Dual networks: How does knowledge network embeddedness affect firms' supply chain learning?

Abstract

Purpose – To explore the mechanism that shapes firms' supply chain learning (SCL) practices, this study examines the relationship between firms' knowledge network embeddedness and their SCL practice in a supply chain network, as well as the moderating role of supply chain network cohesion in this relationship.

Design/methodology/approach – Using patent application data and supply chain partner information from 869 listed firms between 2011 and 2020 in China, this study uses fixed-effect regression models to reduce endogeneity problems by controlling for individual heterogeneity effects that cannot be observed over time.

Findings – Firms' knowledge network embeddedness has an inverted U-shaped effect on their SCL, and this non-linear relationship is conditional on supply chain network cohesion, which strengthens (weakens) the positive (negative) effect of knowledge network embeddedness on SCL.

Practical implications – The findings show that managers can reconcile the downsides of knowledge network embeddedness on SCL by fostering greater supply chain network cohesion.

Originality – Drawing from the network pluralism perspective, this study contributes to supply chain literature by extending the research context of the antecedents of SCL from a single-network setting to a dual-network setting. It extends the network pluralism perspective by showing that not only positive effects but also negative effects of network embeddedness can transfer from one network to another.

Keywords Supply chain learning; Network pluralism; Knowledge network; Network embeddedness; Network cohesion

Paper type Research paper

1. Introduction

Supply chain learning (SCL) exerts a critical impact on firms' competitiveness and supply chain performance (Silvestre *et al.*, 2020; Yang *et al.*, 2018). SCL refers to the collective learning practices among multiple supply chain players (Bessant *et al.*, 2003; Powell and Coughlan, 2020). It includes both internal learning, which occurs in the focal firm (Huo *et al.*, 2021), and interfirm learning, which involves co-creating collective knowledge, collaboration, and knowledge sharing in an interorganizational network established by supply chain actors (Jia *et al.*, 2019; Muthusamy and White, 2005). Such an interorganizational network is a social structure comprising a set of independent organizations as the nodes of the network and a set of dyadic social ties between these organizations as the edges of the network (e.g., supplier–buyer relationship) (Hearnshaw and Wilson, 2013; Mariotti, 2012).

Prior studies have investigated interfirm learning in a *single-network* context (Ahuja *et al.*, 2012; Shipilov *et al.*, 2014) in which firms' identities and relationships are homogeneous. For example, in a knowledge network, organizations are knowledge providers and knowledge receivers, and the key content of their relationships is knowledge (Jaffe *et al.*, 1993). In the same vein, firms are suppliers and customers in a supply chain network (Zhou *et al.*, 2014), with products and services as the key content of their relationships (Hearnshaw and Wilson, 2013). As such, taking a single-network view may not sufficiently explain a firm's strategic practices, because in reality, firms participate in more than one network and attain external resources not only from the supply chain network but also from other networks. By focusing only on a single network (i.e., supply chain network), previous studies have missed the opportunity to provide a comprehensive understanding of how a firm's participation in one network may influence its practices in another network. Our research aims to fill this gap by investigating how a firm's participation in a knowledge network affects its learning practices in a supply chain network. This investigation is important because sourcing external knowledge is critical to build firms' learning capability (Dyer and Nobeoka, 2000; Silvestre, 2015), and their knowledge advantage is a key driver for collective learning (Smart *et al.*, 2007).

Participating in a network may grant the focal firm both advantages and disadvantages. Network embeddedness, or a firm's external relationship arrangement with other organizations to obtain external resources in a network (Granovetter, 1985), explains this circumstance theoretically. When a firm participates in the knowledge network, its embeddedness therein represents its level of participation. Higher knowledge network embeddedness means that the firm has more interactions with other organizations in terms of conducting knowledge exchanges. Extant literature reports both positive and negative effects of knowledge network embeddedness, suggesting that, on the one hand, such embeddedness can bring more novel knowledge and information and boost efficient learning between network partners based on trust (Koka and Prescott, 2002; Zhou *et al.*, 2014); on the other hand, network over-embeddedness leads to lock-in and knowledge redundancy, which eventually hampers firm performance (Boschma, 2005; Uzzi, 1997). For example, being embedded in an R&D collaboration network provides a firm the opportunity to obtain novel knowledge and could eventually enhance its innovation performance (Lin *et al.*, 2009). By contrast, having high network embeddedness destabilizes a firm's collaboration with organizations that have distant knowledge stock, which results in negative effects on the firm's innovation output (Ahuja, 2000a). Given that knowledge network embeddedness has both advantages and disadvantages, a natural question is whether the advantages and disadvantages from a firm's participation in one network can transfer to another network. Therefore, our first research question is, *how does a firm's knowledge network embeddedness influence its learning practices in a supply chain network?*

Among the approaches pertinent to between-network relationship, the network pluralism perspective provides a useful theoretical lens to understand the effects of external relationships in one network on firms' practices in another network. This perspective is rooted in social network theory, whose central tenet is that firms can participate in different networks simultaneously and subsequently gain embeddedness in these networks (Shipilov *et al.*, 2014); embeddedness in one network can then affect that in another network (Jiang *et al.*, 2018; Zhang *et al.*, 2019). The network pluralism perspective thus argues that advantages gained from participating in one network can transfer to another network. We employ this view and extend it by positing that not only advantages but also disadvantages of participating in one network can transfer to another network, as well as the firm's practices. We conceptualize a cost–benefit logic such that the benefit brought by the advantages of knowledge network embeddedness competes with the cost of overcoming the disadvantages brought by such embeddedness. For example, when the benefit overrides the cost, a firm's knowledge network embeddedness should have a positive impact on its SCL practices; vice versa, it should have a negative impact. Therefore, we theorize an inverted U-shaped relationship between the knowledge network embeddedness and SCL practices.

Moreover, the cohesiveness of a supply chain network can affect firms' efficiency in transferring advantage from the knowledge network to the supply chain network. Supply chain network cohesion refers to the connectivity among the focal firm and its partners within the supply chain network (Guler and Nerkar, 2012; Thomaz and Swaminathan, 2015). In a supply chain network, network cohesion functions as a platform for trust building among firms, which fosters firms' willingness to engage in long-term collaborations (Fleming *et al.*, 2007; Guler and Nerkar, 2012). We posit that the cohesion of the supply chain network may influence the relationship between firms' knowledge network embeddedness and their SCL for two reasons. First, network cohesion can amplify the effectiveness of firms' knowledge network embeddedness advantages (Guo *et al.*, 2021; Thomaz and Swaminathan, 2015), because a dense network facilitates more interactions and builds higher levels of trust, which are conducive to more speed and volume of knowledge exchange (Guler and Nerkar, 2012). Second, a dense network can also mitigate the problems of uncertainty and opportunism in collaborations (Guler and Nerkar, 2012; Yu *et al.*, 2011) and thereby weaken the negative impacts of knowledge network embeddedness, such as lock-in and knowledge redundancy, on firms' SCL. Therefore, our second research question is, *how does supply chain network cohesion moderate the effect of knowledge network embeddedness on SCL?*

Our research offers three contributions to the literature. First, drawing from the network pluralism perspective (Shipilov *et al.*, 2014; Zhang *et al.*, 2019), it enriches supply chain literature by investigating the antecedents of SCL under a dual-network context. Whereas prior studies have mainly investigated firms' SCL from an intra- or interorganizational perspective in a single-network context, our research focuses on firms' relationships across networks (i.e., knowledge and supply chain). Such a dual-network analysis approach sheds greater light on the interplay between organizations' networks (Jiang *et al.*, 2018; Zhang *et al.*, 2019)—namely, how a firm's embeddedness in one network affects its practices in another. Therefore, this study provides a novel way (i.e., a dual-network analysis approach) to examine an antecedent of a firm's SCL practices in a dual-network setting.

Second, our research contributes to SCL literature and the network pluralism perspective by theorizing an inverted U-shaped relationship between a firm's embeddedness in a knowledge network and its SCL practices. Research on the network pluralism perspective hold the view that only a firm's advantages from participating in one network can transfer to another network while its disadvantages do not transfer (e.g., Jiang *et al.*, 2018). By contrast, we argue that when two networks have similar resource requirements that lead to resource preemption between them, not only the advantages but also the disadvantages from one network can transfer to the other network. Thus, our research enriches understanding of the role of knowledge network embeddedness in SCL practices.

Third, our research contributes to supply chain literature and the network pluralism perspective by unpacking the boundary condition of the relationship between firms' knowledge network and supply chain network. By positioning supply chain network cohesion as an important theoretical moderator, we answer research calls for a comprehensive investigation into the mechanisms that shape the interplay between these networks (Carpenter *et al.*, 2012; Shipilov *et al.*, 2014).

