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Exploring new knowledge through research collaboration: the moderation of the global and local cohesion of knowledge networks

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Abstract Research collaboration has long been suggested as an effective way to obtain innovative outcomes. Nevertheless, relatively little is known about whether and how different research collaboration strategies inspire or inhibit firms in the exploration of new knowledge. Drawing upon the research collaboration literature and social network theory, this study examines the effects of two specific collaboration strategies (i.e., collaborating widely and collaborating deeply) on new knowledge exploration by recognizing the moderating roles of the local and global cohesion of knowledge networks. We test our hypotheses by using a manually collected sample of 730 Chinese vehicle or parts manufacturers during the period between 1985 and 2011. The empirical results suggest the positive effects of research collaboration breadth and collaboration depth on new knowledge exploration and that the global cohesion of intra-organizational knowledge networks magnifies the effect of collaboration breadth, while local cohesion negatively moderates the effect of collaboration depth on new knowledge exploration. These findings jointly indicate that a research collaboration strategy in combination with the structure of a knowledge base is crucial for obtaining novel knowledge.

Keywords Collaboration breadth · Collaboration depth · Local cohesion · Global cohesion · Knowledge network · New knowledge

JEL Classification O32

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1 Introduction

As an important ingredient of knowledge recombination, new knowledge is associated with the fabrication of a new product, process, or market (Nerkar 2003). Innovation scholars agree that successful innovation depends on the generation and integration of new knowledge in the innovation process (Fleming and Sorenson 2004). A key strategic question thus becomes one of how to efficiently generate knowledge and capabilities (Nickerson and Zenger 2004).

Individual inventors and their firms have realized the necessity of exploiting information and opportunities outside of the firm. Rather than residing exclusively inside firms, sources of novel ideas are commonly found in the interstices between companies, suppliers, customers, universities, and research institutes (Powell et al. 1996). Indeed, complementary knowledge and other critical resources increasingly span firm boundaries (Lipparini et al. 2014). The specialization and cross-fertilization across participants in collaborative networks help in the learning and transference of tacit knowledge (Katz and Martin 1997). External research collaboration is therefore suggested as an important method for knowledge-seeking and knowledge creation. Following Katz and Martin (1997), research collaboration in this paper is defined as the working together of different parties to achieve the common goal of producing new solutions for technological challenges. Based on the concept of the open search strategy, we define two research collaboration strategies: one is cooperation with a broad scope of partners (collaborating widely), and another is repetitive cooperation with actors over time (collaborating deeply). While we know a great deal about how research collaboration contributes to firms' learning and innovation *in general*,[1] we know little about how specific research collaboration strategy contributes to new knowledge exploration *in particular*. Enhancing our understanding about this issue is important, because collaboration breadth and depth determine how a focal firm is engaged in a research collaboration and the type of knowledge that could be accessed by the firm in a joint problem solving arrangement (Mishra et al. 2015).

As the roots of creativity, firms' knowledge base is closely related to the efficiency and efficacy of external research collaborations (Yang et al. 2010; Yayavaram and Ahuja 2008; Zhou and Li 2012). This relationship provides a reasonable perspective from which to examine the impact of research collaboration strategy on new knowledge exploration (Cohen and Levinthal 1990; Powell et al. 1996). In fact, a firm's knowledge base can be depicted as an *intra-organizational knowledge network* (Phelps et al. 2012). Conceptually, knowledge networks are the linkages between kernels of scientific and technological knowledge (Guan and Liu 2016), a "node" within a knowledge network is a knowledge element and a "tie" refers to a combination of two knowledge elements in a prior invention (Yayavaram and Ahuja 2008). The structural features of a knowledge network indicate the extent of combinatorial opportunities in a firm's technical domains and its combinatorial potential with other knowledge elements that exist outside of the firm's knowledge stock (Yayavaram and Chen 2015).

Based on Guler and Nerkar's (2012) work on co-authorship networks, we distinguish knowledge network cohesion between *local cohesion* within the immediate neighbourhood of each knowledge element and *global cohesion* within the overall knowledge network. Specifically, cohesive ties in a locally cohesive knowledge network are limited to certain

[1] For instance, as Powell, Koput and Smith-Doerr (1996) noted, "obtaining access to new markets and technologies, pooling complementary skills, risk sharing, speeding products to market" are four of the main benefits of firm involvement in collaboration.

focal knowledge elements that are cohesively connected to their neighbours but loosely linked with the rest of the knowledge elements of the organization, while globally cohesion depicts a feature of the whole knowledge network where all of the knowledge elements are embedded through dense connections. We posit that the local cohesion and the global cohesion of knowledge networks have differentiated influence on a firm's knowledge-seeking behaviour in external collaborative research.

In sum, although the prior research clearly offers valuable insights into the association between research collaboration and innovation, we lack a sufficient understanding of whether and under what conditions a firm explores new knowledge in the process of designing different research collaboration strategies. Thus, this study aims to adopt a contingency perspective to capture heterogeneity across intra-organizational knowledge networks and understand when and under what conditions collaborating broadly and collaborating deeply are more conducive to new knowledge exploration. Moreover, given that relational contexts and knowledge bases rarely change quickly; instead, both relationship building and tacit knowledge accumulation take a relatively long time period (Burg et al. 2014). It is more reasonable to investigate the effects of research collaborations and a firm's cohesion of knowledge network on new knowledge exploration in different time spans. Following Wang et al. (2014), we test the conceptual model using a dataset of 730 Chinese vehicle or parts manufacturers in two periods (from 1985 through 2006 and from 2007 through 2011).[2]

This study contributes to the research collaboration literature and knowledge network studies in three ways. First, we theoretically developed and empirically examined the specific impact of collaboration breadth and collaboration depth on new knowledge exploration. Research collaboration has long been considered an important method for technology transfer in the "open innovation paradigm" (see, Dahlander and Gann 2010). However, few empirical studies have directly examined the specific effect of collaboration strategy on new knowledge exploration (Terjesen and Patel 2017). Our findings indicate that increasing the degrees of collaboration breadth and collaboration depth enables firms to obtain more novel knowledge elements. Second, we present a holistic model that integrates inter-organizational research collaboration strategy and intra-organizational knowledge network structure, and we investigated their joint influence on new knowledge exploration, which has hitherto been unexplored in the extant literature. Third, the differentiated moderating influence of local cohesion and global cohesion that is explored in this study provides new insights into knowledge network studies by revealing the association between the structural features of a firm's knowledge base and its knowledge-seeking behaviour.

This study is organized as follows. We review the research collaboration related studies in Sect. 2 and develop testable hypotheses in Sect. 3. Section 4 reports methodology and sample collection issues, Sect. 5 shows the result of our empirical analysis. We discuss the main findings and present our conclusions in Sect. 6.

[2] As is shown in the Methodology section, we measured the independent variables in the former period (from 1985 through 2006), and we measured the dependent variable in the latter period (from 2007 through 2011).

2 Benefits and costs of research collaboration

An increasing number of empirical studies explicitly consider the knowledge creation and exchange process as precursors for firms' inventive outcomes (e.g. Belderbos et al. 2015; Walsh et al. 2016). Systematic evidence from this research stream indicates that research collaborations with substantial knowledge transfer mechanisms between firms and their partners provide opportunities to exploit existing knowledge and to gain access to novel ideas that have been developed by other collaborative partners (Battistella et al. 2016). The benefits of knowledge transfer, such as enhanced innovativeness, motivate firms to share and trade knowledge in collaborative activities (Burg et al. 2014). Moreover, research collaboration is complex and can take various forms that range from obtaining general insights and advice to participation in specific research projects (Katz and Martin 1997). The division between collaboration strategies in terms of collaborating widely and collaborating deeply is an important and helpful perspective that enables scholars to learn more about how a focal firm is embedded in various forms of collaborative research activities (Laursen and Salter 2006). Following this logic, extant literature has identified both the benefits and costs of conducting collaborative R&D activities.

