitute a gatekeeper position.
Tan et al. (2015)	–	Innovation Performance	Simulation data of 6151 firms	Degree centrality and spanning structural holes [GK pos.] both positively influence innovation performance in low-density networks. In high-density networks, the impact of degree centrality on innovation performance weakens, and the effect of spanning structural holes [GK pos.] turns negative.
Zaheer and Bell (2005)	–	Firm performance (market share)	Survey data from 77 companies in the mutual fund industry in Canada	Firms' innovative capabilities and bridging structural holes [GK pos.] both enhance firm performance. Furthermore, firms that implement both at the same time get a further performance boost (positive interaction effect).
This Study	**Weak-intensity collaboration (H1) Medium-intensity collaboration (H2) Strong-intensity collaboration (H3)**	**Firm performance (EBITDA)**	**Network data about the 500 largest companies (multi-industry) in Germany over nine years**	**Firms in GK pos. often engage in medium-intensity collaborations and less likely in weak-intensity collaborations, while strong-intensity collaborations are not related. A strong knowledge base increases the benefits of a GK pos. in terms of firm performance.**

Notes: GK Pos. = Gatekeeper Position.

reasoning for our hypotheses.

SNT mainly focuses on the structural properties of networks, such as the centrality of an actor's position (Dong et al., 2017) or the gatekeeper position (Burt, 1992; Carnabuci & Dioszegi, 2015; Gulati, 1998). This position is powerfully illustrated by Burt's (1992) well-known "structural hole" metaphor, which equates the gatekeeper's role to "filling the hole" between two network actors or two parts of the overall network, thereby connecting them and generating value by transferring resources from one actor or part of the network to another, establishing a direct relationship between third parties (matchmaking), and coordinating third parties' actions without creating a direct relationship (Spiro et al., 2013). Because disconnected partners are likely to provide a gatekeeper with access to diverse approaches, perspectives, new network resources, and ideas that are not well-known in the gatekeeper's industry (Faraj et al., 2015; Stam & Elfring, 2008), a gatekeeper can acquire access to more diverse information than those in other positions can (Spiro et al., 2013). Thus, a gatekeeper position can help a firm in this position to acquire diverse, new information that can improve this firm's performance (Carnabuci & Dioszegi, 2015).

In addition, SNT considers the qualitative nature of the relationships and ties (Uzzi, 1996). *Tie strength* refers to the concept that ties can range from strong to weak (Granovetter, 1973; Levin & Cross, 2004): strong collaborative ties are characterized by close, long-lasting, deep relationships with frequent interactions and good information flow between network partners (Capaldo, 2007), whereas weak ties entail infrequent interactions and less intensive information flow between network partners (Michelfelder & Kratzer, 2013). Furthermore, SNT proposes a linkage between the type of tie and the firm's distance from its tie partner: firms have a tendency to establish strong ties with partners from the same or close industries or fields and weak ties with partners outside their industries or fields (Capaldo, 2007; Granovetter, 1973).

To determine how the types of collaboration are related to a firm's gatekeeper position, we consider the collaborative activities that firms perform and categorize them according to their intensity (for a full list of collaborative activities, see Section 3.2; Lee et al., 2001; Schleimer & Faems, 2016). Extant network research suggests that a *weak-intensity collaboration* is characterized by infrequent interactions in which collaborators explore opportunities to innovate, rather than intensive resource exchanges between network partners (typically in non-equity types of collaboration, e.g., participation in networking events and outsourcing) (Michelfelder & Kratzer, 2013; Oerlemans & Knoben, 2010). In weak-intensity collaborations firms mostly partner with firms from other industries or fields to gain access to new, unfamiliar information and new parts of the network (Burt, 1992; Granovetter, 1973).

In contrast, *strong-intensity collaborations* are characterized by close, long-lasting, deep relationships with partners (Bouncken & Barwinski, 2021) in which frequent interactions and information flow between them (mainly in equity types of collaboration, e.g., mergers and acquisitions [M&As], joint ventures). Firms usually strive to strengthen the knowledge they already have and, hence, prefer to have strong partnerships with firms from the same industry or field (Capaldo, 2007; Sullivan & Ford, 2013), even though these partnerships are not likely to provide access to new resources. Strong- and weak-intensity collaboration are two poles of an intensity continuum (Levin & Cross, 2004); firms can also engage in *medium-intensity collaboration* that are characterized by a medium frequency of interaction and a medium distance to their partners and may be represented by (minor) equity (e.g., spin-offs) or non-equity (e.g., joint research projects) types of collaboration. Extant research has not examined this category of collaboration thus far, focusing mainly on strong- and weak-intensity collaborations. Hence, the effectiveness of this type of collaboration in gaining a gatekeeper position remains to be determined. This type of collaboration could yield promising outcomes, considering it could combine the best of both worlds.

A gatekeeper position can affect *firm performance* (assessed herein as financial profit), because integrating diverse approaches and perspectives from other fields into the firm's own knowledge bases increases its potential for innovation and advancement in all areas of activity, such that its performance could improve (Faraj et al., 2015; Un et al., 2010). How well firms translate the new information they acquire in a gatekeeper position into higher firm performance depends heavily on whether they can absorb it and add it to their current knowledge base (Katila & Ahuja, 2002). Therefore, we include *firm's knowledge base*, which refers to the knowledge the firm has accumulated over time (Ahuja & Katila, 2001; Carayannopoulos & Auster, 2010), as a moderating variable on the link between a gatekeeper position and firm performance.

2.2. *Hypotheses*

As explained in the preceding section, we draw on reasoning from the RBV (Barney, 1991) and RFV (Dwyer et al., 1987; Morgan & Hunt, 1994) to derive the theoretical mechanism for our hypotheses. The RBV suggests that firms combine heterogeneous, imperfectly mobile resources to gain competitive advantages (Hunt & Morgan, 1995). Regarding collaboration between companies, the RBV posits that complementary and idiosyncratic resources foster the performance of the collaboration (Jap, 1999). *Complementary resources* are resources that a firm brings into a collaboration that its partners do not have and that thus add to the partners' resource portfolio (Das & Teng, 2001; Hunt et al., 2002).