2. Literature review

2.1 Learning in supply chain network

Prior studies have identified firms' knowledge base and learning-related capabilities as two important components involved in interorganizational learning (Bessant et al., 2003). One stream of SCL literature sheds light on the effects of internal capabilities (e.g., absorptive capacity, management quality), internal resources (e.g., human capital, structural capital), and trust building within organizations on SCL. For example, absorptive capacity is an important antecedent of SCL because it captures firms' capability of recognizing, assimilating, and using external knowledge (Lane and Lubatkin, 1998; Liu and Zhang, 2014). The effective utilization of internal resources contributes substantially to firms' SCL. Firms' investment in intellectual capital, such as human capital and internal social capital, improves their SCL (Zhang and Lv, 2015), and such investment could be integrated into the orchestration of their resources in a multi-tier supply chain to improve SCL (Gong *et al.*, 2018). Moreover, firms' strategic characteristics, such as the intent to leverage interorganizational learning and the openness of their knowledge base to partners, are also important factors influencing collective learning (Liu and Zhang, 2014).

Another stream of research emphasizes the importance of learning from external partners by maintaining existing relationship and building reliable collaboration channels (Mariotti, 2012; Muthusamy and White, 2005). A high level of commitment and trust facilitates collaboration and co-creating activities, because trust based on goodwill and non-opportunism can secure effective learning between supply chain partners (Şengün, 2010), and such a positive effect can be strengthened by a high level of trust in partners' competence (Şengün and Önder, 2011). More important, this effect remains steady in a cross-border setting, as trust mitigates tensions created by sharing confidential knowledge (Jean *et al.*, 2010). By focusing on the interactions between supply chain partners, this stream of literature coincides with supply chain network literature on the relationships between supply chain network actors (Braziotis *et al.*, 2013). An efficient supply chain network offers strong resilience to cope with turbulence and logistics uncertainty (Braziotis *et al.*, 2013), which is conducive to structural flexibility (Hearnshaw and Wilson, 2013) and results in better supply chain performance.

However, examinations of firms' relationships or networks are often set in a single setting, consisting of similar relationships or network actors. For example, in a supply chain setting, relationships are customer–supplier (Zhou *et al.*, 2014), and in a knowledge network setting, firms are connected by the transfer of knowledge, meaning that they are all knowledge providers and receivers (Isaksson *et al.*, 2016). This single-network setting leaves an important gap in SCL research because, in real-life operations, firms simultaneously participate in different networks and build varying relationships with heterogeneous entities (Gulati, 1999; Shipilov *et al.*, 2014; Zhu *et al.*, 2018). Therefore, investigating SCL in a dual-network setting is important.

2.2 Network pluralism perspective: knowledge network and supply chain network

The network pluralism perspective asserts that actors can participate in different networks consisting of heterogeneous social ties at the same time, and the effects of these ties can transfer across networks (Laumann *et al.*, 1978; Shipilov *et al.*, 2014). This theoretical perspective materializes in social network theory as an approach for resolving embeddedness-related dilemmas (Jiang *et al.*, 2018) and altering performance implications of interorganizational networks (Zhang *et al.*, 2019).

Network pluralism emphasizes the importance of jointly considering the impact of organizations' participation in different networks. Prior studies have demonstrated that actors can participate in dual networks with different functions by building social ties across pools of contacts (Burt, 1977). For example, a firm could participate in both an R&D alliance network and an industrial network with distinct identities, and its social ties with other firms in the same industry could bring positive effects to its R&D alliances (Zhang *et al.*, 2019). In addition, firms' embeddedness in different networks can have different natures (Shipilov *et al.*, 2014). Firms' interactions with partners in the network are driven by resource exchange and norms shaped by former interactions in the network (Gulati, 1999), meaning that such interfirm networks often possess different configurations of relationships with network actors, as well as distinct features of interaction patterns (Laumann *et al.*, 1978). Moreover, the different levels of embeddedness formed from distinct interaction patterns may interplay with each other. For example, firms could leverage their novel knowledge gained from one network by using such knowledge to work with partners in another network (Jiang *et al.*, 2018). Thus, when firms participate simultaneously in multiple networks, their distinct embeddedness from these networks may interplay with each other and jointly affect their decisions and behavior (Jiang *et al.*, 2018; Shipilov *et al.*, 2014).

Drawing from the network pluralism perspective, we aim to enrich supply chain literature by examining the relationship between the knowledge network and the supply chain network; thus, our research context is set between these networks. The knowledge network refers to "a set of nodes—individuals or higher-level collectives that serve as heterogeneously distributed repositories of knowledge and agents that search for, transmit, and create knowledge—interconnected by social relationships that enable and constrain nodes' efforts to acquire, transfer, and create knowledge" (Phelps *et al.*, 2012, p. 1117). A supply chain network refers to a "set of 'nodes' that represents autonomous business units as firms who are able to exercise sovereign choices, and a set of 'connections' that link these firms together for the purposes of creating products or services*"* (Hearnshaw and Wilson, 2013, p. 444). We summarize the overlaps and distinctions between the knowledge network and the supply chain network in Table 1.

[Insert Table 1 about here]

In a dual-network setting, the two networks are not necessarily fully independent from each other, as their "nodes" may have some overlap. For example, firm A may partner with firm B in the knowledge network, and A may also have a supplier–buyer relationship with B in the supply chain network. In this situation, both the knowledge network and the supply chain network are built by the same actors. However, firms A and B have different identities and also have different relationships with each other in these networks. This is because the two networks have different types of nodes and relationships. For example, in the supply chain network, the nodes of the network are business units, and the relationship between firms is based primarily on contracts. In addition, the network's critical flow types include material flows (physical products), information flows (coordinating data), and financial flows (monetary resources) (Hearnshaw and Wilson, 2013). By contrast, in the knowledge network, the nodes are not necessarily an organization; they could be knowledge elements such as those embodied in discrete artifacts (e.g., patents, products) (Hearnshaw and Wilson, 2013). In addition, the relationships among the nodes can be cognitive (associations concepts), social (formal and informal collaborations among agents), or associational (Hearnshaw and Wilson, 2013). Different identities and relationships of a firm in different networks will lead to different outcomes of participating in each network; that is, the outcome from one network will affect that in another network (Shipilov *et al.*, 2014). Therefore, examining the between-network effects is worthwhile even if two networks were built by the same set of actors.

2.3 Network embeddedness

Firms' embeddedness reflects the structure of the relationships between the focal firm and other actors in the network (Granovetter, 1985). In the context of knowledge networks, a firm's embeddedness in the network reflects the configuration of its connections with other actors in knowledge exchanging activities (Uzzi, 1997). For example, through R&D collaborations with different organizations such as independent research institutes, universities, and labs, firms establish a knowledge network based on the creation and transfer of knowledge; the more connections and collaborations a firm has with these network actors, the higher is its knowledge network embeddedness. Studies on knowledge network embeddedness have revealed both bright and dark sides of its impact on organizations' behavior and performance.

On the one hand, knowledge network embeddedness positively affects firms' knowledge acquisition and performance. Participating actively in an interorganizational network can bring more tacit knowledge, as knowledge network embeddedness offers more opportunities for knowledge sharing and collaboration (Koka and Prescott, 2002). By maintaining frequent interactions with other firms, a focal firm can take a broker position in the network, which ensures access to more novel knowledge and information (Liu and Wu, 2011). A higher-quality relationship based on such frequent interactions captures the intensity and depth of the relationship, which in turn result in collective benefits (Lin *et al.*, 2009), as building reciprocity in resource exchange can enhance the positive impact of embeddedness (Gulati, 1995; Ibarra *et al.*, 2005). Such positive effects of embeddedness are also evidenced in co-creating activities based on different types of social ties (Rishika and Ramaprasad, 2019).

On the other hand, knowledge network embeddedness can exert a negative impact on knowledge sharing and performance. Studies report that high embeddedness can hamper knowledge/information integration and diffusion (Gilsing *et al.*, 2008; Uzzi, 1997), as it may lead to lock-in and collective blindness, impeding the sharing of novel knowledge (Boschma, 2005). In this case, a firm's ability to search for novel knowledge is weakened. Moreover, continuing to invest in one network may bring diminishing returns, because higher embeddedness involves working with distant partners in the network and the cost of absorbing distant knowledge is relatively high. This, in turn, leads to attention overload, which will dilute a firm’s ability to choose valuable SCL partners and eventually exert a negative impact on co-creating activities (Ahuja and Katila, 2004; Berliant and Fujita, 2011). High network embeddedness also means that a firm has established norms of interacting with partners, which could hinder it from adjusting to new norms when interacting with partners from another network (Gilsing *et al.*, 2008; Jiang *et al.*, 2018).