Specifically, through the lens of a resource based view (RBV), firms can obtain new knowledge from complementary resources that are embedded in linkages with a broad span of knowledge sources (Lavie 2006). Technological breakthroughs typically require a broad range of intellectual and scientific skills that far exceed the resources of any single organization (Powell et al. 1996). Cross-boundary technology transfer among different knowledge sources facilitates knowledge recombination through integrating disparate knowledge elements and improves innovation performance (Miller et al. 2007). Moreover, diverse collaborative partners with different knowledge backgrounds and various skills increase the probability of accessing heterogeneous knowledge. For instance, Hülsheger et al. (2009) find that the task-related dimension of diversity increases the task-related information and perspectives that are available to the group and hence promotes innovation performance. Leiponen and Helfat (2010): 225 also suggested that a firm can improve the odds of obtaining new knowledge by accessing a greater number of knowledge sources because "the likelihood of obtaining a favourable draw from a distribution of payoffs increases as the number of knowledge sources increases". Third, heterogeneous knowledge that is available in the knowledge stock of multiple partners in research collaborations prevents focal firms from falling into the "competency trap" (Levinthal and March 1993). Firms can gain access to diversified knowledge sources through inter-organizational connections, and both horizontal (competitors or other partners) and vertical (buyers and suppliers) collaborations are valuable (Lipparini et al. 2014; Van Echtelt et al. 2008).

Firms can accrue benefits from cooperating deeply with partners as well. First, through the lens of the relational view, the depth of research collaboration reflects the quality of the relationship between a focal firm and its collaborative partners (Dyer and Singh 1998). High-quality relationships are referred to as strong ties, which are characterized by trust and shared understanding. Such relationships improve the efficiency of knowledge sharing in research collaborations (Becerra et al. 2008) and predict renewed cooperation in the future (Gulati et al. 1999). In addition, deep collaborative relationships enhance the willingness of firms to transfer knowledge (Inkpen and Tsang 2005) by alleviating the risks of inadvertent knowledge losses (Dahlander and Gann 2010) and free-riding by others (Dyer and Nobeoka 2000). Second, the establishment of long-term relationships between a focal firm and its partners provides a learned and shared code (von Hippel 1988) and enables successful know-how transfer within collaborations. As Lant (1992) noted, both successes and failures in past cooperation experiences can help individuals to develop a cognitive framework that affects their interpretation of future events within the technology transfer process. The routines and complementary resources that have been developed in past collaboration experiences facilitate the further investigation of combinatorial opportunities (Levitt and March 1988). Third, deep inter-organizational collaborations provide a detailed understanding of partners' technical components that are typically tacit and difficult to transfer (Janowicz-Panjaitan and Noorderhaven 2009). Firms' extensive experiences from past collaborations enable them to build up trustworthy relationships with partners, which allows the transfer of new knowledge to be easier and less costly than with fresh collaborators during the process of joint problem solving arrangements (Becerra et al. 2008). Moreover, firms have fewer burdens in identifying their partners' level of technological sophistication and position in the value chain if they have stable and frequent collaborations with their collaborators (Li and Ireland 2008).

Nevertheless, establishing, developing, and maintaining collaborative research activities comes with costs in terms of time, money and management efforts (Bammer 2008). Generally, the risks of research collaboration include the potential predatory and opportunistic behaviours of collaborators (Dushnitsky and Shaver 2009), the possible loss of core technologies (Parker 2012), and the loss of time due to additional coordination efforts within collaborative activities (Hansen and Nohria 2004). Moreover, the transaction costs that are involved in research collaborations are higher than "regular" internal R&D activities due to the geographic distance and the cognitive distance between collaborators (Parker and Brey 2015). For instance, because of the differences in evaluating the quality of R&D outcomes, firms find it difficult to rate universities as valuable research partners objectively (Howells et al. 2012). Particularly, the costs of research collaboration strategies are twofold. On the one hand, cooperating broadly may erode research effectiveness, since different types of research collaboration lead to varied influence on innovative outcomes. For instance, based on the features of different types of innovation, Tödtling et al. (2009) found that firms that generate more advanced innovations are more likely to collaborate with universities and research organizations, while firms that introduce less advanced innovations rely more on collaborations with the business sector. By examining the differential effects of three inter-temporal patterns of research collaboration,[3] Belderbos et al. (2015) find that only persistent collaboration exerts a systematically positive effect on innovation performance. On the other hand, a potential drawback of cooperating deeply is that the knowledge bases of focal firms and their research partners may become more alike (Coleman 1988). The small variation of knowledge stocks between firms and their collaborators leads their adaptation to become quite local and incremental (Rosenkopf and Nerkar 2001), and therefore inhibits knowledge creation (Mcfadyen and Cannella 2004; Zheng and Yang 2015).

The mixed empirical evidence suggests that whether research collaboration is a source or a barrier to new knowledge exploration often goes unrealized. As collaborating broadly and collaborating deeply come with a set of both benefits and costs, it is imperative to adopt a contingency perspective to capture heterogeneity across intra-organizational knowledge networks and to understand when and under what conditions collaborating broadly and collaborating deeply are more conducive to new knowledge exploration. Building on and extending the existing studies on research collaboration and knowledge

[3] The three inter-temporal patterns are persistent collaboration, recently formed collaboration, and recently discontinued collaboration.

networks, in the following section, we develop a testable theory of the relative effectiveness of research collaboration's breadth and depth in exploring new knowledge, with the differentiated moderating roles of local cohesion and global cohesion of knowledge networks.

3 Hypotheses development

3.1 Intra-organizational knowledge network

Distinct from collaboration networks, which refer to formal or informal social relationships among technical and scientific personnel (Allen et al. 2007) or higher level collectives (Ahuja 2000), knowledge networks in this study refer to the network structure of couplings among knowledge elements within an organizational boundary,[4] which indicates the record of prior successful combinatorial efforts and the future combinatorial potential of knowledge elements (Phelps et al. 2012). As the fundamental building block of an invention (Fleming and Sorenson 2004), the content of a knowledge element includes "tentative conclusions on facts, theories, methods, or procedures about a subject matter by the research community of a scientific or technological field" (Kuhn 1996: 58). Two knowledge elements form a tie when combined in an invention (Fleming and Sorenson 2004), which indicates an underlying connection in the subject matters of two technical domains (Carnabuci and Bruggeman 2009).

The importance of knowledge networks in innovation has been introduced and underscored recently. For instance, Yayavaram and Ahuja (2008) explore the variations of firms' knowledge-base structures and find that a nearly decomposable knowledge base increases innovations' usefulness in terms of patent citations. Using the patent data of a leading U.S. microprocessor manufacturer, Wang et al. (2014) find that researchers with knowledge elements rich in structural holes explore fewer new knowledge elements, while the effect of the average degree of the centrality of knowledge elements on exploratory innovation is curvilinear (inverted-U shaped). More recently, Guan and Liu (2016) investigate the effects of structural features of knowledge networks on exploitative and explorative innovation in the nano-energy field. Brennecke and Rank (2017) conduct a multi-level network study on the influence of knowledge networks on inventors' work-related interactions in a German high-tech firm.

However, due to a preoccupation with social networks in the existing literature, very few studies have examined the structural features of knowledge couplings at the firm level, and none of them have taken a contingency approach: examining the network-level characteristics of knowledge elements within a firm and investigating the moderating effects of these structural features on the firm's exploration of new knowledge. Since a firm's search for new knowledge is likely grounded in its current knowledge base (Stuart and Podolny 1996) and the efficacy of knowledge exploration depends on the extent of combinatorial opportunities and combinatorial potential of knowledge elements (Wang et al. 2014), we contend that the degrees of local cohesion and global cohesion of a firm's knowledge networks play contingent roles when the firm tries to explore new knowledge in collaborative research.