From a network perspective, it appears valuable for firms to engage in collaborative relationships that offer complementary resources with the aim of achieving a gatekeeper position. This refers not only to the new information gained by building a particular tie with a partner, but also to the network surrounding the potential new partner, as a gatekeeper position is particularly strong when synergy effects can be created between diverse parts of the overall network. In terms of the theoretical outline of SNT, the greater the distance between two potential partners, the less familiar is the new knowledge. According to the RBV, unfamiliar knowledge and access to other parts of the overall network promise greater resource complementary and as such should be more beneficial to the collaboration. In contrast, closer partners usually do not provide many complementary resources and are not likely to enable a gatekeeper position, as this network of partners is already likely to have a high overlap or be intertwined with the extant network of the acting firm.

For the second mechanism, we refer to the RFV, which poses that *commitment* within a relationship improves collaboration success, as partners are highly motivated to make their collaboration a success (Castañer & Oliveira, 2020; Mohr & Spekman, 1994). This commitment decreases with increasing distance of partners, because less trust, communication, and shared values comes with higher distance (Hunt et al., 2002; Morgan & Hunt, 1994). In the same vein, knowledge flow and integration will be much lower with more distant partners than with close partners. Hence, the more a firm's partners stem from outside its own field or industry, the less likely commitment is associated with these relationships.

Altogether, the premises and performance implications of the RBV suggest an increasingly positive role of complementary resources as distance increases and, as such, the strength of ties. In contrast, the implications of the RFV suggest a decreasing commitment with increasing distance between partners. Fig. 1 illustrates the effects of RBV and RFV according to our line of argumentation, which we further develop to derive our hypotheses and the resulting joint effect next. The main idea for the joint effect is that firms need resource complementarity as well as commitment to achieve their goals. Both input factors are important and cannot perfectly substitute each other. A very low commitment makes resource complementarity useless, while a high commitment of firms that cannot benefit from each other in terms of resources is also not valuable for goal-achievement. Fig. 1 shows the

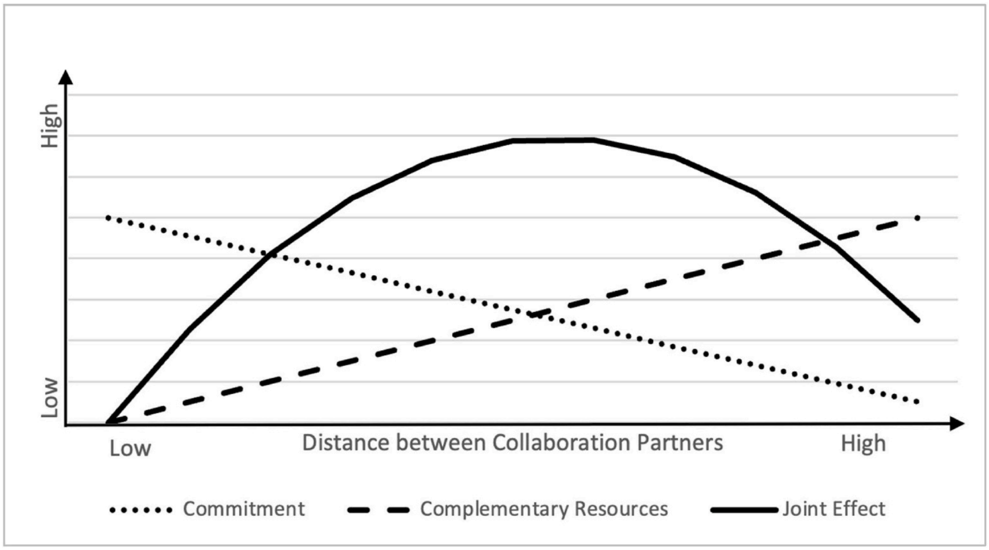

Fig. 1. Effect of collaboration intensity on gatekeeper position.

effect of distance on these two input factors and depicts with a multiplicative joint effect, that the sweet spot should not be expected at the extremes but somewhere in the middle.

The prevailing wisdom among network theorists for the past 50 years is that weak-intensity collaboration is particularly suitable for firms that aim to explore innovative opportunities (Michelfelder & Kratzer, 2013; Oerlemans & Knoben, 2010). They team up with partners that have new kinds of information (Burt, 1992; Granovetter, 1973), mainly outside their own industry or field. With greater access to unfamiliar information, firms are exposed to a greater diversity of ways of thinking. Intuitively, we would expect these firms to be successful in gaining a gatekeeper position by collaborating with partners from diverse fields, as the resources they offer are complementary.

However, recent work has begun to disentangle these arguments and has found that weak-intensity collaborations do not always offer the benefits that Granovetter's (1973) work suggests (Aral & Van Alstyne, 2011). Drawing on the introduced mechanism regarding commitment, the greater distance between partners in weak-intensity collaborations is often associated with lower commitment to these collaborations. Firms do not know their potential collaboration partners well enough and the collaboration environment is not stable enough; typically accompanied by less trust and shared values (Bouncken et al., 2020). In addition, the information and access to the new parts of the network acquired through weak-intensity collaboration is rather unfamiliar that firms have difficulties making appropriate use of these complementary resources. Altogether, we hypothesize that connecting partners from diverse knowledge fields in a network is difficult for firms, which in turn makes becoming a gatekeeper less likely. Therefore, we propose the following:

H1. Weak-intensity collaboration is negatively associated with a gatekeeper position.

Medium-intensity collaborations have characteristics of both strong- and weak-intensity collaborations. Firms can engage in medium-intensity collaborations with other firms that are not overly dissimilar to acquire new information and gain access to new parts of the network that offer complementary resources, but they also engage in them to broaden and extend the knowledge they already have by cooperating with partners from the same or neighboring industries (Levin & Cross, 2004). Hence, the information that firms acquire from medium-intensity collaborations is usually more familiar than it is in a weak-intensity collaboration. Similarly, compared with weak-intensity collaborations, the number of network connections gained by medium-intensity collaborations is lower and, thus, offers fewer complementary resources.

On the beneficial side, because of the shorter distance between their own and their collaborators' fields, it is generally easier for firms to cultivate a more committed relationship with more similar partners. In medium-intensity collaborations, partners communicate with each other more frequently, the relationship is deeper, and the knowledge flow is much better organized than is the case in weak-intensity collaborations (Capaldo, 2007; Granovetter, 1973). Hence, firms can better process and more easily make use of the information and access to new parts of the network they gain by creating synergy effects between diverse parts of the network (Piezunka & Dahlander, 2015).

