

The Roles of Supply Networks and Board Interlocks in Firms' Technological Entry and Exit: Evidence from the Chinese Automotive Industry

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ABSTRACT In this research, we explore how supply networks and board interlocks – as distinct, yet parallel interorganizational networks – jointly influence firms' entry into new technology domains and exit from old technology domains. Drawing from the perspectives of social networks and organizational learning we highlight the relevance of the interdependency between these networks for a firm's technological entry and exit decisions. We argue that a firm that maintains a large number of supplier ties is more likely to enter new technology domains and exit from old technology domains instead. We further find empirical evidence that the degree centrality of a firm in its board interlock network strengthens these effects. Our theoretical arguments are supported through stochastic actor-based modeling analysis for the longitudinal and multilevel networks of 86 firms active in the Chinese automotive during 2011–2015. These findings inform the literature on interorganizational network dynamics as we insert relational pluralism to examine the complexities of organizational relationships as antecedents to a firms' technological entry and exit. Finally, we imagine the implications of our analysis for management as they shed light on how multiple interorganizational relationships affect firms' decisions on new technology entry and old technology exit.

KEYWORDS Chinese automotive industry, corporate board interlocks, stochastic actor-oriented modeling (SAOM), supply networks, technology entry and exit

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INTRODUCTION

Researchers are becoming increasingly interested in how firms continuously renew their technological knowledge to sustain competitive advantage (Aalbers, McCarthy, & Heimeriks, 2021; Leten, Belderbos, & Looy, 2016). The organizational ambidexterity literature has outlined the relevance of simultaneous pursuing exploratory and exploitative opportunities for upgrading the knowledge base (Luger, Raisch, & Schimmer, 2018; March, 1991). A firm might explore novel

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technologies through entering new technology domains (NTDs), the so-called *technological entry* (Candiani, Gilsing, & Mastrogiorgio, 2022; Leten et al., 2016). It may also refine and extend existing technologies by exploiting old technology domains (OTDs), or it will stop exploiting existing technologies by exiting from the OTDs that no longer fit the future technology profile, the so-called *technological exit* instead (Malerba & Orsenigo, 1999; Miller & Yang, 2016). This ongoing quest to adapt to the changing environment makes it vital to understand the dynamics of firms' technological entry and exit (Chang, 1996; Malerba & Orsenigo, 1999; Miller & Yang, 2016).

A network-based view of the firm, observing organizations as simultaneously connected through different types of relationships, provides a theoretical lens to address the relational dynamics undergirding a firm's technological entry and exit decisions (Beckman, Schoonhoven, Rottner, & Kim, 2014; Shipilov, Gulati, Kilduff, Li, & Tsai, 2014; Zhang, Jiang, Wu, & Li, 2019). This emerging network pluralism perspective highlights that the multiple networks firms are embedded in simultaneously may be heterogeneous and can interplay with each other in affecting innovation activities (Shipilov et al., 2014; Zhang et al., 2019). Recently, supply chain scholars have examined the innovation effects of buyer–supplier ties which evolve from operational product flows (Bellamy, Ghosh, & Hora, 2014; Gao, Xie, & Zhou, 2015; Sharma, Pathak, Borah, & Adhikary, 2020), while the strategy scholars have examined how firms explore novel technologies through board interlock ties which facilitate strategic knowledge exchange beyond product flows (Li, 2019, 2021; Srinivasan, Wuyts, & Mallapragada, 2018).

However, prior work has mostly treated the two types of operational and strategic relationships independently from one another. Limited research has examined the interaction between supply networks and board interlocks as a result, with the study by Mahmood, Zhu, and Zajac (2011) as a notable exception. By focusing on the intragroup ties in business groups, Mahmood et al. (2011), for instance, revealed that the centrality of a group affiliate's position in the intragroup director network reinforces the positive relationship between the centrality in the buyer–supplier network and its R&D capability. Moreover, while prior network research has focused more on innovation outputs than innovative behavior (e.g., entry in NTDs and exit from OTDs), the implications of multiple networks on technological entry/exit decisions have remained largely unexamined. Thus, it is valuable to investigate the interactive effects of co-occurring supply networks and board interlocks on a firm's technological entry/exit choices from the network pluralism perspective. Following this logic, we address the following research question: *What is the joint influence of a firm's supply network and board interlock network on the firm's entry into NTDs and exit from OTDs?*

Drawing from the perspectives of social networks and organizational learning, our study first examines the role of supply networks in a firm's technological entry and exit. By prioritizing our investigations on the role of the supplier rather than the buyer in the context of automotive manufacturing (Narasimhan & Narayanan,

2013; Sharma et al., 2020), we argue that a focal firm will enter into NTDs and exit from OTDs by leveraging knowledge spillovers from a larger number of suppliers. Second, we further argue that as board interlocks function as an alternative communication mechanism that helps to identify the trustworthiness of partners, facilitate interpersonal trust, and increase mutual understanding and goodwill (Aalbers, Dolfsma, & Koppius, 2014; Mizruchi, 1996), firms that occupy a central position in the board interlock networks are more likely to benefit from supply networks to enter into NTDs and also exit from OTDs.

We test our theoretical arguments using stochastic actor-based modeling (SAOM) for multilevel network dynamics on a set of 86 publicly listed firms active in the Chinese automotive industry during the period 2011–2015. We find evidence of both a firm's operational supply network and its interplay with the strategic board interlock network as foundations for a firm's technological entry and exit. Specifically, we find that a firm's indegree centrality in its supply network is positively associated with the likelihood of the firm's entry into NTDs and exit from OTDs, while a firm's degree centrality in its board interlock network will strengthen these effects.