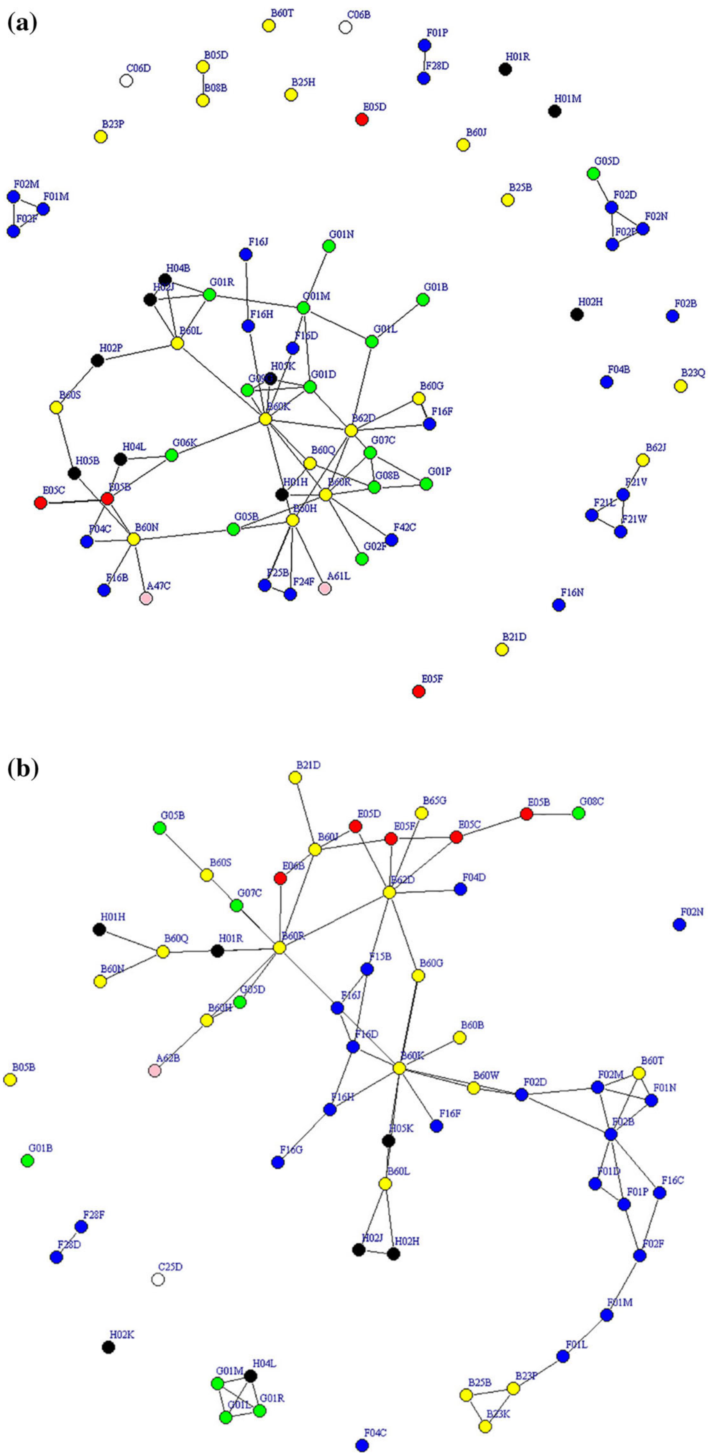
[4] Some recent studies focused on the sector level knowledge networks (e.g. Guan and Liu 2016).

3.2 The moderating role of local cohesion of knowledge networks

Local cohesion of a firm's knowledge network depicts the extent to which intra-organizational knowledge elements link to their immediate neighbourhood (see Fig. 1 as an illustration). We posit that firms explore less novel knowledge in deep collaborative relationships when the firms have a high level of local cohesion of knowledge networks. First, from the perspective of organizational learning, the increase in local links among knowledge elements lessens the possibility of new knowledge combinations, because learning is generally associative and search is often local (March 1991). In particular, a group of highly connected knowledge elements at a local level within a knowledge network indicates a strong and enduring learning orientation and technological trajectory (Calantone et al. 2002), which generates resistance to change and undermines the motivation of knowledge exploration. Meanwhile, deeply collaborative relationships not only help firms establish inter-organizational routines in terms of efficient knowledge transfer and mutual communication (Zheng and Yang 2015) but also consolidate the impetus of the firms' rigid learning orientation. Thus, the interaction between the learning attributes of the local cohesiveness of a firm's knowledge network and the firm's deep collaborations with partners inhibits new knowledge exploration.

Second, from the competitive advantage perspective, local cohesion of multiple knowledge elements signals a firm's technological advantage (Fleming and Sorenson 2001; Yayavaram and Ahuja 2008). The trustworthy relationships established by deep collaborations help firms obtain collaborators' experiences of knowledge combination (Dyer and Nobeoka 2000), and the mutual understanding of technological sophistication between a firm and its partners paves the way for the firm to receive insightful suggestions of how to combine existing knowledge elements. Given the uncertainty and cost of new knowledge exploration (March 1991), firms with local cohesive knowledge elements are more likely to expand their existing technological advantages by combining scattered knowledge elements within organizational boundaries rather than acquiring new knowledge from repeated collaborations with partners. In addition, similar to memberships in cohesive networks (Nahapiet and Ghoshal 1998), knowledge elements that have dense connections with their neighbours may suffer from reduced openness to heterogeneous ideas and limited combinatorial opportunities, thus inhibiting the generation of combinations with novel technologies through deep collaborations.

Third, according to the *inside-out process* model, firms profit from shifting the locus of technological exploitation outside of the firm's boundaries in their approach to the licensing of intellectual property and/or multiplying technology (Enkel et al. 2009: 312). We claim that the inside-out process model can be applied to explain why firms explore less new knowledge in deep research collaborations if they have a local cohesive knowledge network. On the one hand, local cohesive knowledge elements indicate core technological competency (Fleming and Sorenson 2004). The established interface in cumulative collaboration experiences paves the way for the transfer of these mature inventive outputs from the focal firms to their partners (Li and Ireland 2008). On the other hand, firms tend to foster the building of core competencies and protect their intellectual property from knowledge leaking unintendedly into innovative collaborations (Laursen and Salter 2014). Firms with local cohesive knowledge networks may invest more in generating profits by transferring ideas to their familiar research partners rather than searching for new knowledge through repeated collaborations. Taking the above arguments together, we formulate the following hypothesis.


(a)
B60T
C06B
F01P
F28D
H01R
C06D
B05D
B08B
B25H
E05D
H01M
B23P
B60J
G05D
B25B
F02D
F02N
F02F
F02M
F01M
F02F
F16J
G01N
H04B
H02J
G01R
G01M
G01B
H02H
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F16H
G01L
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B60L
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B62D
H04L
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B60Q
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E05B
F21L
F21W
B60H
G05B
F04C
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G02F
F16B
A47C
F25B
F24F
A61L
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B21D
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E05D
B65G
E05B
G08C
G05B
B60J
E05F
E05C
B60S
E06B
B62D
F04D
G07C
F02N
H01H
B60Q
H01R
B60R
F15B
B60G
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H02J
H02H
F02F
C25D
F01M
H02K
F01L
G01M
H04L
G01R
G01L
B25B
B23P
B23K
F04C

◀ **Fig. 1** Illustration of two knowledge network configurations. **a** Knowledge network of BYD Company Limited (1985–2006) with low global cohesion (0.033) and high local cohesion (0.271). **b** Knowledge network of Chery Automotive Co., Ltd. (1985–2006) with high global cohesion (0.046) and low local cohesion (0.268)

Hypothesis 1 The higher the level of local cohesion in a firm's knowledge network, the weaker the positive effect of research collaboration depth on new knowledge exploration.

3.3 The moderating role of global cohesion of knowledge networks

Global cohesion of knowledge networks portrays the structural feature of overall connectedness of intra-organizational knowledge elements (see Fig. 1 as an illustration). In contrast to the moderating role of local cohesion, we argue that firms tend to seek novel knowledge through collaboration more with diversified partners when they have globally cohesive knowledge networks for three reasons. First, globally cohesive knowledge networks with few isolated technical domains enable a firm to explore new knowledge elements effectively from a broad spectrum of partners because of the well-connected knowledge base (Cohen and Levinthal 1990; Yayavaram and Ahuja 2008). While the diversity of technical domains may contribute to the generation of novel ideas, integration is more important for the identification, evaluation and selection of the best novel ideas (Harvey and Kou 2013). The primary advantage of research collaboration in strategic alliance is knowledge accession (Joshi and Nerkar 2011), while the acquisition of knowledge involves learning-by-doing and sometimes requires the establishment of specialized networks within an alliance (Pollitte et al. 2015). A globally cohesive knowledge network indicates a well-connected knowledge base (Yayavaram and Ahuja 2008) and rich experiences of successful combinations of different knowledge elements (Phelps et al. 2012) that enable firms to obtain novel information and skills from collaborating with a broad scope of partners.