Overall, firms can maximize the value of the complementary resources to which they are exposed and profit from it effectively through committed relationships. Similar to a Cobb–Douglas production function, both inputs in the form of complementary resources and commitment are needed to create the desired output, i.e., a gatekeeper position. Hence, both inputs cannot be completely substituted by each other and are related in a multiplicative manner. As an implication of the above argumentation, medium-intensity collaboration with associated medium levels of resource complementarity and commitment is highly likely to be related to a gatekeeper position in a network. Accordingly, we propose the following:

H2. Medium-intensity collaboration is positively associated with a gatekeeper position.

Strong-intensity collaboration is particularly useful for strengthening the knowledge a firm already has (Granovetter, 1973). This type of collaboration is usually characterized by high relationship commitment and interaction between the partners (Granovetter, 1973). These similarities between partners may be beneficial for generating, for example, economies of scale or fostering communication processes between partners (Filiou & Massini, 2018).

However, they are likely not as beneficial for achieving a gatekeeper position. According to the RBV's theoretical mechanism, in this scenario other firms' knowledge does not offer sufficiently complementary resources (i.e., diverse knowledge and access to new parts of the network). Firms that cooperate with partners from their industry and field typically find they have similar information, and with regard to the additional—and ideally diverse—network connections gained through the collaboration partners, the benefits are rather limited as partners in one's industry tend to have similar and redundant networks (Capaldo, 2007; Carnabuci & Dioszegi, 2015). Thus, complementary resources in the form of new information and access to different parts of the overall network is not associated with strong-intensity collaboration and, hence, do not provide the necessary basis to foster a gatekeeper position. To be able to bridge firms in a network, a firm must have access to partners that do not know one another (Spiro et al., 2013), which is unlikely if the collaboration is situated in a single industry in which most of the players know each other. Hence, we hypothesize the following:

H3. Strong-intensity collaboration is negatively associated with a gatekeeper position.

To profit from the gatekeeper position and thus improve performance, firms must find ways to apply the diverse information they acquire to their overall activities. As recent research suggests, a firm must master the task of integrating diverse information into its knowledge base (Piezunka & Dahlander, 2015); and this knowledge base has an effect on whether the firm will be successful in applying the new information to its activities. Only firms that can integrate diverse information into their knowledge bases can discover the value of that information to their organizations and take advantage of the benefits of the gatekeeper position (Katila & Ahuja, 2002). Whereas some research suggests that a strong knowledge base might hinder firms' ability to integrate new information because firms tend to stick to their familiar ways of thinking (Katila & Ahuja, 2002), most studies emphasize the knowledge base's positive effects and posit that it supports the integration of external information in several ways (Tsai, 2001).

One way is that a firm's knowledge that is embedded in individual skills, business routines, and processes determines whether it can provide the environment necessary to integrate external information into its knowledge base (Inkpen, 2000; Un et al., 2010). For example, firms that have a strong internal knowledge base are more likely to understand innovative new technologies and business practices and apply them to their innovation efforts (Tsai, 2001). A second way is when a strong knowledge base helps a firm recognize its knowledge deficits and internalize new information to address them. Thus, a strong knowledge base should strengthen the benefits that a firm can gain from a gatekeeper position in terms of integrating diverse knowledge. Therefore, we hypothesize the following:

H4. The positive effect of a gatekeeper position on firm performance is greater when the firm has a strong knowledge base than when it does not.

Building on this theoretical outline, Fig. 2 depicts the proposed framework of this research. The framework features three linkages from weak-, medium-, and strong-intensity collaboration to a gatekeeper position (H1–H3), as well the gatekeeper position's effect on firm performance, which could theoretically be moderated by the focal firm's knowledge base (H4).

3. Methodology

3.1. Sample and data collection

This study uses a unique data set of large-scale, quantitative, longitudinal data from the 500 largest companies in Germany. To identify these companies, we used a list from *Die Welt*, a well-recognized national daily newspaper that covers the 500 German companies listed on the stock market as well as privately held firms, that had the highest sales in 2013 and that work in various industry sectors and regions of Germany. We collected data for our empirical analysis from two secondary data sources by matching data about cooperation between companies that were collected via a machine-based data-crawling approach with performance data manually collected from annual reports of these 500 companies.

The innovative machine-based data-crawling tool we developed to obtain cooperation data collected and analyzed press releases about the 500 companies. Press releases are often used to obtain company-related information in studies that analyze stock market prices (e.g., Schumaker & Chen, 2006). We relied on press preleases to obtain information about a company's collaborative ties because firms are usually eager to inform stakeholders of a new cooperation initiative to improve their image. Using this innovative approach, we gathered panel data about the companies' collaborative activities over the nine years from 2006 to 2014 and applied a five-year moving time window to analyze these data. Thus, we were able to reconstruct the collaboration network dynamically among these 500 companies over a long period of time, such that we captured the new network ties that firms established every year during the period of observation.

The data-crawling tool scanned four national databases that contain press releases from German companies—Wisonet, Spiegel Online, Presseportal, and Google News. We entered the names of the 500 companies and a list of keywords that refer to a collaborative tie (e.g., "alliance," "spin-off," "cluster"). The crawling tool extracted a press release if it contained at least two of the 500 company names and at least one keyword (e.g., "BMW," "SAP," "alliance"). Using this approach, we identified 3,818 companies that engaged in collaborations (e.g., joint ventures, spin-offs, alliances, research projects) from 2006 to 2014.