In supply chain literature, studies examining the relationship between network embeddedness and firms’ supply chain performance (De Stefano and Montes-Sancho, 2018; Swierczek, 2019) have focused on intraorganizational-level relationships, suggesting that firms with higher embeddedness have greater discretion in choosing partners (Gulati, 1999) and can benefit from knowledge spillover (Isaksson *et al.*, 2016). A few studies have investigated this relationship at the interorganizational level, which highlights the importance of building relationships based on commitment. However, as noted previously, the research context of these studies is bound in a single network, which assumes that firms have homogeneous social ties (Muthusamy and White, 2005). As such, literature remains silent on how embeddedness can affect firms’ SCL in a dual-network setting. Therefore, examining the effects of firms’ knowledge network embeddedness on their SCL from the theoretical lens of the network pluralism perspective can generate a more comprehensive understanding of the drivers of SCL.

2.4 Network cohesion

Supply chain network cohesion refers to the connectivity among the focal firm and its partners within the supply chain network (Guler and Nerkar, 2012; Thomaz and Swaminathan, 2015). It reflects the overall closeness between network actors, such that more frequent or a higher level of connections between actors means high cohesion in the network (Moody and White, 2003; White and Harary, 2001). High cohesion indicates a higher level of resource exchanges among actors who have similar characteristics and appropriate expectations, while low cohesion in a network indicates firms' discretion in attaining varying kinds of resources (Carpenter *et al.*, 2012). Studies measuring network cohesion with varying approaches tend to take different theoretical lenses, and recent studies have used this concept interchangeably with constructs such as network density and clustering coefficient (Gilsing *et al.*, 2008; Guo *et al.*, 2021). Network cohesion can also be examined at different levels (e.g., intraorganizational, interorganizational). For example, Guler and Nerkar (2012) employed it to understand the mechanism of intrafirm relationships between R&D scientists and a firm's innovation performance. At an interfirm network level, network cohesion could increase the positive effects of market alliance on market sale (Yu *et al.*, 2011).

Network cohesion is critical to a firm's supply chain performance (Carnovale *et al.*, 2019) because it supports trust building with other firms in the interorganizational network, which enhances the firm's willingness to engage in long-term partnerships

(Fleming *et al.*, 2007; Guler and Nerkar, 2012). Moreover, network cohesion mitigates collaboration risks by improving the effectiveness of alliance choices (Thomaz and Swaminathan, 2015), and it strengthens the positive effects of cohesive behaviors on collaboration stability (Guo *et al.*, 2021). Therefore, examining the role of network cohesion in the relationship between knowledge network embeddedness and SCL can shed light on the interplay between dual networks.

3. Hypotheses development

3.1 Direct effects of knowledge network embeddedness

We consider a cost–benefit logic to theorize an inverted U-shaped relationship between knowledge network embeddedness and SCL in a supply chain network. As research suggests that knowledge network embeddedness has both advantages and disadvantages, we propose that not only its positive effects but also its negative effects can transfer from the knowledge network to the supply chain network, subsequently affecting firms' SCL practices. We show the theoretical framework in Figure 1.

[Insert Figure 1 here]

3.1.1 Benefits of knowledge network embeddedness

Drawing from the network pluralism perspective, previous research has taken the view that firms' active participation in different networks can generate positive between-network effects, because firms can leverage the benefits gained from one network to another (Shipilov *et al.*, 2014). For example, when firms participate in both exploratory and exploitative alliance networks, its participation in the exploratory network can subsequently benefit its practices in the exploitative network (Jiang *et al.*, 2018). This is because adding new exploratory partners brings non-redundant information, providing opportunities for the focal firm to identify and develop new exploitative partners (Burt, 1992; Jiang *et al.*, 2018). In other words, the advantages a firm gains in one network can benefit its practices in another network.

In a similar vein, we argue that a firm can leverage the advantages gained in the knowledge network on its SCL practices in the supply chain network. By participating in a knowledge network, a firm can gain more access to new knowledge and valuable information (Koka and Prescott, 2002), which helps it raise its social status and impact when choosing supply chain partners for collaborations. Such benefits, in turn, help the firm earn credibility and supply chain partners' trust (Dyer and Singh, 1998), which can secure co-creating activities and generate collective benefits (Gulati, 1995). Moreover, because increased knowledge network embeddedness gives the firm access to supply chain network actors that have more collaboration experience and higher social impact (Choi *et al.*, 2010; Lyu *et al.*, 2017), the firm is more likely to benefit from learning with these actors.

3.1.2 Cost of knowledge network embeddedness

Prior research has investigated the negative effects of knowledge embeddedness, but these investigations took place in a single-network setting (i.e., within a firm's knowledge network) not in a dual-network setting. Drawing from the network pluralism perspective, we argue that the negative effects of knowledge embeddedness can transfer from one network to another. Most prior studies have ignored the transferability of the negative effects between interorganizational networks and focused on the positive ones. According to our literature view, the only study to shed light on the transferability of negative effects of network embeddedness is Jiang *et al.* (2018). Their study suggests that negative embeddedness in one network does not transfer to another. In their setting, when firms participate in both exploratory and exploitative alliance networks, the two networks require different resources and capabilities of the firm. Subsequently, the firm's resource input in one network will not preempt that in another. In turn, the negative effects of participating in one network will not be able to affect another network. As such, Jiang *et al.* (2018) conclude that no negative effects transfer from one network to the other.

However, our research context differs from theirs. When a firm conducts knowledge exchange activities in the knowledge network and undertakes SCL in the supply chain network at the same time, the resources and capabilities required are closely related. For example, both activities involve creating, absorbing, and transferring knowledge and information and forming collaboration routines (Argote and Miron-Spektor, 2011; Gulati, 1999). In this situation, the resources required for engaging in both networks will preempt each other, such that an increase in knowledge network embeddedness limits the available resource input for the firm's SCL practices. Such resource preemption, in turn, enables the transfer of the negative effect of network embeddedness in one network to the other network. For example, the negative effects of high knowledge network embeddedness such as attention overload will affect the knowledge network by impeding the firm from searching for useful knowledge sources; this resource depletion will transfer to the supply chain network by inhibiting the firm's ability to identify valuable SCL opportunities (Ahuja and Katila, 2004; Berliant and Fujita, 2011) and subsequently sabotage its SCL practices. Therefore, when resources between networks are preempted, the negative effect of network embeddedness will transfer from one network to the other.

3.1.3 Taking both views into account

While a firm may enjoy the benefits of knowledge network embeddedness such as novel knowledge and credibility, it may also suffer from higher maintenance costs and attention overload at the same time, given the negative effects of such embeddedness. Drawing from the network pluralism perspective, we argue that both positive and negative effects of knowledge network embeddedness can transfer from the knowledge network to the supply chain network. Thus, when examining the overall effect of knowledge network embeddedness on SCL, we need to take both views into account. A firm's embeddedness in a knowledge network can be low, moderate, or high, and the varying degree of knowledge network embeddedness can make its benefits or costs more or less salient.

When the level of knowledge network embeddedness increases from low to moderate, the benefits such as novel knowledge and information, credibility, and trust gained from knowledge network embeddedness become more salient (Dyer and Singh, 1998; Koka and Prescott, 2002). Moreover, the negative effect of knowledge network embeddedness is less prominent, and thus the costs of its negative effects do not overwhelm its benefits. In this situation, novel knowledge and non-redundant information gained from the knowledge network can provide the firm opportunities to conduct SCL activities with more supply chain network actors, whereas the credibility and trust secure the quality of SCL activities (Choi *et al.*, 2010; Lyu *et al.*, 2017). In this situation, the firm can transfer the advantages in the knowledge network into more benefits in the supply chain network. As a result, the overall impact of knowledge network embeddedness on SCL should be positive.

When the level of knowledge network embeddedness moves from moderate to high, the additional benefits attained increase rather incrementally, but the cost of high network embeddedness becomes salient and begins to override its benefits and impede firms' SCL. In this situation, the cost of maintaining high embeddedness gradually increases, as the firm needs more resource input to identify and absorb varying kinds of knowledge that are distant from its knowledge base, which lessens the firm's efficiency in employing and allocating resources (Tiwana, 2008; Tortoriello and Krackhardt, 2010). In turn, too much knowledge also leads to attention overload and lock-in, causing a higher cost in maintaining high knowledge network embeddedness and diluting the benefits to leverage in the supply chain network (Alhakami and Slovic, 1994; Berliant and Fujita, 2011; Boschma, 2005). Therefore, in this case, an increase in knowledge network embeddedness triggers higher costs and undermines its benefits.