Second, through the lens of the knowledge-based view, firms act as integrators and generators of knowledge to *establish* and *exploit* a sustainable competitive advantage (Grant 1996). A highly integrated network of knowledge elements suffers from few recombinatorial opportunities within the existing stock of technologies. To create innovative outcomes, firms with a globally cohesive knowledge network will struggle for new combinatorial opportunities by exploring new knowledge elements from cooperating with a variety of external actors (Leiponen and Helfat 2010). Moreover, the extent of natural relatedness between the subject matter of knowledge elements and the subject matter of other knowledge elements determines a firm's combinatorial potential (Wang et al. 2014). When the average linkage among a firm's knowledge elements is high (i.e., high global cohesion), the firm tends to explore more combinatorial opportunities through those knowledge elements, and thus will seek more new knowledge elements through joint problem-solving arrangements with diversified collaborators.

Third, a well-connected knowledge network may nurture beliefs among a firm's partners in the fruitfulness of potential knowledge element combinations (Yayavaram and Chen 2015). The knowledge network of a firm with a high level of global cohesion suggests that the technological system of the focal firm is well-established with successful combinations among the knowledge elements. This is particularly useful when the firm works jointly with a broad scope of external partners, because a globally cohesive knowledge network signals its rising legitimacy as a feasible and desirable technical domain (Yayavaram and Ahuja 2008). The scientific, technological, and commercial value of combining a knowledge element with new knowledge elements increases with the improved level of global cohesion of a firm's knowledge network. In contrast, a low degree of connection of a firm's knowledge network indicates that knowledge elements of that firm have been combined with few other knowledge elements, with low visibility in not only the firm-wide knowledge stock but also in the knowledge network among its collaborative partners (Wang et al. 2014). Thus, we formulate the following hypothesis.

Hypothesis 2 The higher the level of global cohesion in a firm's knowledge network, the stronger the positive effect of research collaboration breadth on new knowledge exploration.

4 Methodology

4.1 Sample firms and data collection

The sample firms of this research are Chinese vehicle or parts manufacturers. There are three reasons for this choice. First, as one of the top ten Chinese revitalization industries,[5] the automotive industry in China has experienced significant development in terms of technology upgrades and market enlargement during the last three decades (Liu and Tylecote 2009). Moreover, automakers typically have a strong intention to protect their innovation efforts through patenting (Dechezlepretre et al. 2015), which allows us to use patent data to portray their knowledge structure and to track their knowledge search activities. In addition, exclusively focusing on the automobile sector avoids the confounding effect caused by systematic differences in the use of patents across industries (Levin et al. 1987).

Wang et al. (2014: 488) have noted, "A firm's stock of knowledge is codified, stored, and retrievable as rules, routines, procedures, or technical documents, such as patents." We thus used patent records that were retrieved from the Patent Information Services Platform (PISP)[6] to construct a knowledge network of Chinese vehicle or parts manufacturers. A patent record in the PISP includes the patent application number, application date, inventors, applicants, and technological classification codes. A technological classification code represents a technological domain that has been adopted as a valid proxy for knowledge elements in prior related studies (e.g. Carnabuci and Operti 2013; Dibiaggio et al. 2014; Yayavaram and Chen 2015). Following Wang et al. (2014) and Guan and Liu (2016), we used the four-digit level class of International Patent Classification (IPC) as the proxy for a knowledge element.[7] Accordingly, a tie is found in a knowledge network if two knowledge elements have co-occurred in a patent.

[5] The ten industries are the automotive, steel, information and communication, logistics, textile, equipment manufacturing, ferrous metal, light industry, petrochemical, and shipbuilding industries. More details can be obtained from the following website: http://finance.sina.com.cn/focus/10chanye/.

[6] For details about the PISP, please refer to the following website: http://www.chinaip.com.cn/.

[7] IPC is a hierarchical patent classification system, within which classification terms consist of symbols such as A01B 1/00. The first letter is the "section symbol". The following two-digit numbers are the "class symbol". The four-digit letter makes up the "subclass". The subclass is then followed by a one-to-three-digit "group" number, an oblique stroke and a number of at least two digits that represent a "main group" or "subgroup". More details can be obtained from the following website: http://www.wipo.int/classifications/ipc/en/.

Overall, a total of 1105 Chinese vehicle or parts manufacturers were granted at least one patent during the period from 1985 through 2006 (former period) that continued to engage in patenting activities during the observation period from 2007 through 2011 (latter period). To construct a knowledge network, a total of 730 vehicle or parts manufacturers with more than one knowledge element (IPC at four-digit level) in the former period are included in our sample.[8] In addition, the State Intellectual Property Office of the P.R. China (SIPO) typically publishes patents according to their grant date rather than their application date, which prohibits us from accessing all of the patents that were applied for after 2011.[9] To avoid selection bias, we used 2011 as the ending point of the data observation period. Given that a cooperative relationship may decay or dissolve, a long-time window may not reveal changes in the patterns of interactions among organizations. While collaborative partnerships may be sticky and retain importance even after collaborative events end, a short time window may expose fewer interactions among organizations (Wang et al. 2014). To achieve a balance, following the prior studies (e.g. Rosenkopf and Padula 2008), we used a 5-year window spanning 2002 to 2006 to measure the patterns of inter-organizational research collaborations.

4.2 Variable measurement

4.2.1 Dependent variable

As suggested by Wang et al. (2014), a new knowledge element is identified if it was only included in the focal firm's knowledge base in the latter observation period but absent in the knowledge base in the former observation period. We measured a firm's new knowledge exploration by calculating the number of new knowledge elements that were explored, advanced, and incorporated into a focal firm's patenting activities during the latter observation period from 2007 through 2011, which were new to the firm's knowledge stock in the former observation period (from 1985 through 2006).

4.2.2 Independent variable

4.2.2.1 Research collaboration breadth Given that different organizations are in possession of heterogeneous knowledge bases and knowledge structures (Dibiaggio et al. 2014), and research collaborations are often incorporated in patenting activities (Guan and Liu 2016), we calculated a firm's research collaboration breadth using patents that were jointly applied by the focal firm and its collaborators in the 5-year window during the period from 2002 to 2006 as follows:

$$Breadth = \sum C_i \tag{1}$$

where C_i represents the number of firm i's inter-organizational partners that are embedded in the firm's joint-applied patents from 2002 to 2006.

4.2.2.2 Research collaboration depth Based on the measurement of open search depth (Laursen and Salter 2006), research collaboration depth was calculated as follows:

[8] There is a possibility that a firm may have one IPC class at the four-digit level but more IPC classes at the five- or six-digit level.

[9] We collected the patent data from PISP during April through June in 2015.

$$Depth = \frac{\sum_i^N (\sum CP_i)}{N} \quad (2)$$

where i represents a partner of the focal firm, and N represents the number of the focal firm's partners. CP_i stands for the number of the focal firm's inter-organizational collaborations with partner i, which is reflected in their joint-applied patents from the period from 2002 through 2006.[10]

4.2.3 Moderating variables

4.2.3.1 Local cohesion Based on the method that was used by Guler and Nerkar (2012), we measured the level of local cohesion of an automaker's knowledge network by calculating the weighted overall clustering coefficient of the network that reflects the average of the connections of all knowledge elements neighbourhoods (Hanneman and Riddle 2005). The higher the level of this variable, the greater the possibility that all of the knowledge elements in the knowledge network will be embedded in cohesive local neighbourhoods.