In the next step, we performed a manual quality check to determine whether an actual collaboration existed between each pair of the companies identified by the data-crawling tool. To this end, we carefully analyzed each of the 3,818 press releases in three steps to determine if we could count the collaboration mentioned in it as a valid company pair. First, we manually checked the relevant sentence in the press

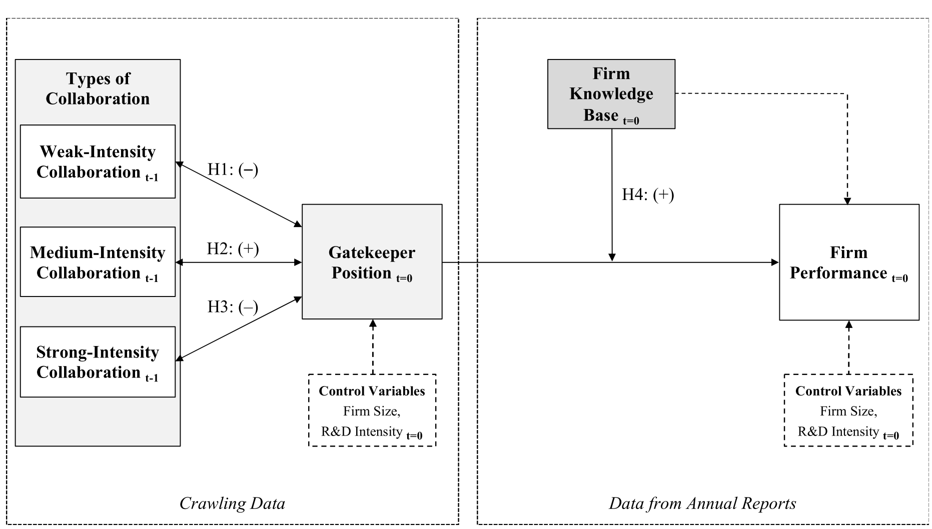

Fig. 2. Study framework.

release that the crawling tool marked as an identified company pair (e.g., Peugeot Germany and Deutsche Bahn announce the start of a new collaboration project to increase the number of electric charging stations in Germany). Second, if the marked sentence did not offer enough information to validate a company pair, we looked at the full press release to determine the validity of the company pair. After the first two steps, we had identified 1,466 valid company pairs. In the third step, we accounted for redundancy and eliminated 13 company pairs for which different press releases had the same wording. After this three-step validity check, 1,453 valid company-pairs remained in the final sample for analysis.

To identify the number of each category of collaborative ties for each company and year, we accounted for whether the same collaboration between two companies was mentioned in multiple press releases. If multiple press releases reported on a collaboration effort and they were not identical, we considered this collaboration particularly meaningful for companies' actions and outcomes. Hence, the number of the times that a collaboration appeared in press releases determined how often this specific collaboration was counted as a tie when we computed the number of each firm's collaborative ties for our independent variables, which is in line with extant literature in the field of network analysis (e.g., Ahuja, 2000).

We enriched our cooperation data with financial performance data by manually extracting financial data from annual reports of the 500 companies. When an annual report was not available, we relied on financial databases like Bundesanzeiger and Hoppenstedt. We extracted data on firm performance (EBITDA [earnings before interest, taxes, depreciation, and amortization]), number of registered patents, number of employees, and R&D intensity (R&D expenditures/revenue) from 2010 to 2014, our time frame for the analysis. When gathering these data, we took care to separate data for parent and subsidiary organizations. In general, we used data from the subsidiary organizations, except for 24 cases in which we used parent organization data because subsidiary data were not available. Furthermore, we eliminated 8 subsidiary cases from the sample because they belonged to the same parent organization and we wanted to ensure that we did not include parent organization data twice. Using both data-collection processes resulted in a data set collected from two independent secondary sources, which significantly increases data validity and reduces the potential for common method bias (Podsakoff et al., 2003).

Our sample companies represent diverse industry sectors (Table 2). The most common sectors were the machinery/electronics industry (20.2%), the retail/consumer goods (24.5%), and the service provider (17.4%) sectors. The sample also includes firms from the chemical/pharmaceutical sector (9.0%), the software/information technology sector (4.4%), and other industries (24.2%). This diversity increases the generalizability of our findings and avoids potential biases resulting from certain industry characteristics.

Table 2
Sample composition.

Industry sector		Yearly sales volume in millions of euros	
Chemicals/pharmaceuticals	9.0%	< €1,000	13.2%
Machinery/electronics	20.2%	€1,000–€1,500	18.9%
Software/IT	4.4%	€1,501–€2,000	12.0%
Retail/consumer goods	24.5%	€2,001–€3,000	17.3%
Services	17.4%	€3,001–€5,000	11.8%
Other	24.2%	€5,001–€10,000	10.2%
		€10,001–€25,000	10.4%
Number of full-time employees		> €25,000	6.2%
<1,000	18.1%		
1,000–2,500	14.6%		
2,501–5,000	13.7%		
5,001–10,000	16.7%		
10,001–15,000	10.9%		
15,001–50,000	14.2%		
>50,000	11.8%		

The firms in the sample average 19,813 employees, although 18.1 percent of the firms employ fewer than 1,000 people, and 28.3 percent of the firms have between 1,000 and 5,000 employees. Most of the firms in our sample are larger: 16.7 percent have between 5,000 and 10,000 employees, 10.9 percent have between 10,000 and 15,000, employees, and 14.2 percent have between 15,000 and 50,000 employees. Around 10 percent are large multinational corporations with more than 50,000 employees. The sample firms averaged €6.3 billion in yearly sales, with 13.2 percent of the companies having less than €1 billion, 60 percent having €1 billion –€5 billion in sales, 20.6 percent having €5 billion–€25 billion in sales, and 6.2 percent having above €25 billion in sales.

Our sample includes firms that have only a few collaborative ties, as well as firms that have many. This heterogeneity suggests no self-selection by firms that do not engage in much cooperation or by firms that are more open to collaboration.

3.2. Measures

We rely on objective data from secondary sources to operationalize our dependent, independent, and control variables. Our manual validity check of the company links extracted by the data-crawling tool identified 19 types of collaborative relationships among our sample firms. We used selection criteria established according to extant literature (e.g., Capaldo, 2007; Chesbrough & Brunswicker, 2013; Lee et al., 2001). For each of the various types of collaborative activities, we carefully assessed the interaction intensity and categorized them into three levels based on theoretical grounds (e.g., Levin & Cross, 2004; Michelfelder & Kratzer, 2013) and previous research (Capaldo, 2007; Schleimer & Faems, 2016) in order to operationalize the strength of the collaboration: *Weak-intensity collaborations* consisted of agreements regarding joint interests, participation in associations, participation in competitions and campaigns, outsourcing, and participation in networking events; *medium-intensity collaborations* consisted of interest in a company with less than 50 percent share, joint interests of multiple network partners in a company, clusters, joint projects, joint research projects, consortia, joint sales activities, partnerships, and spin-offs; and *strong-intensity collaborations* consisted of M&As, joint ventures, joint organizations, strategic partnerships, and strategic alliances. Then we counted the number of collaborative ties of every firm in our sample in each category as a representation of the firm's direct ties with its network partners.