Taking both the bright and dark sides of knowledge network embeddedness into account, we propose that not only the positive but also the negative impacts of firms' knowledge network embeddedness will influence their SCL in the supply chain network. In particular, when benefits brought by knowledge network embeddedness override its costs, the impact of knowledge network embeddedness on SCL will be positive; when the costs prevail, an increase in knowledge network embeddedness will bring more negative effects to SCL. Taken together, we propose the following:

H1. Knowledge network embeddedness has an inverted U-shaped relationship to SCL.

3.2 Contingent role of supply chain network cohesion

Following a cost–benefit logic, we theorize the contingent role of supply chain network cohesion in shaping the relationship between knowledge network embeddedness and SCL. Network cohesion improves the togetherness and connectivity of supply chain networks (Moody and White, 2003; White and Harary, 2001). On the one hand, when knowledge network embeddedness is at low to moderate levels, network cohesion enhances the benefits of leveraging the embeddedness advantage, because a higher level of network cohesion allows the firm to learn from more supply chain partners and engage in long-term relationships based on trust (Yayavaram and Ahuja, 2008). For example, network cohesion strengthens the firm's ability to search external partners for co-creating activities, because the firm will have more partners to choose from in a supply chain network with high cohesion (Guler and Nerkar, 2012; Xu *et al.*, 2019). Moreover, in a interorganizational network learning setting, network cohesion positively moderates the relationship between firms' knowledge similarity and network stability, suggesting that network cohesion contributes to the stability of interorganizational learning activities (Guo *et al.*, 2021). In turn, the firm can better transfer its advantage in its knowledge network into SCL with greater supply chain network cohesion, as the firm can undertake more long-term collective learning activities with more supply chain partners.

On the other hand, when knowledge network embeddedness is at moderate to high levels, network cohesion alleviates the negative effects of knowledge network embeddedness on SCL. Research suggests that distant knowledge brings diminishing returns to knowledge exchange activities (Uzzi, 1997; Zhou *et al.*, 2014), as less novel and more irrelevant knowledge is available to improve firms' learning performance (Tortoriello and Krackhardt, 2010). Strong network cohesion in a supply chain network can mitigate the diminishing return problem, because it facilitates more frequent knowledge exchanges and actors in a cohesive network share more common beliefs, which can benefit co-creating activities (Yayavaram and Ahuja, 2008). This gives the firm more opportunities to undertake collective learning activities in the supply chain network. Moreover, high cohesion in the supply chain network can alleviate the problem of attention overload caused by high knowledge network embeddedness. This is because supply chain network cohesion helps firms form subgroups within which more exchanges of less diverse knowledge take place. Such a knowledge exchange pattern within each subgroup reduces the overall cost of learning (Thomaz and Swaminathan, 2015). In this case, the negative effect of attention overload will be offset. Furthermore, high network cohesion secures valuable learning opportunities by reducing collaboration costs (e.g., opportunism behavior, risk aversion behavior) (Alhakami and Slovic, 1994; Yu *et al.*, 2011). Therefore, supply chain network cohesion can alleviate the negative effects caused by high knowledge network embeddedness. Thus:

> *H2.* Supply chain network cohesion strengthens the positive effects and weakens the negative effects of knowledge network embeddedness on SCL.

4. Data and methodology

4.1 Sample

To test the hypotheses, we used a sample of Chinese listed firms. To gain access to cutting-edge knowledge on competence, firms needed to participate in various kinds of knowledge networks. For most listed firms, explicit knowledge residing in the knowledge network is one of the key elements for innovation and interorganizational learning. Thus, the patent dataset of listed firms is critical for empirical research examining firms' knowledge acquisition (Jaffe *et al.*, 1993).

We took three steps to collect the sample. First, we use firms' patent citations appearing in the China National Intellectual Property Administration (CNIPA) database from 2010 to 2019, to reflect the knowledge exchange relationship ties (edges of knowledge network) between these firms (nodes of knowledge network). CNIPA's patent data included all listed firms and recorded the citation information of every patent. This is helpful for mapping the knowledge exchange activities of the firms. From these ties, we build a knowledge network to compute the knowledge network embeddedness of each listed firm. We obtained 51,147 observations from the knowledge exchanges between 2669 listed firms from 2010 to 2019.

[Insert Figure 2 here]

Second, to capture firms' SCL practices, we operationalize SCL using the information of all listed firms' top five suppliers and top five customers from 2011 to 2020 in the China Stock Market & Accounting Research database. According to the records, most of the names of the listed firms' top five supply chain partners are not fully disclosed. For example, some firms only report "Bank A in China" or "Customer one" rather than a customer's specific name, making such records impossible to use to build the supply chain network. Moreover, many recorded private companies do not publicly report their financial data; therefore, accessing other information about these companies is impossible. Thus, we include only the records of listed firms whose partners and customers are also listed firms. We depict the relationship in Figure 2. Here, we record the supplier–customer relationship in the adjacency list and base the supply chain network on it. In this way, we can more accurately investigate firms'

SCL practices. We obtained 6956 observations from the supply chain collaborations between 2493 listed firms from 2011 to 2020.

Third, we choose the listed firms participating in both the knowledge network and the supply chain network. We match the two sets of data obtained by their stock codes and company names and apply a one-year lag to the independent variables to eliminate reverse causality. We obtained 2100 observations from 869 listed firms that participated in both networks from 2011 to 2020.

We provide the characteristics of the sample in Table 2. More than 70% of the sample firms are from the manufacturing industry. In terms of firm size, near 60% of the firms are below the mean value of the sample. We list the variables' definitions and measurements in Table 3.

[Insert Table 2 and Table 3 here]

4.2 Operationalization of variables

4.2.1 Dependent variable

Following Argote and Miron-Spektor (2011), we measure firms' *SCL* as learning practices. Organizational learning research has increasingly used the practices approach because of its advantage in capturing both tacit and explicit knowledge exchange, which are critical for SCL (Bessant *et al.*, 2003). Specifically, learning among suppliers and customers is often measured by collective practices, such as collaborations and alliances (Huo *et al.*, 2021; Simonin, 1997; Yang and Lai, 2012). This is because collaborations and alliances facilitate the exchange of complex know-how and tacit knowledge about product-specific information and collaboration routines (Gulati, 1999; Li *et al.*, 2010; Zhou *et al.*, 2014). Therefore, according to prior studies (Ahuja, 2000b; Muthusamy and White, 2005), collaboration among supply chain partners is a suitable measure of a firm's collective learning practices in the supply chain. To operationalize SCL in the supply chain network, we follow Gulati (1999) and Jiang et al. (2018) and measure the level of SCL practices in a supply chain network as

$$DC_{i,t} = \sum_{j=1}^{n} a_{ij},$$

where $DC_{i,t}$ is the total number of collaborations of firm i in year t with other firms j in the supply chain network and the adjacent matrix a_{ij} counts the number of collaborations between firms i and j. More collaboration activities mean a higher level of SCL practices.

4.2.2 Independent variable

We follow the approach of Jiang et al. (2018) and Burt's (1992) network constraint measure to capture a firm's *knowledge network embeddedness*. Specifically, we measure a firm's knowledge network embeddedness by its network constraint:

$$C_{it} = \sum\nolimits_{i \neq j} (p_{ij} + \sum_{q, q \neq i, q \neq j} p_{iq} p_{qj})^2,$$

where C_{it} is the network constraint in year t, p_{ij} is the proportion of firm i's total ties invested in partner j, p_{iq} is the proportion of firm i's total ties invested in partner q, and p_{qj} is the proportion of firm q's total ties invested in partner j. Taken together, this measurement is the function of the direct ties between firm i and partner j and the ties between partner j and firm q in the supply chain network of firm i. According to Burt

(2015), high network constraint means either that the ties between firm *i* and *j* are primary among all the ties of firm *i* or that most partners of firm *i* also have ties with firm *q*. Either way, firm *i* is highly embedded in the knowledge network, and its knowledge exchange activities are highly dependent on these partners (Burt, 2015).

4.2.3 moderating variable

We measure a firm's *supply chain network cohesion* following Guler and Nerkar's (2012) approach, using the network density (Marsden, 1993) of the focal firm's supply chain network to capture the connectedness and togetherness between the firm and its partners:

$$NC_{ijt} = \frac{\sum_i \sum_j l_{ij}}{\mathrm{n}(\mathrm{n}-1)/2}\ , i\ \neq j,$$

where NC_{ijt} denotes the focal firm's supply chain network cohesion in year *t*, *n* indicates the number of actors in the network, and l_{ij} is the number of linkages formed in the network. The higher the network density, the more cohesive the network may be.