4.2.3.2 Global cohesion Following Guler and Nerkar (2012), we measured the global cohesion in the knowledge network using the density of the overall network. The pure network density only considers whether there is a co-occurrence among elements; however, it neglects the frequency of this co-occurrence. The weighted density incorporates the co-occurrence frequency and better reflects a firm's combination and recombination of its knowledge elements. In other words, while the measurement of pure density focuses on whether there is a connection between two nodes, the measurement of weighted density takes the strength of the ties into consideration[11] (Wasserman and Faust 1994), which is more appropriate for our research purpose.[12] Specifically, in an undirected graph with n nodes, the maximum possible number of ties is $\frac{n(n-1)}{2}$, and l_{ij} denotes the strength of the tie between node i and node j. Then, the weighted density of a network is defined as

$$Density = \frac{\sum_i \sum_j l_{ij}}{n(n-1)/2}, \quad i \neq j \quad (3)$$

The higher value of this variable captures a higher global cohesion of a firm's knowledge network. We used UCINET 6.487 to calculate all the knowledge network measures.

Local cohesion and global cohesion reflect different aspects of a knowledge network structure. As Schilling and Phelps (2007: 1118) noted, "While network density captures the density of the entire network, the clustering coefficient captures the degree to which the overall network contains localized pockets of dense connectivity. A network can be globally sparse and still have a high clustering coefficient". We chose two automakers in our dataset to further illustrate the structure differences of knowledge network cohesion.

[10] For a specific cooperative patent, the collaboration depth between the focal firm and its partner i equals to 1/(n-1) when they jointly applied for a patent with the other n-2 actors.

[11] The detailed calculation of weighted density can be obtained in the "Appendix".

[12] We calculated the local cohesion with the consideration of tie strength as well by using the weighted overall clustering coefficient of a firm's knowledge network.

Figure 1 shows the configuration of the knowledge network of the BYD Company Limited[13] and Chery Automotive Co., Ltd.[14] in the former observation period from 1985 through 2006. As plot *a* illustrates, the knowledge network of BYD is characterized by a highly connected cluster with 46 knowledge elements, which leads the BYD's other 32 knowledge elements scattered in different components within the knowledge network. BYD's knowledge network is found to have high local cohesion (0.271) and low global cohesion (0.033). In contrast, the knowledge network of Chery (plot b) is characterized by a loose but large cluster with approximately 80% of Chery's knowledge elements (62 knowledge elements in total), which allows fewer isolated knowledge elements outside of the cluster. Chery's knowledge network reflects low local cohesion (0.268) and high global cohesion (0.046) compared to BYD.

4.2.4 Control variables

4.2.4.1 Patent stock While exploratory innovation is closely related to research input, the R&D expenditure information is usually not accessible for most unlisted firms in China. Given that patent stocks have been shown to be highly correlated with annual R&D expenditures (Schilling and Phelps 2007), following the prior studies (e.g., Guan and Liu 2016), we controlled for a firm's research input using the natural logarithm of the number of a firm's patents in a 5-year window period.

4.2.4.2 Cognitive distance This variable refers to the dissimilarities among knowledge elements within a firm's knowledge base (Colombelli et al. 2013). Similarity among knowledge elements enhances the level of substitutability of a firm's knowledge base, which is found to be beneficial for new knowledge exploration (Dibiaggio et al. 2014). If the number of knowledge elements within a firm is N, C_{kn} represents the joint occurrence of elements k with all other elements, and C_{ln} represents the joint occurrence of elements l with all other elements. Thus, the measure of knowledge similarity is calculated as follows (Nooteboom 2009):

$$S_{kl} = \frac{\sum_{n=1}^{N} C_{kn} C_{ln}}{\sqrt{\sum_{n=1}^{N} C_{kn}^2}\sqrt{\sum_{n=1}^{N} C_{ln}^2}} \tag{4}$$

The cognitive distance between element k and l is calculated by $d_{kl} = 1 - S_{kl}$. The degree to which element l is related to the other elements in a firm weighted by patent count P_k is obtained as follows:

$$WAR_l = \frac{\sum_{k \neq l} d_{kl} P_k}{\sum_{k \neq l} P_k} \tag{5}$$

The firm-level cognitive distance is defined as the weighted average of WAR_{kl} measure:

$$CD = \sum_{k \neq l} WAR_l \times \frac{P_l}{\sum_l P} \tag{6}$$

[13] For details about BYD, please refer to the following website: http://www.byd.com/indexglobal.html.

[14] For details about Chery, please refer to the following website: http://www.cheryinternational.com/.

The cognitive distance index indicates a firm's combination of its core technologies with unfamiliar technological fields. A firm with higher cognitive distance faces greater difficulty or cost in exploring new knowledge, and it is characterized by discontinuities with regard to the paradigmatic shifts of its knowledge base (Colombelli et al. 2013).

4.2.4.3 Related knowledge variety Firms with a diversified knowledge base may be more innovative because of internal knowledge flows among the diverse technological fields (Garcia-Vega 2006). Nevertheless, firms do not extend the range of their innovative activities in a random way; instead, they diversify their innovative activities across related technological fields (Breschi et al. 2003). Given that related diversified knowledge stock provides firms with more opportunities to combine knowledge with less cost and risk (Quintana-García and Benavides-Velasco 2008), we controlled for a firm's *related knowledge variety (RKV)* in the former period from 1985 through 2006 using the entropy index.

Specifically, the overall knowledge variety can be decomposed into related knowledge variety and unrelated knowledge variety. Related knowledge variety refers to within-entropy, which reflects the average degree of variety within the subsets (measured by four-digit level of a technological subclass), while unrelated knowledge variety refers to between-entropy, which focuses on the subsets that measure the variety across them (measured by a second-digit level of a technological subclass) (Colombelli et al. 2013). Thus, the related knowledge variety is measured as follows:

$$RKV = \sum_{j=1}^{J} PS_{ij}\left(\sum_{k\in j} PS_{ik} \times \ln\left(\frac{1}{PS_{ik}}\right)\right) \tag{7}$$

where PS_{ik} is firm i's patent share for technological subclass k at the fourth-digit level, where PS_{ij} is firm i's patent share for technological subclass j at the second-digit level.

4.2.4.4 Firm age The prior studies have suggested that firms with a short duration need to broaden their knowledge base to improve their long-term performance (Levinthal and March 1993), while older firms tend to develop rigid structures with collaborators (Sørensen and Stuart 2000). To address these potential effects of firm age, we controlled for firm age using the natural logarithm of years since a firm's establishment.

4.2.4.5 Ownership A firm's ownership, to a large extent, affects its access to political, financial or technical support, which further influences its strategic decisions and inventive orientation. As in China, state-owned enterprises (SOE) typically receive more support in capital and policy subsidy, while foreign invested enterprises (FIEs) have more opportunities to learn advanced technologies overseas (Choi et al. 2011). We therefore use two dummy variables to indicate firm ownership (SOE = 1, others = 0; FIE = 1, others = 0).

4.2.4.6 Group affiliation In a comparative institutional lens, business groups play an indispensable role in facilitating affiliated firms' innovation, especially in the emerging economies (Chang et al. 2006, Choi et al. 2011). We thus use a dummy variable to indicate a firm's group affiliation (Groupaff = 1 if a firm belongs to a corporate group; Groupaff = 0 otherwise).

In addition, it is expected that R&D activities thrive in regions with high economic and industrial development (Li et al. 2014; Rodríguez-Pose and Crescenzi 2008). These regions attract more foreign and domestic investment for innovation (Fu 2012), which promotes the exploration of new knowledge. We thus use *provincial GDP* as a proxy to control for the effect of regional economic development on firms' exploratory innovation. We also expect that institutional environments across regions affect firms' innovative behaviour (Kafouros et al. 2015). The province-level index of marketization reflects the regional policies has been developed by the NERI (Fan et al. 2006). Marketization takes four elements, that is, regulatory separation, depolarization, liberalization and privatization of state-owned enterprises, into consideration (Henisz et al. 2005) and comes up with an overall assessment of the institutional environment at the provincial level. This index, at first, was widely employed in finance and economics (Chen et al. 2010) and then was introduced to the management literature (Gao et al. 2010; Schotter and Beamish 2011, Shi et al. 2012). Thus, we use provincial marketization as a proxy to control for the effect of regional institutional environment on firms' exploratory innovation.