We operationalized the *gatekeeper position* by betweenness centrality, which has been widely used in research (e.g., Faraj et al., 2015; Guan et al., 2015; Sytch et al., 2011). It measures how often a node appears on the shortest paths between nodes in the network (Faraj et al., 2015; Hinz et al., 2011). When a node appears on the shortest paths, it controls information flow between two parts of the network that otherwise would not be connected (Salman & Saives, 2005). In such case, it serves as a gatekeeper or a bridge, which enjoys the benefits of being in the middle of the communication between two or more other parts of the network. Betweenness centrality represents the bridging score of a node and therefore is an important indicator for a firm's gatekeeper position (Dong et al., 2017; Gilsing et al., 2008). Technically, it is computed as follows:

$$C_B(v) = \sum_{s \neq v \neq t \in V} \frac{\sigma_{st}(v)}{\sigma_{st}},$$

where

σ_{st} = the total number of shortest paths from node s to node t and
$\sigma_{st}(v)$ = the number of those paths that pass through a node v.

To compute the betweenness measure for each firm, we considered the firm's position in a collaboration network at a given point in time (t = 0) that resulted from the firm's collaborative over the preceding five years. For example, a firm's betweenness centrality measure in 2014 results from its collaborative ties in 2010, 2011, 2012, 2013, and 2014 (Fig. 3). This innovative measure depicts a firm's gatekeeper position at a certain point in time that results from firms' past and present collaborative ties.

We use the number of registered patents as a proxy for a *firm's knowledge base*. This measure represents the knowledge a firm has accumulated over time. Because the number of registered patents closely corresponds to the conceptual abstraction of a firm's knowledge base, patents have been used as proxy for the knowledge base in extant research (Ahuja & Katila, 2001). A firm's accumulated knowledge determines how well it can absorb new approaches, trends, and concepts into its actions. We assess *firm performance* as financial profit (EBITDA), which is in line with extant studies in the field (e.g., Green et al., 2012; Tuominen et al., 2004). Regarding control effects, employing fixed-effects models that already capture time-invariant unobserved heterogeneity at the firm level reduced the possibility that other non-measured company-specific characteristics account for the variance in our dependent variable (Wooldridge, 2002). Nevertheless, similar to other scholars who rely on fixed-effects models (e.g., Frankort, 2016; Lin et al., 2009), we included two additional variables to control for the influences of certain firm characteristics on the dependent variables—*firm size*, measured as the number of full-time employees, and *R&D intensity*, operationalized as R&D expenditures as a percentage of a company's total revenue—to control for the differences in companies' innovation orientation that could have led to differences in collaborations. Note that research that examines collaborations has often employed R&D intensity as a control variable in (e.g., Belderbos et al., 2014).

3.3. Model specification and hypotheses tests

To test our hypotheses on direct and moderating effects, we employed two fixed-effects models with two-way ordinary least squares (OLS) estimates that captured time-invariant unobserved heterogeneity at the firm level (Wooldridge, 2002). In the first model, we test H1, H2, and H3 using panel data; that is, we use cross-sectional (N = 500 companies) data plus a time-series (t = 5 years) dimension, with 2,500 observations (N × t). We also include the one-year time-lagged effects of our independent variables (t = −1), because it takes some time to observe performance effects of collaborative ties. The data for weak-, medium-, and strong-intensity collaboration are from 2009 to 2013 (t = −1; time series length 5), whereas the data for the rest of the variables in the model are from 2010 to 2014 (t = 0; time series length 5). For the variable "gatekeeper position" we also have time series length 5 (2010–2014). The score for a firm's betweenness centrality in each of these years is from the firm's collaborations from the past five years. Therefore, to compute betweenness centrality for 2010–2014, we use collaboration data from 2006 to 2014. Thus, the first fixed-effects model includes the direct effects of time-lagged weak-, medium-, and strong-intensity collaboration on a gatekeeper position. We also controlled for firm size and R&D intensity. Our first empirical model is as follows:

$$\text{Gatekeeper position}_t = \alpha_0 + \alpha_1 WC_{t-1} + \alpha_2 MC_{t-1} + \alpha_3 SC_{t-1} + \gamma_1 \text{Firm size}_t + \gamma_2 \text{R\&D intensity}_t + \text{Error}_t$$

where

WC = Weak-intensity collaboration
MC = Medium-intensity collaboration
SC = Strong-intensity collaboration

We tested H4 in the second model, estimating the direct link of a gatekeeper position on firm performance and the moderating effect of the firm's knowledge base on this link. We employed firm size, R&D intensity, and the direct effect of the firm's knowledge base as controls. For the second fixed-effects model, our sample size is 340 companies because data on financial performance were not available for all 500 of the companies; for instance, some companies provide profit data only for parent (or subsidiary) companies or were exempted from public publications of their profits. To test H4, we used cross-sectional (N = 340 companies) and time-series (t = 5 years) data with a panel structure with 1,700 observations (N × t). Our second empirical model is as follows:

$$\text{Firm performance}_t = \alpha_0 + \alpha_1 \text{Gatekeeper position}_t + \alpha_2 \text{Gatekeeper position}_t \times FKB_t + \gamma_1 \text{Firm size}_t + \gamma_2 \text{R\&D intensity}_t + \gamma_3 FKB_t + \text{Error}_t$$

where FKB = firm knowledge base.

To compute the interaction term, we multiplied the mean-centered values of the corresponding constructs (Atuahene-Gima et al., 2005). We also applied Hausman's test and determined that the fixed-effects model is suitable for our data (significant at the .01% level). To measure the effect sizes in both models, we use Cohen's r (Pearson's correlation) and partial η^2_p (variance explained by the effect) as standardized, objective measures of the continuous variables (Cohen, 1988).