4.2.4 Control variables

We also include a set of variables that could control for the firms' features and environmental influences. First, we calculate *firm size* as the log value of the firms' total assets, as larger firms may collaborate more with their partners for collective learning. Second, we measure *firm age* as the log value of the current year minus the year the firm listed; firms in the market for a longer time may have stronger collaboration capability. Third, the intensity of firms' R&D reflects their effort to absorb and produce knowledge and thus may influence their SCL choices and motivation. We measure *R&D intensity* by calculating a firm's R&D expenditure per year divided by its total assets. Fourth, we also control for *firm financial performance* by using Tobin's q ratio, as greater market performance indicates a higher propensity to invest more in knowledge production, which could lead to a higher level of SCL. Fifth, we control for firms' *state ownership*, because it may mitigate the impacts of market turbulence and uncertainty (Zhang *et al.*, 2019). We measure connections by whether the firm is state-owned, where state ownership equals 1 when firms are state-owned and 0 otherwise. Finally, to control the time-varying macroeconomic forces that may cause endogeneity, we also include GDP growth rate (*GDP*), change of the head of government (*Leader change*), and marketization at the provincial level (*Marketization*), to counter the possible higher-level impacts of the external environment (An *et al.*, 2016; Gulen and Ion, 2015; Wang *et al.*, 2007).

4.3 Econometric specification

The mean variance inflation factor of the explanatory variables is 1.22; thus, the multilinearity between variables is low. Tables 4 and 5 provide descriptive statistics and correlations of the variables. To mitigate any endogeneity problems and control for individual firms' time-invariant effects (Blundell *et al.*, 1995; Galasso and Simcoe, 2011), we use a fixed effect model with a stepwise approach to examine the hypotheses. Moreover, to account for reverse causality, we lag all explanatory variables, moderators, and control variables to the dependent variable by one year. The final model specification is as follows:

$$SCL_{it} = \beta_0 + \beta_1 KNE_{t-1} + \beta_2 KNE_{t-1}^2 + \beta_3 SCNC_{t-1} + \beta_4 SCNC \times KNE_{t-1} + \beta_5 SCNC \times KNE_{t-1}^2 + \beta_6 Control\ Variables_{t-1} + \alpha_i + u_{it}.$$

[Insert Table 4 and Table 5 here]

4.4 Results

The regression results in Table 6 report the coefficients of variables in different models. Model 1 is the baseline model with only the control variables. Model 2 introduces the inverted U-shaped effect of knowledge network embeddedness, and Model 3 adds the interaction term.

H1 posits an inverted U-shaped relationship between a firm's knowledge network embeddedness and SCL. Model 2 shows a statistically significant inverted U-shaped effect; thus, H1 is supported. As Model 2 shows, knowledge network embeddedness is positive related to a firm's SCL ($\beta = 0.643$, $p < 0.001$), while the squared term indicates a negative effect ($\beta = -2.430$, $p < 0.001$). In Model 3, this effect remains statistically significant with a slight difference in the coefficient; thus, the sign and significance are consistent with Model 2. We conducted a U-test (Lind and Mehlum, 2010) to examine whether the peak of the curve is within the sample's data range and found that the reflection point is indeed within the range, which again confirms H1. Model 3 reports the results with all variables. Again, with all variables into the model, the inverted U-shaped effect is still statistically significant.

H2 predicts that supply chain network cohesion moderates the curvilinear relationship between knowledge network embeddedness and SCL, such that it strengthens the positive effects and weakens the negative effects of knowledge network embeddedness on SCL. That is, overall level of SCL improves when the supply chain network cohesion is strong. We employed a mean-centered approach to eliminate multicollinearity issues in the model (Zhou et al., 2014). In Model 3, the first-order interaction term between knowledge network embeddedness and SCL (β = –9.635, $p < 0.001$) is negative, while the second-order interaction term shows a strong positive effect (β = 212.756, $p < 0.001$). To demonstrate the moderating effect, we plot the effect of high supply chain network cohesion at its mean value and higher value (one standard deviation higher from the mean value) in Figure 3. The overall moderating effect of supply chain network cohesion is positive. Specifically, at the left side of the turning point, where knowledge network embeddedness is at low to moderate levels, the positive relationship between knowledge network embeddedness and SCL is strengthened by high supply chain network cohesion. Then, at the right side of the turning point, where knowledge network embeddedness is at moderate to high levels, the negative effect is attenuated by the high level of supply chain network cohesion. Therefore, H2 is supported.

[Insert Figure 3 and Table 6 here]

4.5 Robustness check

Considering the nature of the dependent variable, a nonnegative integer, we use a fixed-effect Poisson model to conduct alternative analysis (Blundell *et al.*, 1995).

Moreover, as SCL from partners includes both supplier and customer learning (Huo *et al.*, 2021), we chose supplier learning as an alternative measure for the dependent variable. We also adjust the sample (exclude observations with only one member in group and only one year) for the analysis. Table 7 reports the regression results of fixed effect ordinary least squared model using this alternative dependent variable, and Table 8 shows the results using Poisson regression. As Table 7 shows, the results are consistent with our previous analysis. In Table 8, Models 1–3 show the results using Poisson regression with an alternative dependent variable, and Models 4–6 show the stepwise regression using Poisson regression with the original measure of SCL.

[Insert Table 7 and Table 8 here]

In Models 1–6, the results are consistent with previous findings. Model 2 demonstrates that the inverted U-shaped effect of knowledge network embeddedness on a firm's learning from suppliers is still significant. In Model 3, the first interaction term between knowledge network embeddedness and SCL is no longer statistically significant, while the second-order term remains significant ($\beta = 32.607$, $p < 0.001$). Similarly, Model 5 evidences the nonmonatomic effect of knowledge network embeddedness on SCL. In Model 6, the moderating effect of supply chain network cohesion on the inverted U-shaped relationship is strongly supported and significant.

We ran an additional analysis on the joint significance of the variables and the inverted U-shaped curve. We also conducted a Sasabuchi test based on previous approaches (Haans *et al.*, 2016; Wales *et al.*, 2013) and tested the reflection point of the curve using Fieller's standard error method (Lind and Mehlum, 2010). Table 9 shows that the peak of the curve is within the sample range. For the main effect, the curve peaks at a higher level of knowledge network embeddedness when supply chain network cohesion increases. The joint significance test shows that each set of variables are significant.

[Insert Table 9 here]

5. Discussion

In this study, we examine how a firm's knowledge network embeddedness affects its SCL and the contingent role of supply chain network cohesion. Using two panel datasets of Chinese listed firms, we find that knowledge network embeddedness has an inverted U-shaped effect on SCL and this effect is moderated by supply chain network cohesion. This finding provides novel insights into the importance of a dual-network approach for SCL.

5.1 Theoretical contributions

First, this study contributes to SCL literature, which to our knowledge has not taken a dual-network setting into account when investigating drivers of SCL. Previous studies investigating SCL in a single-network setting based on supplier–customer relationships indicate the importance of a firm's ability to develop absorptive capacity and build social ties with supply chain partners (Huo *et al.*, 2021; Swierczek, 2019). Focusing solely on the single-network setting, however, misses the opportunity to examine the possibility of dual-network effects among the different networks in which a firm participates. Drawing from the network pluralism perspective (Jiang *et al.*, 2018; Shipilov *et al.*, 2014), we examine the effect of knowledge network embeddedness on firms' SCL in supply chain networks. Our findings show that a firm's embeddedness in the knowledge network can affect its learning practices in the supply chain network. They also indicate that a firm's participation in one network can exert an impact on its practices in another network. Therefore, this study advances literature on the drivers of SCL by theorizing and evidencing the importance of extending the research context from a single-network setting to a dual-network setting.

Second, we contribute to SCL literature and the network pluralism perspective by theorizing an inverted U-shaped relationship between knowledge network embeddedness and SCL. Prior studies on network embeddedness (Andersen, 2013; Zhou *et al.*, 2014) have revealed both bright and dark sides of its impact on organizations' behavior and performance in a single network; however, when examining its effect in a dual-network setting, studies only consider a positive effect and thus only partially capture the impact (Jiang *et al.*, 2018; Shipilov *et al.*, 2014). Our research extends the network pluralism perspective by showing that not only positive effects but also negative effects of network embeddedness can transfer from one network to another. This finding differs from Jiang *et al.*'s (2018) finding that negative embeddedness in one network does not transfer to another. As we explain, this is because whether negative embeddedness can transfer from one network to another depends on whether resource preemption occurs between networks, which is not the case in Jiang *et al.*'s (2018) context. By contrast, in our context, resources and capabilities are closely related for knowledge exchange activities and SCL practices. In turn, the focal firm's resource input in the knowledge network preempts the resource input in the supply chain network and further enables the transfer of negative effects (e.g., attention overload) from the knowledge network to the supply chain network. Therefore, we show that whether negative embeddedness transfers from one network to another is context dependent.