4.3 Statistical method

The longitudinal design framework of this article was adopted from Wang et al. (2014). Specifically, we constructed a firm's knowledge network in the former period during 1985–2006 and measured collaboration breadth and collaboration depth in the 5-year window of 2001–2006 while computed the dependent variable in the latter period of 2007–2011. Since the dependent variable (i.e. number of explored knowledge elements new to the existing knowledge stock) is a count variable and has a non-negative integer value, the Poisson regression is suggested. However, the conditional variance of our independent variable is much bigger than its conditional mean (Mean = 5.76, S.D = 9.24), which reveals the over-dispersion problem of our sample data. Thus, we used negative binomial regression model to overcome the over-dispersion problem in the present study (Long 1997).

5 Analysis

5.1 Descriptive statistics and correlations

Table 1 reports descriptive statistics and correlations of all variables. The correlation matrix shows that most of correlation coefficients are well below the threshold value of 0.7 (except for $r_{\text{Patent stock} \sim \text{Related knowledge variety}} = 0.66$, $r_{\text{Global cohesion} \sim \text{Cognitive distance}} = 0.63$). To deal with the problem of multicollinearity, we calculated the variance inflation factor (VIF) for each estimation and find that the average VIF is 1.68, indicating that the estimating results of this research suffer little from the potential bias caused by the multicollinearity problem (Belsley 1991). Moreover, for the ease of interpreting moderations of local and global cohesion, all independent variables were mean-centered before entering into the estimating models (Echambadi and Hess 2007).

5.2 Estimating results

Table 2 presents the results of the negative binomial regression analysis. Model 1 includes the control variables and provides a baseline estimate. Three control variables are significant with expected signs. Specifically, patent stock ($\beta_{\text{patent stock}} = 0.199$, $p < 0.01$),

Table 1 Descriptive statistics and correlations (N = 730)

Variables	Mean	S.D.	Min	Max	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1 New elements	5.76	9.24	0.00	91.00	1.00													
2 Ln (patent stock)	1.32	1.06	0.00	5.59	0.41	1.00												
3 Cognitive distance	0.55	0.39	0.00	1.00	−0.06	−0.21	1.00											
4 Related knowledge variety	0.55	0.63	0.00	2.99	0.43	0.66	−0.18	1.00										
5 Ln (firm age)	2.04	0.68	0.00	4.06	0.09	0.24	−0.09	0.13	1.00									
6 Group affiliation	0.17	0.38	0.00	1.00	0.03	0.15	−0.09	0.09	0.23	1.00								
7 SOE	0.08	0.27	0.00	1.00	0.07	0.09	−0.01	0.03	0.23	0.18	1.00							
8 FIE	0.22	0.42	0.00	1.00	0.14	0.11	−0.03	0.11	−0.01	−0.09	−0.16	1.00						
9 Ln (provincial GDP)	8.99	0.64	6.17	9.80	−0.05	−0.03	0.01	0.03	0.00	0.06	−0.23	0.10	1.00					
10 Provincial marketization	7.50	1.44	2.91	9.22	−0.04	0.00	0.03	0.01	0.03	0.00	−0.22	0.17	0.62	1.00				
11 Local cohesion	0.29	0.58	0.00	4.61	0.08	0.29	−0.05	0.36	−0.01	0.02	0.00	0.04	0.01	0.01	1.00			
12 Global cohesion	0.59	0.60	0.00	4.00	−0.21	−0.32	0.63	−0.39	−0.15	−0.12	0.01	−0.03	−0.01	0.04	0.18	1.00		
13 Collaboration breath	0.18	0.72	0.00	10.00	0.24	0.29	0.00	0.15	0.13	0.17	0.25	0.00	−0.05	0.04	0.04	−0.10	1.00	
14 Collaboration depth	0.37	1.90	0.00	23.50	0.31	0.25	0.00	0.20	0.00	0.02	0.07	0.10	−0.02	0.04	0.06	−0.09	0.45	1.00
VIF					1.38	2.10	1.84	2.40	1.17	1.13	1.24	1.09	1.69	1.72	1.47	2.46	1.43	1.35

$p < 0.05$ for value of correlation coefficients is bigger than 0.07 or smaller than −0.07

related knowledge variety ($\beta_{\text{related knowledge variety}} = 0.498$, $p < 0.01$) and foreign invested ownership ($\beta_{\text{FIE}} = 0.250$, $p < 0.01$) are positively associated with a firm's new knowledge search performance.

Model 2 includes both the linear and squared terms of collaboration depth. The linear term is positive and significant ($\beta_{\text{Collaboration depth}} = 0.087$, $p < 0.1$) while the squared term is negative and insignificant ($\beta_{\text{Collaboration depth squared}} = -0.002$, $p > 0.1$). The results predict a linear and positive relationship between research collaboration depth and new knowledge exploration. Similarly, the linear term of collaboration breadth is positive and significant ($\beta_{\text{Collaboration breadth}} = 0.270$, $p < 0.05$) but its squared term is negative and insignificant ($\beta_{\text{Collaboration breadth squared}} = -0.020$, $p > 0.1$), indicating the positive association between collaboration breadth and new knowledge exploration.

Models 4–5 present the results for Hypothesis 1 and Hypothesis 2.[15] Hypothesis 1 suggests that local cohesion negatively moderates the relationship between collaboration depth and new knowledge exploration. In Model 4, we find that the interaction term of collaboration depth with local cohesion is negative and significant ($\beta_{\text{collaboration depth} \times \text{local cohesion}} = -0.064$, $p < 0.05$), whereas the positive effect of collaboration depth on new knowledge exploration is converted into a negative effect beyond a certain level of local cohesion of a knowledge network. Meanwhile, Hypothesis 2 suggests that global cohesion positively moderates the relationship between collaboration breadth and new knowledge exploration. We find that the interaction term of research collaboration breadth with global cohesion is positive and significant ($\beta_{\text{collaboration breadth} \times \text{global cohesion}} = 0.245$, $p < 0.05$), indicating that the positive effect of collaboration breadth on new knowledge exploration is magnified with the increase in the global cohesion of a firm's knowledge network. When the curvilinear effects of collaboration depth and breadth (i.e. the squared terms) are introduced in Model 5, the negative moderation of local cohesion and the positive moderation of global cohesion are still significant. Thus, Hypothesis 1 and Hypothesis 2 are supported.

We draw two moderating plots in Fig. 2 to further illustrate the moderating roles of local cohesion and global cohesion. As plot *a* shows, the positive slope of a "middle level of local cohesion" (blue dotted line) is smaller than the positive slope of a "low level of local cohesion" (red solid line), and the slope of a "high level of local cohesion" (green dash line) even becomes negative. This is consistent with Hypothesis 1 and indicates that the local cohesion of a knowledge network attenuates the positive relationship between research collaboration depth and new knowledge exploration. However, in plot *b*, the positive slope of a "high level of global cohesion" (green dash line) is much steeper than the slopes of a "middle level of global cohesion" (blue dotted line) and a "low level of global cohesion" (red solid line). This is consistent with Hypothesis 2, which predicts that the positive relationship between research collaboration breadth and new knowledge search will be stronger with the improvement of the global cohesion level of a knowledge network.

5.3 Robustness checks

We conducted several analyses to check the sensitivity of our findings. First, there is potential moderation of local cohesion on collaboration breadth and of global cohesion on collaboration depth. We included these potential moderations into regressions and found

[15] Following similar studies (e.g. Berchicci 2013; Grimpe and Kaiser 2010, Kafouros et al. 2015), we do not introduce the interactions between the moderators and squared terms.