Table 3 shows the correlations and descriptive statistics for all variables. Our sample companies engaged in an average of three weak-intensity collaborations and three medium-intensity collaborations over the period 2010–2014 and an average of approximately one strong-intensity collaboration. The companies had invested about 2 percent of their sales in R&D and had registered an average of 237 patents. However, the companies varied widely in terms of the number of patents they had registered.

The correlations between our study's variables are low or medium. In particular, the correlations between weak-, medium-, and strong-intensity collaborations range from $r = .16$ to $r = .30$, indicating weak correlations, and the correlations between weak-intensity collaboration and a gatekeeper position, between medium-intensity collaboration and a gatekeeper position, and between a gatekeeper position and firm performance are medium. The correlation between firm size and firm performance is at a higher level, which is common, considering that larger companies tend to have higher profits. We tested for multicollinearity (Aiken & West, 1991) by calculating the variance inflation factors, which were below 4 for all variables (Hair et al., 2013), indicating that multicollinearity does not appear to be an issue.

4. Results

We performed a preliminary analysis to find support in our data for the SNT's proposition that firms enter primarily weak-intensity collaborations with partners outside their own industries and enter primarily strong-intensity collaborations with partners from their own industries (Granovetter, 1973; Michelfelder & Kratzer, 2013). We calculated how

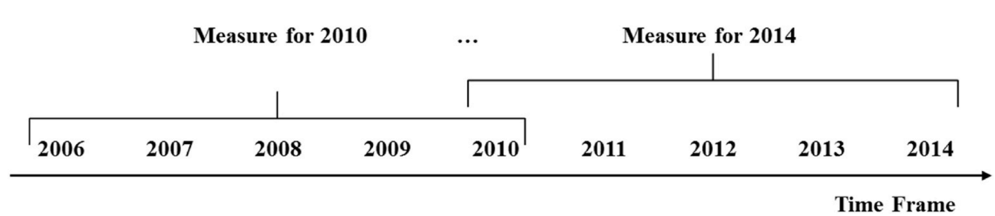

Fig. 3. Computation of the betweenness centrality measure.

Table 3
Descriptive statistics and correlations.

Variables		1	2	3	4	5	6	7	8	VIF
1	Weak-intensity collaboration									1.3
2	Medium-intensity collaboration	.30								1.2
3	Strong-intensity collaboration	.16	.17							1.2
4	Gatekeeper position	.56	.54	.26						1.2
5	Firm performance	.44	.38	.23	.58					n/a
6	Firm knowledge base	.04	.04	.01	.04	.23				1.0
7	Firm size	.27	.24	.13	.42	.78	.15			1.3
8	R&D intensity	.02	.03	.02	.02	.01	.05	.03		1.1
Mean		.27	.30	.07	3.20	684 M.	237	19,813	2%	
Standard deviation		1.39	1.72	.45	10.88	2.1 B.	3,325	58,382	11.7%	

Notes: Number of observations = 2,500 (N × t); number of observations for firm performance = 1,700; r > .09, $p = .05$; r > .12, $p = .01$; two-tailed tests; VIF = variance inflation factor; n/a = not applicable.

many weak, medium, and strong collaborative ties firms had with partners outside their own industries and found that 64.4 percent of the weak-intensity collaborations were with partners from other industries. This percentage is lower in medium-intensity collaboration (58.9%), supporting the notion that firms cooperate with partners from other industries as well as with partners from their own industry. Only 31.8 percent of strong-intensity collaborations were with partners from other industries, again supporting the SNT's proposition that firms engage in strong-intensity collaborations mostly with partners from their own industries (Granovetter, 1973). Parameter tests comparing the percentage values between the different subsamples underscore that significant differences exist in the extent to which firms cooperate with partners from other industries (weak vs. strong: $p < .01$; medium vs. strong: $p < .01$; weak vs. medium: $p < .10$).

Table 4 shows the results of the first fixed-effects model with the OLS estimator, including the regression coefficients, their significance levels, and standard errors. These results are based on 2,500 (N = 500 × t = 5) observations. To determine the model's fit, we relied on R^2_{within} and F-values, in line with other scholars in the field who have employed fixed-effects models that capture within-variance (e.g., Lin et al., 2009). Our model shows a good exploratory power, as our dependent variable explains 52 percent of the within-variance (variance between different points in time) (adjusted R^2_{within}= .52; F-value = 16.74, $p < .01$).

We find support for H1, which hypothesized a negative relationship between weak-intensity collaboration and a gatekeeper position (β = −16.60, $p = .001$), as the values of the effect size are high (r = .56; η^2_p = .32, $p = .001$) (Cohen, 1988). Medium-intensity collaboration exerts a positive influence on a gatekeeper position (β = 15.86, $p = .001$), which supports H2, as the values of the effect size are also high (r = .54; η^2_p = .29, $p = .001$). However, we do not find support for H3, which predicted that strong-intensity collaboration is antithetical to a gatekeeper position (β = −.82, $p = .86$), as strong-intensity collaborations does not exert any influence on such a structural network position. Regarding the control effects, neither firm size (β = .0003, $p = .31$) nor R&D intensity (β = −.04, $p = .83$) has significant effects in this fixed-effect model.

Finally, to complete the hypothesized causal chain, we employed a second fixed-effects model to test the relationship between a gatekeeper position and firm performance and to test the moderating effect of firm knowledge on this relationship (see Table 5). These results are based on 1,700 (N = 340 × t = 5) observations. Again, the explanatory power of the final model is high, as the dependent variable explains 72 percent of the within-variance (adjusted R^2_{within} = .72; F-value = 18.42, $p < .01$). We find a positive, significant effect of a gatekeeper position on firm performance (β = 280.96, $p = .038$) with a high effect size (r = .58; η^2_p = .35, $p = .001$), which supports prior research (e.g., Kratzer et al., 2016; Tan et al., 2015). We also find support for H4, which predicted a positive moderating effect of the firm's knowledge base on the relationship between a gatekeeper position and firm performance (β = 218.00, $p = .032$). This effect exerts a moderate effect size (r = .34; η^2_p = .12, $p = .001$). Regarding the control effects, firm size is positively related to firm performance (β = .01, $p = .001$) with a high effect size (r = .78; η^2_p = .63, $p = .001$), but neither R&D intensity (β = −2.78, $p = .08$) nor the firm's knowledge base (β = .002, $p = .92$) has a significant effect.