Moreover, to account for both positive and negative effects of knowledge network embeddedness on SCL, we adopt a cost–benefit logic and theorize an inverted U-shaped relationship between the two. We show that the relationship is positive when knowledge network embeddedness is at a low to moderate level, because the benefit gained from its positive effects prevails over the cost of overcoming its drawbacks. By contrast, the relationship is negative when knowledge network embeddedness is at a moderate to high level, because costs override the benefit. The empirical evidence lends strong supports to our theorization. As such, we extend the double-edge sword of embeddedness in a dual-network setting, evidencing that not only advantages but also disadvantages in one network will affect firms' practices in another network.

Third, we contribute to the supply chain and network pluralism literature streams by examining the boundary condition between knowledge network embeddedness and SCL. We position supply chain network cohesion as a theoretical moderator and empirically show that it enhances the overall level of firms' collective learning by strengthening the positive effect and alleviating the drawbacks of high knowledge network embeddedness. As we delineate, when knowledge network embeddedness is at a low or moderate level, high supply chain network cohesion helps firms strengthen their existing relationships based on trust gained from frequent interactions, as such cohesion entails more long-term collective learning activities with more supply chain partners. In this way, cohesion amplifies the benefits transferred from knowledge network embeddedness to the supply chain network. Moreover, when knowledge network embeddedness is high, the problem of over-embeddedness can also be mitigated, because a cohesive network will entail more trust-based interactions between supply chain partners within a cohesive subgroup in the network. Such interactions facilitate more tacit knowledge exchange (Guler and Nerkar, 2012; Jiang *et al.*, 2018) and, in turn, alleviate the problem of knowledge redundancy and collaboration opportunism due to high embeddedness, thereby lowering the cost of overcoming the drawbacks of high embeddedness. Therefore, the examination of the contingent role of network cohesion contributes to a comprehensive understanding of the mechanism that shapes the interplay between networks (Carpenter *et al.*, 2012; Zhou *et al.*, 2014).

5.2 Practical implications

This study provides practical implications for firms' SCL and co-creating collaborations. First, we emphasize the importance of tackling supply chain hurdles in a wider context. Managers should consider improving SCL not only by building up their learning capabilities within the supply chain network but also by assessing other networks (Shipilov *et al.*, 2014) in which they participate. This is especially the case when a firm is engaging in substantial knowledge creation and exchange activities (e.g., patenting). For example, to gain advantages from its knowledge network, the technology corporation Huawei, one of the largest telecommunications equipment providers in China, maintained close collaborations with universities and laboratories in terms of R&D (Liefner *et al.*, 2019). During the COVID-19 pandemic, many firms may have tried to collaborate closely with their partners to overcome the negative impacts, but not all firms had advantages of novel knowledge stock and technologies to secure supply chain collaborations. With cutting-edge 5G technology at hand, Huawei secured supply chain stability and signed contracts for many 5G projects worldwide under the new political climate and global pandemic (Xiong, 2020).

Second, managers need to pay attention to the over-embeddedness problem (Zhou *et al.*, 2014). Investing in novel knowledge by participating in knowledge networks with innovation actors is critical for maintaining strategic competence, but negative influences may arise when the costs of resources and attention exceed the benefits firms can obtain in keeping a high embeddedness position. Such negative effects can restrict firms' SCL and eventually decrease their operation performance.

Third, firms can rely on supply chain network cohesion to better leverage the advantages gained from participating in the knowledge network and mitigate the negative effects of high knowledge network embeddedness. This is because strong network cohesion not only helps firms build stable relationship with more supply chain partners but also reduces collaboration costs, thus alleviating the negative impacts of high embeddedness. For example, to mitigate the negative external impacts of the COVID-19 pandemic and political uncertainty, Huawei introduced a range of new corporate supply chain policies to enhance production/sales coordination and introduced smarter digital operations (Xiong, 2020). Approaches such as all-party collaboration alignment and planning significantly strengthened the network cohesion in Huawei's supply chain network by establishing close collaborations among its suppliers and customers. As such, the negative effects of knowledge network embeddedness (e.g., attention overload, opportunism behaviors) were alleviated, leading to better performance in supply chain collaborations.

5.3 Limitations and future research directions

Our study has limitations that future research could address. Our study of firms' SCL does not shed light on the different types of knowledge exchange—explicit and tacit. Future research could thus interpret the SCL mechanism in a more comprehensive way by including both explicit and tacit knowledge. For example, studies could incorporate contract-based supply chain interactions (Zhou *et al.*, 2014) and strategic alliance–based trust building (Gulati, 1999) into the SCL process for a fully unveiled explanation.

Whereas we highlighted the impacts of network embeddedness in this study, future research could consider different types of network features. For example, the supply chain network is commonly viewed as having a small-world feature (Hearnshaw and Wilson, 2013), which results in the problem of network stability when facing major turbulence and uncertainty. Following this logic, future research could explore the interplay of different network features from multiple networks.

While data collected from Chines listed firms support the findings of our study, the generalizability of such findings should be further tested in different empirical settings, as the importance of interorganizational interactions is dependent on the Chinese cultural background of *guanxi* (Chen and Chen, 2004). To validate such theoretical stances, cross-country research or in-depth case studies in other countries and regions would be beneficial.

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Tables

Table 1 The overlaps and distinctions between the knowledge network and the supply chain network

Networks	Knowledge network	Supply chain network
Definition	A network defined by a set of "nodes" (individuals or higher-level collectives) that serve as heterogeneously distributed repositories of knowledge and agents that search for, transmit, and create knowledge, and by a set of "connections" that are interconnected by social relationships that enable and constrain nodes' efforts to acquire, transfer, and create knowledge (Phelps *et al.*, 2012).	A network defined by a set of "nodes" that represent autonomous business units as firms that are able to exercise sovereign choices and by a set of "connections" that link these firms together for the purpose of creating products or services (Hearnshaw and Wilson, 2013).
General network structure	**Nodes** Knowledge elements, Organizations **Relationships** Cognitive, social, technological, or associational (Hearnshaw and Wilson, 2013).	**Nodes** Business units **Relationships** Contracts, material flows, information flows, financial flows (Hearnshaw and Wilson, 2013).
Distinctions	**Nodes** Knowledge elements, Individual or social collectives. **Content of relationship** Knowledge exchange through novel knowledge production (e.g., patenting).	**Nodes** Business units (firms) **Content of relationship** The acquisition of specific, complex product and process knowledge, instead of novel knowledge (Zhou *et al.*, 2014).
Overlaps	**Nodes** Firms in supply chain **Content of relationship** Tacit, difficult-to-imitate knowledge (Isaksson *et al.*, 2016; Li *et al.*, 2010).	

Table 2 Sample profile

Industry	N	%	*Year*	N	%
Agriculture, forestry, livestock and fisheries	9	0.429	2011	95	4.524
Mining	105	5.000	2012	210	10.000
Manufacturing	1508	71.810	2013	293	13.952
Electricity, heat, gas and water supply	56	2.667	2014	200	9.524
Construction	62	2.952	2015	231	11.000
Retail and wholesale	36	1.714	2016	248	11.810
Transportation	21	1.000	2017	266	12.667
Information services	159	7.571	2018	248	11.810
Finance	76	3.619	2019	211	10.048
Real Estate	15	0.714	2020	98	4.667
Rental and business services	4	0.190	**Total**	2100	100
Scientific Research and Technical Services	12	0.571			
Water, Environment and Public Facilities Management	16	0.762			
Education	5	0.238			
Entertainment	8	0.381			
General	8	0.381			
Total	2100	100			

Firm size (ln): Log value of total assets	N	%
Less than 19.03 (Mean – 2SD)	0	0
Between 19.03 and 21.08 (Mean – SD to Mean – 2SD)	244	11.619
Between 21.08 and 23.13 (Mean –SD to Mean)	1007	47.952
Between 23.13 and 25.18 (Mean to Mean + SD)	587	27.952
Between 25.18 and 27.23 (Mean + SD to Mean + 2SD)	154	7.333
More than 27.23 (Mean + 2SD)	108	5.143
Total	2100	100