Table 2 Negative binomial regressions: determinants for new knowledge exploration (5-year window)

	Model 1	Model 2	Model 3	Model 4	Model 5
Control variables					
Ln (patent stock)	0.199***	0.173***	0.147***	0.149***	0.146**
	(0.052)	(0.053)	(0.055)	(0.056)	(0.057)
Cognitive distance	−0.014	−0.025	−0.054	0.033	0.035
	(0.165)	(0.164)	(0.163)	(0.153)	(0.155)
Related knowledge	0.498***	0.481***	0.525***	0.487***	0.491***
Variety	(0.094)	(0.094)	(0.093)	(0.094)	(0.094)
Ln (firm age)	0.087	0.095	0.088	0.074	0.074
	(0.081)	(0.081)	(0.080)	(0.079)	(0.079)
Group affiliation	0.090	0.081	0.057	0.073	0.077
	(0.133)	(0.133)	(0.135)	(0.135)	(0.135)
SOE[a]	0.055	0.029	−0.074	−0.135	−0.153
	(0.181)	(0.179)	(0.178)	(0.172)	(0.173)
FIE	0.250**	0.222**	0.250**	0.227**	0.222**
	(0.099)	(0.100)	(0.099)	(0.099)	(0.100)
Ln (provincial GDP)	−0.095	−0.075	−0.064	−0.062	−0.069
	(0.087)	(0.088)	(0.088)	(0.088)	(0.088)
Provincial	−0.012	−0.028	−0.035	−0.039	−0.037
Marketization	(0.038)	(0.038)	(0.038)	(0.038)	(0.038)
Local cohesion (LC)	−0.074	−0.062	−0.083	−0.044	−0.045
	(0.095)	(0.093)	(0.088)	(0.083)	(0.083)
Global cohesion (GC)	−0.134	−0.132	−0.122	−0.193*	−0.196**
	(0.149)	(0.143)	(0.129)	(0.099)	(0.099)
Direct effects					
Collaboration depth		0.087*		0.041**	−0.016
		(0.049)		(0.020)	(0.053)
Collaboration depth		−0.002			0.003
Square		(0.003)			(0.003)
Collaboration breadth			0.270**	0.208***	0.252**
			(0.108)	(0.069)	(0.123)
Collaboration breadth			−0.020		−0.001
Square			(0.013)		(0.013)
Moderation effects					
Collaboration				−0.064**	−0.082**
Depth × LC				(0.032)	(0.038)
Collaboration				0.245**	0.261**
Breadth × GC				(0.121)	(0.128)
Constant	1.710**	1.714**	1.711**	1.730**	1.770***
	(0.679)	(0.683)	(0.683)	(0.682)	(0.679)
Observations	730	730	730	730	730
Log likelihood	−1946.164	−1942.447	−1941.088	−1936.630	−1936.143
Chi^2	202.33	234.57	236.86	278.15	358.31
Pseudo R^2	0.052	0.054	0.054	0.057	0.057

Table 2 continued

	Model 1	Model 2	Model 3	Model 4	Model 5
VIF	1.62	2.35	1.95	1.68	3.33

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

[a] The reference group is other types of firms

no substantial change to the results that are reported in Table 2. Second, we tested the robustness of our results using different time windows (e.g., a 3-year window and a 4-year window), and our estimates remain materially unchanged. Third, we removed insignificant cognitive distance and included alternative measures such as knowledge coherence and knowledge depth, and our main results remain robust and largely unaffected. For brevity, the results are not reported and are available upon request.

6 Discussion and conclusions

6.1 Summary of findings

It is widely agreed that research collaboration is "a good thing" (Katz and Martin 1997) as it is central to increasing innovativeness and reducing time to market (Enkel et al. 2009). However, it is unclear whether such a "good thing" motivates new knowledge exploration. Integrating the research collaboration literature and social network theory, this study examined the effect of a specific research collaboration strategy on new knowledge exploration by taking into consideration the moderation of intra-organizational knowledge network cohesion. Based on a manually collected database of 730 Chinese vehicle or parts manufacturers, the empirical results indicate that both collaboration breadth and collaboration depth have a positive influence on new knowledge search performance. However, the local cohesion and the global cohesion of a firm's knowledge network play differentiated roles in moderating the effects of collaboration breadth and depth on new knowledge exploration. Specifically, local cohesion attenuates the positive relationship between collaboration depth and new knowledge search, while an increase in the global cohesion of a knowledge network makes the relationship between collaboration breadth and new knowledge exploration even stronger. Taken together, the findings of this research highlight the importance of a more holistic approach to the design of a firm's collaboration strategy in the knowledge exploration process by considering the structural features of knowledge networks.

6.2 Theoretical implications

Our study has several theoretical implications for the extant literature. First, the findings of this study extend the research collaboration literature by examining the effect of a specific research collaboration strategy on new knowledge exploration. The majority of the prior studies on research collaboration has stressed the beneficial role of different types of collaboration in facilitating innovation performance (Lehmann and Menter 2016), whereas few attempts have been made to examine the specific strategy that is associated with the

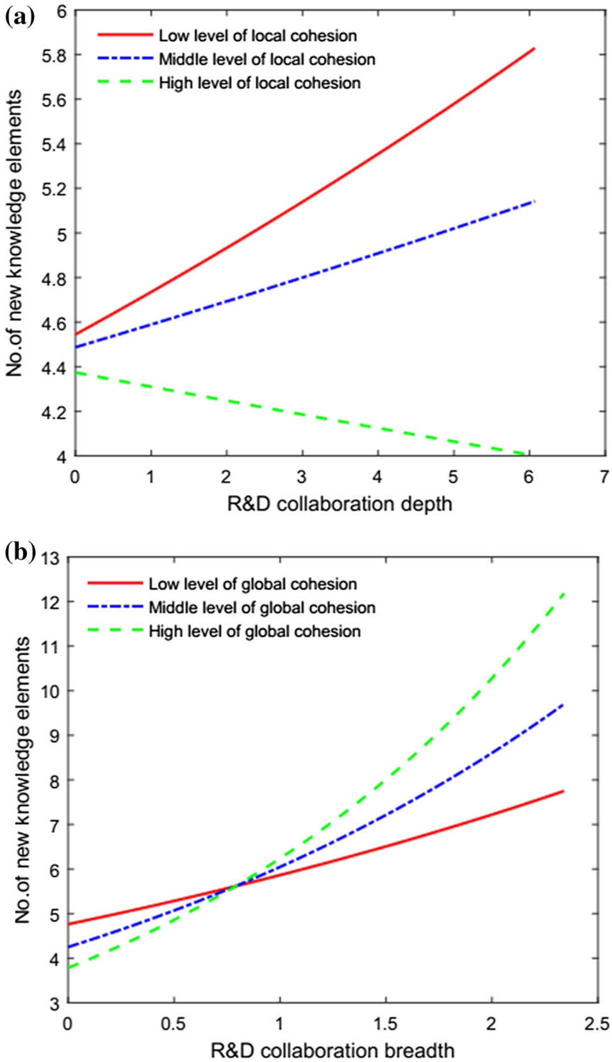

Fig. 2 Moderating effects of the local and global cohesion on the relationship between R&D collaboration and new knowledge exploration

research collaboration of firm-partners. Moreover, innovation is a multifaceted phenomenon, including not only knowledge exploration but also knowledge exploitation (Sidhu et al. 2007). Few empirical studies have directly explored the effect of research collaboration on new knowledge exploration by considering specific research strategies of collaboration breadth and depth. Therefore, our research represents one of the first attempts to consider specific strategies of firm research collaborations and their influence on new knowledge exploration.

The second contribution of our study arises from the examination of the moderating effects of knowledge network structure on the relationship between research collaboration strategy and new knowledge exploration. Specifically, our findings extend the argument that "a firm's value and ability as a collaborator is related to its internal assets" (Powell et al. 1996: 119) by illustrating how collaboration strategies and knowledge network features together contribute to firm knowledge search behaviours. With regard to the local cohesion of knowledge networks, our study explicitly shows that an increasing degree of local cohesiveness will attenuate the positive role of collaboration depth in new knowledge exploration. This finding provides greater nuance to the collaboration management literature by suggesting that the local cohesive structure of a knowledge base is particularly detrimental to new knowledge exploration when a firm maintains repetitive partnerships within its external collaborations. Moreover, the discussion and comparison of the local and global cohesion of networks in the prior studies is scant. The extant literature suggests that the benefits of cohesive network structure are more likely to be obtained from an actor's immediate neighbours, while global cohesion does not offer additional advantages for innovation (Guler and Nerkar 2012). However, in our study, we find that firms with high knowledge network cohesion at the global level explore more knowledge by cooperating with a variety of different partners, which implies that global cohesion is a catalyst for new knowledge acquisition when a firm adopts a strategy of cooperating widely. This finding not only offers important insight into the knowledge search literature regarding when and to what extent firms can obtain more new knowledge in diversified partnerships but also extends our understanding of the knowledge network literature by recognizing the nuanced effects of different types of cohesive network structure.