To increase confidence in the robustness of our results, we tested our baseline model with two-year lagged effects of the independent variables (t = −2). The results remained the same as in our main model with one-year lagged effects (t = −1). We also operationalized the betweenness measure for each firm that resulted from its collaborative

Table 4
Results: Impact of collaboration type on gatekeeper position.

Dependent variable	Gatekeeper position			
	Model 1		Model 2	
	Coef.	SE	Coef.	SE
Control variables				
Firm size	.00	.00	.00	.00
R&D intensity	−.04	.20	−.04	.19
Main effects				
H1: Weak-intensity collaboration			−16.60**	1.98
H2: Medium-intensity collaboration			15.86**	1.20
H3: Strong-intensity collaboration			−.82	4.59
R^2_{within}	.16		.52	
Adjusted R^2_{within}	.16		.52	
F-value	28.26**		16.74**	
Observations	2,500		2,500	

Notes: ** $p < .01$; * $p < .05$; two-tailed tests; number of observations in sample = 2,500 (N × t); coef. = unstandardized coefficients; SE = standard errors; fixed-effects model; OLS-estimator; time series length 5.

Table 5
Results: Impact of gatekeeper position on firm performance.

Dependent variable	Firm performance					
	Model 1		Model 2		Model 3	
	Coef.	SE	Coef.	SE	Coef.	SE
Control variables						
Firm size	.01**	.01	.01**	.01	.01**	.02
R&D intensity	−2.84	1.57	−2.80	1.57	−2.78	1.56
Firm knowledge base	.02	.05	.02	.05	.00	.05
Main effect						
Gatekeeper position			449.15*	.20	280.96*	.20
Moderating effect						
H4: Firm knowledge base					218.00*	75.09
R^2_{within}	.64		.71		.72	
Adjusted R^2_{within}	.64		.71		.72	
F-value	23.88**		18.29**		18.42**	
Observations	1,700		1,700		1,700	

Notes: ** $p < .01$; * $p < .05$; two-tailed tests; number of observations in sample = 1,700 (N × t); coef. = unstandardized coefficients for main and standardized for interaction effects; SE = standard errors; fixed-effects model; OLS-estimator; time series length 5.

ties over the previous three years and another measure considering the firms' collaborations over the previous four years. The results remained the same as in our main model, where the betweenness measure was operationalized by considering collaborations over the previous five years. Taken together, these tests lend strong support to the robustness of our results.

5. Discussion

Extant research has long recognized that a gatekeeper position in a collaborative network is valuable as a source of competitive advantage and for firm performance. However, the literature lacks knowledge regarding how such a network position can be achieved. Against this background, this study investigates which types of collaborations are associated with gatekeeper positions of firms. In addition, this study also examines how firms can best profit from this network position based on the strength of their knowledge base. In so doing, the study delivers multiple implications for scholars and practitioners.

5.1. Research implications

The study extends what we know about collaborations' characteristics, as well as how effective collaborations are in connecting diverse fields of knowledge in a network and in providing firms an intuition on how to function as gatekeepers. We propose and empirically support that a collaboration's interaction intensity is related to whether a firm can access new knowledge and new parts of the network. Whereas weak-intensity collaborations might be suitable for acquiring complementary resources, the lower commitment may make it difficult for firms to create synergies. As a consequence, they are less often used by gatekeepers. Moreover, contrary to our theoretical reasoning that strong-intensity collaborations may be negatively related to a gatekeeper position, we find that they have neither a positive nor a negative association with such a position. Our results also show that medium-intensity collaborations are highly related with firms in gatekeeper positions, likely as a consequence of the optimal trade-off between complementary resources and commitment. In the following, we discuss these findings and explain our contributions to the broader field.

Extant network research only partially investigates the ramifications of a gatekeeper position. After Granovetter's (1973) classic work on the strength of weak ties, sociologists have attempted to refine the measurement of a gatekeeper position (e.g., Brandes, 2001; Everett & Valente, 2016; Freeman, 1977), while others have examined the outcomes of a gatekeeper position at individual and firm levels (e.g., Rodan & Galunic, 2004; Spiro et al., 2013). However, network research does not explain how firms can become gatekeepers in their networks (Rodan & Galunic, 2004; Walker et al., 1997). With its longitudinal perspective, the current study contributes to social network research by showing that not all types of cooperation are related to the highly valuable gatekeeper position, in which actors transform their network structure by connecting otherwise disconnected partners. A reason may lie in the kind of acquired knowledge: While strong-intensity collaborations (e.g., M&As) in the same industry or field create rather economics of scale as opposed to new knowledge, weak-intensity collaborations focus on information exchange but lack the necessary commitment for deeper interrelationships. Medium-intensity collaborations instead may be most supportive of organizational learning, because initiatives such as joint projects, consortia, and spin-offs create impactful new knowledge. Future research should be aware of the different types of collaboration, which may have advantages and disadvantages for different outcomes. In this context, it may also be worthwhile to split up the different categories of collaboration further and, for example, distinguish between equity, minor equity, and non-equity types of collaboration that may influence the collaborations on a more fine-grained level and thereby contribute to the debate about the interdependence of relationship characteristics and the share of equity (e.g., Majocchi et al., 2013; Reddy et al., 2002).

Within the broader theoretical scheme, network research distinguishes between structural and relational conceptions of network relationships (Rodan & Galunic, 2004). Network researchers acknowledge that applying the structuralist conception (i.e., the structural properties of a gatekeeper position) alone is not sufficient to explain how a firm becomes a gatekeeper; for that, researchers must augment the structural conception with the relational perspective to take specific aspects of the relationships into account (Rodan & Galunic, 2004). In the relational dimension, particular attention must be paid to the characteristics of collaborative relationships and to the content transferred through these relationships. Therefore, an investigation of these relationships calls for the application of other concepts, as exemplified in this study by the RBV and the RFV that theoretically provide the grounds for different nuances of the relational conception as part of network research. Future studies may follow this route and should more deeply reflect on different perspectives and dimensions of network relationships, which has the potential to resolve some of the debates in this field.