Firm revenue (ln): Log value of operating income	N	%
Less than 12.95 (Mean – 2SD)	68	3.238
Between 12.95 and 17.31 (Mean – SD to Mean – 2SD)	1	0.048
Between 17.31 and 21.67 (Mean –SD to Mean)	788	37.524
Between 21.67 and 26.03 (Mean to Mean + SD)	1177	56.048
Between 26.03 and 30.39 (Mean + SD to Mean + 2SD)	66	3.143
More than 30.39 (Mean + 2SD)	0	0
Total	2100	100

Table 3 Model variable definitions

Definitions	Measurement
Supply chain learning (SCL)	The collective learning that happens among multiple supply chain players (Bessant *et al.*, 2003). Measured by a firm's times of collaborations with partners in the supply chain network.
Knowledge network embeddedness (KNE)	Embeddedness is referred as the structure of a focal firm's relationship with other organizations (Ahuja, 2000b; Granovetter, 1985). Measured by a firm's network constraint (Burt, 1992) in the knowledge network.
Supply chain network cohesion (SCNC)	The connectedness and togetherness among actors within a network (Marsden, 1993). Measured by the overall density of supply chain network (Marsden, 1993).
SCNC × KNE	Interaction term of SCNC and KNE (First order term).
SCNC × KNE^2	Interaction term of SCNC and KNE^2 (Second order term).
Control variables	
Firm size	Logarithm of a firm's total assets.
Firm age	Logarithm of the number of years a firm has been listed
Tobin's q	The ratio of the market value of an asset to its replacement cost.
R&D intensity	A firm's R&D expenditure divided by its total assets.
State ownership	Whether the firm is state-owned. Equals 1 when firm is state-owned, and 0 otherwise.
GDP	GDP growth rate of the province the focal firm locate in.
Leader change	Whether there is a change of the head of the provincial government. Equals to 1 if the head of the provincial government is replaced in year t and 0 otherwise;
Marketization	An assessment of relative progress in marketization for China's provinces (Wang *et al.*, 2007).

Table 4 Summary statistics

Variables	Mean	SD	Min	Median	Max
Supply chain learning	2.040	1.990	1	1	22
Knowledge network embeddedness	0.532	0.331	0.040	0.467	1.540
Supply chain network cohesion	0.003	0.080	0	0	2.841
Firm size (ln)	23.130	2.047	19.506	22.738	31.036
Firm age (ln)	2.170	0.798	0.000	2.398	3.332
Tobin’s q	1.816	1.239	0.734	1.398	13.313
R&D intensity	0.024	0.034	0	0.019	0.700
State ownership	0.513	0.500	0	1	1
GDP	0.104	0.042	0.003	0.096	0.265
Leader change	0.446	0.497	0	0	1
Marketization	8.943	1.586	-0.161	9.192	11.494

Table 5 Correlations

		1	2	3	4	5	6
1	Supply chain learning		.077**	.106**	.074**	-.021	-.136**
2	Knowledge network embeddedness	.052*		-.011	-.369**	-.175**	.139**
3	Supply chain network cohesion	.128**	.002		.053*	.014	-.041
4	Firm size (ln)	.123**	-.311**	.079**		.423**	-.649**
5	Firm age (ln)	-.037	-.178**	.006	.313**		-.260**
6	Tobin's q	-.061**	.087**	-.019	-.413**	-.107**	
7	R&D intensity	.010	-.086**	-.017	-.204**	-.087**	.189**
8	State ownership	.128**	-.150**	.037	.451**	.410**	-.240**
9	GDP	.153**	.155**	-.008	-.035	-.111**	-.055*
10	Leader change	-.010	-.014	-.034	-.019	-.007	-.040
11	Marketization	-.092**	-.093**	.005	-.002	-.098**	.117**

		7	8	9	10	11
1	Supply chain learning	-.073**	.130**	.111**	-.012	-.140**
2	Knowledge network embeddedness	-.141**	-.152**	.123**	-.019	-.083**
3	Supply chain network cohesion	-.010	.056**	.028	-.052*	-.015
4	Firm size (ln)	-.386**	.491**	-.022	-.018	-.065**
5	Firm age (ln)	-.185**	.426**	-.092**	-.009	-.106**
6	Tobin's q	.369**	-.383**	-.025	-.004	.117**
7	R&D intensity		-.230**	-.013	-.034	.151**
8	State ownership	-.135**		.070**	-.041	-.237**
9	GDP	.021	.062**		.007	-.137**
10	Leader change	.003	-.041	-.004		-.017
11	Marketization	.121**	-.210**	-.195**	-.024	

Notes: Pearson correlations are below the diagonal; Spearman correlations are above the diagonal.
** $p < .05$, ** $p < .01$, *** $p < .001$*

Table 6 Regression results

	Model 1		Model 2		Model 3	
Firm size (ln)	-0.160	(-0.98)	-0.099	(-0.60)	-0.063	(-0.40)
Tobin’s q	-0.031	(-0.53)	-0.015	(-0.26)	-0.017	(-0.29)
Firm age (ln)	-0.829***	(-4.18)	-0.798***	(-4.03)	-0.792***	(-4.12)
R&D intensity	2.578	(1.58)	2.659	(1.63)	2.604*	(1.65)
State ownership	-0.634	(-1.19)	-0.711	(-1.34)	-0.705	(-1.36)
GDP	5.738***	(4.42)	5.101***	(3.87)	4.809***	(3.75)
Leader change	-0.076	(-0.88)	-0.055	(-0.63)	-0.032	(-0.37)
Marketization	-0.412***	(-3.49)	-0.393***	(-3.34)	-0.375***	(-3.28)
Knowledge network embeddedness			0.643***	(2.83)	0.621***	(2.81)
Knowledge network embeddedness^2			-2.430***	(-3.83)	-1.683***	(-2.70)
Supply chain network cohesion					-3.341***	(-4.33)
Supply chain network cohesion × Knowledge network embeddedness					-9.635***	(-3.20)
Supply chain network cohesion × Knowledge network embeddedness^2					212.756***	(7.93)
Constant	10.993***	(3.10)	9.325***	(2.61)	8.335**	(2.39)
N	2100		2100		2100	
Within R-squared	0.1329		0.1436		0.1930	
Firm fixed effects	YES		Yes		YES	

*Notes: t statistics in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$*

Table 7 Robustness check 1

DV: SCL from suppliers	Model 1		Model 2		Model 3	
Firm size (ln)	-0.343***	(-2.66)	-0.310**	(-2.39)	-0.296**	(-2.30)
Tobin's q	0.048	(1.04)	0.057	(1.25)	0.057	(1.26)
Firm age (ln)	-0.385**	(-2.45)	-0.374**	(-2.38)	-0.376**	(-2.41)
R&D intensity	2.516*	(1.94)	2.571**	(2.00)	2.552**	(1.99)
State ownership	-0.049	(-0.11)	-0.120	(-0.28)	-0.120	(-0.28)
GDP	5.008***	(4.88)	4.736***	(4.54)	4.577***	(4.39)
Leader change	-0.078	(-1.14)	-0.066	(-0.97)	-0.065	(-0.95)
Marketization	-0.255***	(-2.72)	-0.244***	(-2.62)	-0.240***	(-2.58)
Knowledge network embeddedness			0.330*	(1.83)	0.329*	(1.83)
Knowledge network embeddedness^2			-1.874***	(-3.73)	-1.673***	(-3.31)
Supply chain network cohesion					-1.707***	(-2.72)
Supply chain network cohesion × Knowledge network embeddedness					-4.304*	(-1.76)
Supply chain network cohesion × Knowledge network embeddedness^2					62.112***	(2.85)
Constant	11.491***	(4.10)	10.670***	(3.77)	10.344***	(3.66)
N	2100		2100		2100	
Within R-squared	0.1182		0.1282		0.1364	
Firm fixed effects	YES		YES		YES	

Notes: t statistics in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 8 Robustness check 2