Third, an increasing number of open search studies has identified the downsides of searching broadly or deeply, including increased coordination costs that are caused by a broad scope of partners (Knudsen and Srikanth 2014) and muted efficiency incentives within repeated partnerships (Holloway and Parmigiani 2016). Our findings support the beneficial role of broad collaboration and deep collaboration in helping firms to obtain novel knowledge, and the robustness checks show little evidence of the inverted-U shape relationships that have been suggested by the prior studies (e.g., Laursen and Salter 2006; Mcfadyen and Cannella 2004). This finding contributes to the emerging, but still inconsistent, literature on open search by focusing on the specific effects of collaboration breadth and depth on new knowledge exploration. Furthermore, most of the prior studies on collaboration strategy have used primary data (e.g. Mishra et al. 2015) or case studies (e.g. Dittrich and Duysters 2007), which has lead them to suffer from small sample problems and made it difficult to obtain the causal relationship between collaboration strategy and new knowledge search (Savino et al. 2017). Our study addresses this gap by using manually collected data from a relatively large sample of vehicle or parts manufacturers from public sources, and the longitudinal framework of our empirical analysis enables us draw conclusions about the causal impact of inter-organizational research collaboration and intra-organizational knowledge networks on new knowledge exploration.

6.3 Practical implications

The findings of our study provide several implications for practising managers with regard to the question of how to design a research collaboration strategy for obtaining new knowledge. Specifically, the positive effects of collaboration breadth and collaboration depth on new knowledge exploration suggest that an open knowledge search strategy is applicable for firms that seek to establish collaborative relationships with external actors. For example, Procter & Gamble (P&G) invested over half of its R&D expenditure on collaborating with external actors, which has made it a top-tier player in breakthrough inventions (Dodgson et al. 2006). The empirical results of this study show that, compared to collaboration depth, collaboration breadth exerts a greater impact on new knowledge exploration. We thus recommend that managers design a collaboration strategy that emphasizes establishing a broad scope of different partnerships with external actors.

Second, the negative moderation effect of local cohesion on a knowledge network suggests that firms that maintain repetitive collaborations with external actors should pay attention to the level of local cohesion of their knowledge base when they attempt to obtain new knowledge through these partnerships. The empirical results further indicate that the negative moderation effect of local cohesion can sometimes outweigh the benefits of collaborating with repetitive partners when the level of local cohesion of a firm's knowledge network exceeds a certain level (0.93 in our study). This finding implies that deep research collaboration may become detrimental to the exploration of new knowledge when firms have extremely high levels of local cohesion in their knowledge network.[16]

Third, the positive moderation effect of the global cohesion of a knowledge network implies that firms can obtain more new knowledge elements by implementing a strategy of collaborating widely if they have a well-connected knowledge base. We encourage managers of multi-partner collaboration projects to invest heavily in internal cooperation across the different subject areas of their technologies. Although absorptive capacity scholars suggest that internal R&D investment will help firms absorb external ideas and technologies (Cohen and Levinthal 1990; Zahra and George 2002), our study indicates the precise direction of such investment by recommending internal communications and cooperation across different technological domains. Such investment allows firms to obtain more new knowledge elements in diverse collaboration arrangements across organizational boundaries. Along these lines, we believe that the comprehensive designation of an external research collaboration strategy and internal linkages among different knowledge elements serve as a good starting point from which to obtain more new knowledge from external sources.

Finally, it is worth noticing that managers must examine the diversity of the technological domains they already have and improve the degree of related knowledge variety when they intend to search for external new knowledge. Moreover, given that state-owned enterprises (SOEs) are less proactive in seeking new knowledge than foreign counterparts (FIEs), policy makers of Chinese government should take concerted efforts to build excellent institutional environment and refine the policies and regulations associated with acquiring and integrating external intelligence (Li et al. 2016; Zhang et al. 2010) in order to strengthen the exploratory innovation capability of domestic enterprises.

6.4 Limitations and future research recommendations

Our study has several limitations that may serve as directions for future research. The first limitation arises from the use of patent data to measure research collaboration strategies and construct a knowledge network. Patents are perhaps the most valid and robust indicators of knowledge creation and records of joint collaborative research (Trajtenberg 1990). Following prior studies (e.g. Guan and Liu 2016; Walsh et al. 2016; Wang et al. 2014), we measured sample firms' collaborative research activities by using patent data. However, besides co-patenting, there are various types of research collaboration, such as joining alliances or forming a joint venture.[17] In our research setting of the Chinese automobile sector, during the period from 2005 through 2011, the proportion of the number

[16] In our study, a total of 53 firms whose collaboration depth is greater than 1 accounted for 7.3% of the whole sample.

[17] We thank one reviewer who points this out.

of international joint ventures (IJVs) increased from 11% (300 firms) to 12% (388 firms) while the share of IJVs' total sales revenue decreased from 29% (297.3 billion RMB) to 17% (552.7 billion RMB).[18] Thus, we recommend future studies replicate our study by using data of different types of joint research activities. Moreover, the knowledge network that we considered is only that of a single type (i.e., the co-occurrence of two IPC categories at the four-digit level) that was based on combinations of knowledge elements. Future studies should consider integrating couplings of knowledge elements with other types of ties (e.g., subject category) and investigate how features of multi-dimensional knowledge affect the performance of searches for new knowledge.

Second, to rule out the potential effects of organizational features on new knowledge exploration, we included several organizational characteristics that had been suggested by the prior studies as being important for knowledge search (Savino et al. 2017). Future studies can shed new light on new knowledge exploration if they can incorporate not only these organizational level factors but also include sectoral level and regional level characteristics (e.g., technological turbulence, IPR enforcement) into the framework developed in our study. In addition, although the empirical findings of this study do not support the diminishing returns of research collaboration, we encourage future studies to further investigate the possibility that the global cohesion of knowledge networks may attenuate the diminishing returns of research collaborations.[19]

Third, although we used a longitudinal framework for empirical analysis by using data in two periods, future studies should consider examining the findings of this research using a panel dataset with moving time windows, which can improve the ability to infer causality among the key variables of interest in our study. Finally, the generalizability of our findings might be limited since our empirical analysis only focused on the automotive sector in China. However, as the theoretical underpinning of this study is largely derived from Western theories, we expect our findings to be generalizable to those Western samples. Nevertheless, we strongly recommend future studies to replicate and extend our findings by collecting data from different settings.

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Appendix

To better understand the measurement of weighted density, an example is given to illustrate how weighted density is calculated. If a firm's knowledge network is as follows (the matrix in Table 3), the weighted density (WD) of the firm's knowledge network then can be calculated as:

[18] We calculated these statistics using data collected from various issues of Statistic Yearbook of Automobile Industry at http://tongji.cnki.net/kns55/Dig/dig.aspx.

[19] We thank one of the reviewers who pointed this out.

Table 3 An example of a firm's knowledge network in the form of symmetric matrix

	H02K	H02P	H02J	F03D	H02H
H02K		16	12	12	1
H02P	16		12	12	1
H02J	12	12		8	0
F03D	12	12	8		1
H02H	1	1	0	1	

$$WD = \frac{(16 + 12 + 12 + 12 + 12 + 8 + 1 + 1 + 1)}{\frac{5(5-1)}{2}} = \frac{75}{10} = 7.5$$

By constrast, the pure density neglects the frequency of this co-occurrence and thus the pure density (PD) of the firm's knowledge network can be calculated as:

$$PD = \frac{9}{\frac{5(5-1)}{2}} = \frac{9}{10} = 0.9.$$

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