Previous studies have shown that whether firms can integrate external information from network relationships into their own knowledge bases depends heavily on the strategic context, such as their capacity to interpret and internalize external information (Tsai, 2001). More specific, extant work on knowledge transfer suggests that a strong internal knowledge base might block the firm's ability to assimilate and make use of diverse external information because such firms tend to stick to familiar ways of thinking (Katila & Ahuja, 2002); in contrast, our study indicates that a strong knowledge base may support the integration of external information, which has implications for research on knowledge transfer at large: Current firm knowledge embedded in individual skills, business routines, and processes can help the firm interpret novel external information and apply it to improve its own innovation efforts. Subsequent research should continue to question extant knowledge regarding the strength of different knowledge bases, whose performance implications may be affected by the context, which may be framed by—but is not limited to—different positions within a network.

5.2. Managerial implications

Every company, regardless of its size or industry, engages in collaborations with partners, at least to some extent. Hence, firms are embedded in a network of collaborative relationships (Capaldo, 2007). However, in everyday practice, managerial attention and resources are often devoted to the effective management of specific collaborative relationships. Managers often lack a "bird's-eye view" of their entire portfolio of collaborative relationships (Van Wijk & Nadolska, 2020), so they rarely consider their network position, perhaps because of the abstract nature of networks and firms' positions in them. This study informs managers of the benefits of identifying their network positions by, for example, using social network analysis. The study also emphasizes for managers the value of the gatekeeper position and which types of collaborations are suitable to acquiring such a position, which ultimately can increase firm performance (Iacobucci & Hoeffler, 2016; Michelfelder & Kratzer, 2013).

To more likely become gatekeepers in their networks, firms should engage in medium-intensity collaborations like joint research projects, regional clusters, and spin-offs that are characterized by moderate levels of interaction between partners, moderate depth and duration, and good knowledge flow with partners that offer at least a medium degree of complementary resources. In medium-intensity collaborations, firms know their network partners well enough to be at least moderately committed and to engage in matchmaking. In doing so, a firm generates immediate access to more diverse information than firms in other network positions can and is likely to become a gatekeeper.

When firms engage in weak-intensity collaborations, they can acquire unfamiliar knowledge and access to more remote parts of the network because weak-intensity collaborations usually take place with partners from other industries. However, because of the greater distance and low interaction intensity between partners, firms are usually less committed to these types of collaboration. Although weak-intensity collaboration might be beneficial for other network-related outcomes, firms cannot gain a gatekeeper position by engaging only in weak-intensity collaboration, and our results show that doing so can even be harmful for such a position. However, weak-intensity collaborations might function as staging for later collaborations with higher collaboration intensity and, thus, serve as investments that may pay out in the future but that come with some costs in the meantime.

To benefit the most from a gatekeeper position in a collaboration network, a firm must be able to apply the diverse information it acquires to its overall firm activities. A strong knowledge base is highly useful in this endeavor, because it means that a firm has a sound understanding of the value of new, innovative technologies and the business practices necessary to benefit from them (Xu & Cavusgil, 2019). For example, chip manufacturer Infineon Technologies AG is highly successful as company also due to its knowledge base,[1] which allows it to make extensive use of its network across different industries, as recently shown by its cooperation with 3D specialist PMD Technologies AG to jointly develop a highly innovative 3D image sensor that is used in augmented reality applications. Another example is Infineon's recent leadership role in the rising area of quantum computing where Infineon makes use of its network and its high-tech capabilities to move this technology forward (Infineon, 2021). To build a strong knowledge base over time, firms must foster internal knowledge-creation, knowledge-capture, and knowledge-transfer processes. In addition, because knowledge is captured in individual skills, business routines, and processes, firms must constantly reevaluate and adjust these actions so it is easy to integrate diverse knowledge into them.

5.3. Limitations and avenues for further research

This study takes into consideration that collaboration networks change; that is, firms establish different amounts and types of collaborative ties over time. In so doing, it responds to the call for investigations that examine the dynamics of network relationships (Spiro et al., 2013). Drawing on a large-scale longitudinal data set, we investigate how engaging in different kinds of network relationships influences a firm's position in a collaboration network in the long term. Moreover, by identifying the gatekeeper positions from the past five years, we take the dynamics of firms' past network relationships into account. One aspect of dynamic network relationships that we do not account for herein is that the interaction intensity of a specific network relationship might change over time. Future research should consider that a particular collaborative tie might have lower or higher interaction intensity at the beginning of the relationship than it does later. Such investigations would offer new insights into how firms might shift their focus in the course of a single tie and the implications of that shift for firms' gatekeeper positions.

Spiro et al. (2013) take into consideration that a gatekeeper can fulfill many roles in a network, functioning as a coordinator between two other network members that belong to the same industry or acting as a representative or a broker between members from different industries. Our study does not differentiate between these roles but operationalizes a gatekeeper position in terms of the firms' betweenness centrality. This quantitative measure does not allow us to make assumptions about whether a gatekeeper is more active in one role than the other. By augmenting a quantitative assessment of a gatekeeper position with a qualitative measurement of the gatekeeper role, future studies could clarify which kinds of collaborative ties are most useful for a particular gatekeeper role.

The largest 500 companies in Germany provide a useful database for investigating collaborative links between companies in diverse industry sectors. These companies have become closely intertwined over the past 10–15 years—a process that has been accelerated by digitization and data as a common resource base—and thus they are appropriate for a close examination of their gatekeeper positions. However, this sample consists of large companies that have the necessary resources to engage in a variety of collaborative ties to access unfamiliar information, and the implicit assumption that managers generally have free choice to engage in any collaborative tie they want may not be generalizable. Future studies should examine how small and young companies can become gatekeepers, given their limited resources and collaborative experience, and, thus, the limited collaborations in which they can engage. Although young companies face such restrictions, they may be more open to seeking unfamiliar information than their larger counterparts and, therefore, are likely to be more successful in, for example, their weak-intensity collaborations. Hence, the proposed effects in our study framework might differ in small and/or young firms.

Acknowledgement

This work has been performed in the context of the DFG funded Collaborative Research Center (SFB) 1053 Multi-Mechanism-Adaptation for the Future Internet (MAKI) – Subprojects B3 and C5.

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[1] Whereas the DAX price index that contains the 30 largest public companies in Germany gained about 22% in the past five years, the stock price of Infineon increased by about 180%.

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