	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6	
Dependent variable	SCL from suppliers		SCL from suppliers		SCL from suppliers		SCL		SCL		SCL	
Firm size (ln)	0.114***	(5.20)	0.128***	(5.68)	0.131***	(5.85)	-0.090	(-1.19)	-0.067	(-0.88)	-0.054	(-0.71)
Tobin's q	0.032	(1.14)	0.035	(1.23)	0.037	(1.30)	-0.017	(-0.68)	-0.016	(-0.64)	-0.016	(-0.65)
Firm age (ln)	-0.183***	(-4.02)	-0.170***	(-3.73)	-0.170***	(-3.73)	-0.343***	(-3.99)	-0.321***	(-3.71)	-0.320***	(-3.70)
R&D intensity	1.451**	(2.32)	1.635***	(2.62)	1.647***	(2.64)	0.954	(1.34)	0.997	(1.40)	0.990	(1.39)
State ownership	0.271***	(3.06)	0.258***	(2.93)	0.243***	(2.77)	-0.306	(-1.07)	-0.334	(-1.18)	-0.333	(-1.18)
GDP	4.154***	(7.06)	3.664***	(6.03)	3.523***	(5.79)	1.781***	(3.26)	1.512***	(2.71)	1.459***	(2.61)
Leader change	-0.047	(-1.00)	-0.033	(-0.69)	-0.028	(-0.58)	-0.028	(-0.72)	-0.017	(-0.43)	-0.008	(-0.22)
Marketization	-0.074***	(-3.07)	-0.075***	(-3.08)	-0.076***	(-3.15)	-0.201***	(-3.66)	-0.189***	(-3.44)	-0.182***	(-3.32)
Knowledge network embeddedness			0.333***	(3.06)	0.328***	(3.01)			0.299***	(2.89)	0.297***	(2.87)
Knowledge network embeddedness^2			-1.388***	(-4.15)	-1.296***	(-3.86)			-1.196***	(-4.01)	-1.091***	(-3.65)
Supply chain network cohesion					-0.798**	(-2.48)					-0.350	(-1.47)
Supply chain network cohesion × Knowledge network embeddedness					-1.511	(-1.18)					-0.717	(-0.92)
Supply chain network cohesion × Knowledge network embeddedness^2					32.607***	(3.75)					21.289***	(3.26)
N	1376		1376		1376		1706		1706		1706	
Wald chi2	154.99		173.21		190.53		181.49		198.21		216.49	
Firm fixed effects	YES		YES		YES		YES		YES		YES	

Notes: t statistics in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 9 Test of inverted U-shaped relationship

Curve type	Inverted U-shape
Estimated extreme point	.184***
95% confidence interval	[.077; .474]
Test of joint significance of control variables (p-value)	chi2(8) = 16.09***
Test of joint significance of all variables	chi2(13) = 22.4***

* *p < 0.05,* ** *p < 0.01,* *** *p < 0.001*

Figures

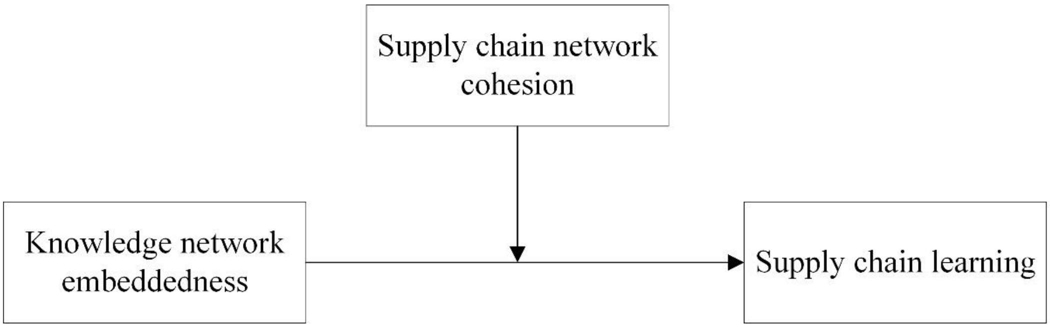

Figure 1 Conceptual framework

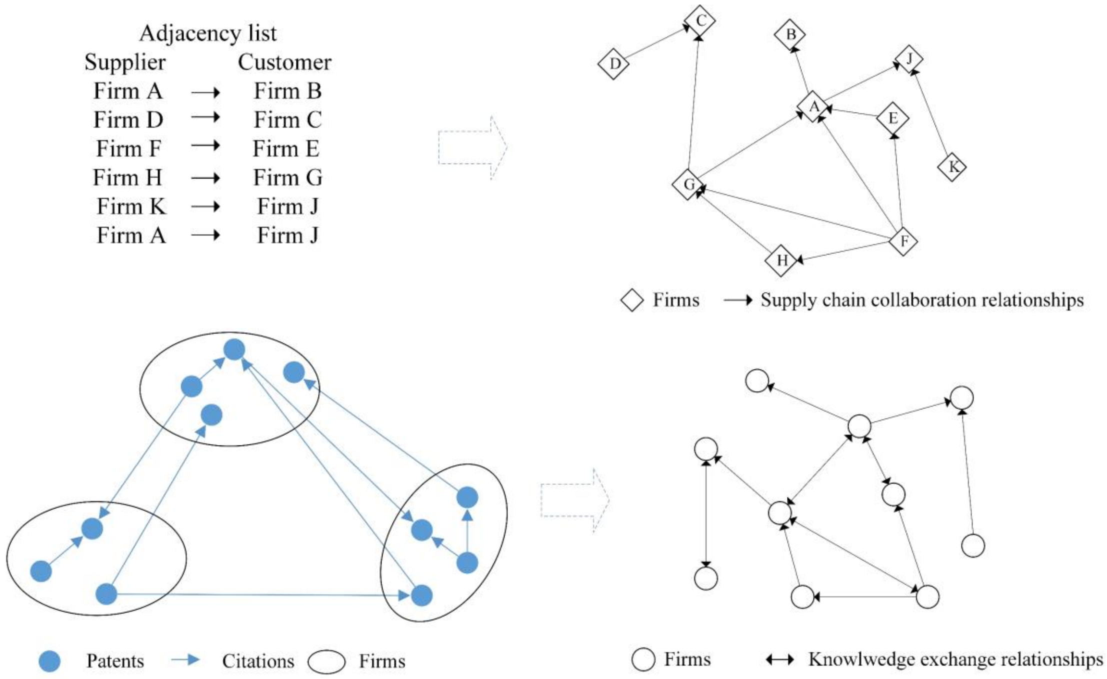

Figure 2 Construction of networks

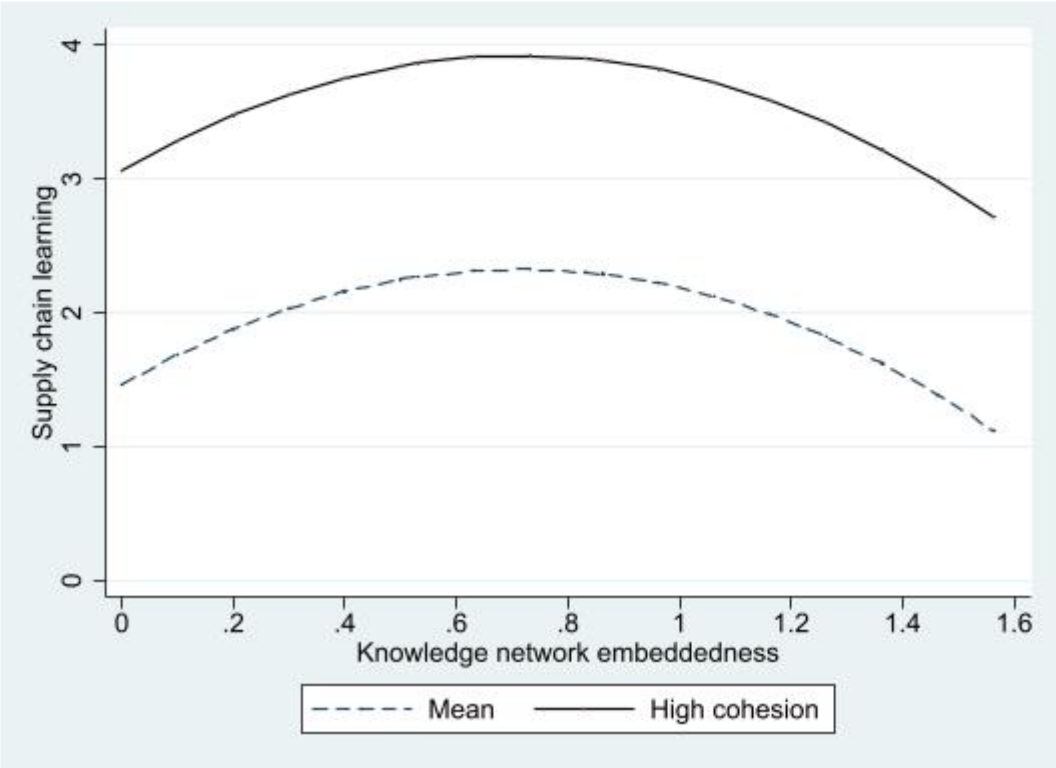

Figure 3 Moderating effect of supply chain network cohesion