Our study contributes to the literature on technological dynamics from a network pluralism perspective by highlighting the joint role of different types of networks in determining a firm's decisions to enter and exit technology domains. We also contribute to the rich literature on supply networks and board interlocks by showing that the effectiveness of underlying supplier relations is influenced by a firm's position in its strategic board interlock network that provides access to the industry-wide exchange of knowledge at the highest managerial level.

THEORETICAL BACKGROUND

Technological Entry and Exit

According to a dynamic knowledge-based perspective of the firm, a firm is not only an accumulation of knowledge, but is also engaged in a continuous search and selection process to enter into NTDs and exit from OTDs (Miller & Yang, 2016). Technology domains have specific meanings within the context of patented invention, that is the technological classes (e.g., the International Patent Classification (IPC)) to which a firm applies for a patent (Gilsing, Nooteboom, Vanhaverbeke, Duysters, & Van Den Oord, 2008; Guan & Liu, 2016). Here, an NTD refers to a technology domain where the firm has no prior active invention activity (Gilsing et al., 2008), while an OTD refers to an existing technology domain in which the firm has previously engaged in inventive activity (Guan & Liu, 2016). A firm's decisions to enter into NTDs or exit from OTDs are motivated by the changes in technology opportunities in the external environment (Leten et al., 2016). Firms are constantly searching externally for new technologies to enter, and internally for existing technologies to expand or contract (and eventually

exit) (Chang, 1996). In this article, we conduct a joint examination of the firms' technological entry and exit decisions over time, aiming to advance our understanding of the dynamics of firms' knowledge base.

Organizational Learning Through Interfirm Networks

Organizational learning, a process of acquiring and integrating knowledge (Huber, 1991), occurs when a firm changes its innovative behavior by leveraging the external knowledge. Drawing from social network and organizational learning perspectives, we focus on two possible learning processes that explain technological entry and exit through interfirm networks: vicarious learning and experiential learning (Li, 2021). First, a focal firm might seek to emulate the technologies that exist in the portfolios of connected firms, hence imitating successful routines or gaining knowledge by observing other firms, so-called vicarious learning (Kim & Miner, 2007). Second, firms could engage in searching for technologies from experience, so-called experiential learning. Firms can increase their knowledge through new experiences in performing novel tasks (Katila & Ahuja, 2002). Our theorizing from an organizational learning perspective on interfirm networks allows us to study the heterogeneous learning mechanisms through strategic as well as operational networks.

In comparison to a supplier tie that holds direct relationships to the operational ongoing of a firm, a board interlock tie develops when members of an executive or supervisory board of one firm also occupy positions in the board of another firm (Haunschild, 1993; Westphal, Seidel, & Stewart, 2001). A growing body of literature has emphasized the influence of board interlock networks on various corporate decisions and actions (Mizruchi, 1996; Srinivasan et al., 2018). Hence, firms are connected through both buyer–supplier relations as well as board interlock relations interacting at various managerial tables simultaneously (Mahmood et al., 2011). Whether and how firms learn from their supply network is finalized by corporate leaders, who, if embedded in the board interlock network, identify a unique future of relational pluralism that abridges across the operational and strategic intent of the exchange. This underpins the importance to build on the network pluralism perspective, to examine how supply networks and board interlock networks jointly influence firms' technological entry and exit decisions.

HYPOTHESES DEVELOPMENT

The Role of Supply Network in Firms' Technological Entry and Exit

The supply chain management literature has long acknowledged the advantages of embedding suppliers in the innovation process (Choi & Hong, 2002; Choi & Krause, 2006). Deriving knowledge from external sources such as suppliers is evidently a substantial part of organizational learning that helps an organization

innovate (Sharma et al., 2020). For instance, firms in the automotive are increasingly relying on knowledge assets of specialized suppliers to produce next generation of products and services (Narasimhan & Narayanan, 2013; Sharma et al., 2020). Firms have higher indegree centrality in supply network when they have a larger number of supplier partners (Lu & Shang, 2017; Potter & Wilhelm, 2020). In this article, we focus on the role of suppliers (i.e., indegree centrality) in firms' technological entry and exit.

Indegree centrality in supply network and firms' technological entry. To enter into NTDs, a firm can learn about various technological opportunities through suppliers. Supply network research suggests that firms connected with a large number of suppliers demonstrate greater innovation output because these networks provide generous access to novel knowledge and expertise for buyer firms (Bellamy et al., 2014; Gao et al., 2015). As mentioned, firms can benefit from their suppliers via two possible learning processes.

First, firms can imitate successful routines or gain knowledge by observing the outcomes from the connected supplier firms through vicarious learning (Kim & Miner, 2007). As the number of suppliers increases, a firm can gain more opportunities to involve suppliers in product design and development activities. The supplier firm that initiates technological exploration may inspire the focal firm to adopt similar practices and explore new technological domains, thus facilitating the transfer of knowledge from suppliers toward the innovation process (Lawson, Krause, & Potter, 2015). For instance, through the mechanism of guest engineering, automakers involve technical personnel of suppliers to incorporate their knowledge into the product design and its innovation (Choi & Hong, 2002). The automakers such as Toyota can also increase the frequency of supplier-laboratory knowledge spillovers at its central R&D laboratory (Potter & Paulraj, 2021). Therefore, firms with high indegree centrality in supply networks have an increased likelihood of exploring technologies of connected supplier firms, resulting in NTD entries via direct knowledge spillovers.

Second, a focal firm may also enter into broad NTDs through experiential learning that enables firms to accumulate industrial experience by performing novel tasks (Katila & Ahuja, 2002). Having high indegree centrality in supply network may allow the focal firm to consider different product or process innovation issues, understand recent technological developments, and see altogether different worlds related to emerging technologies (Beckman & Haunschild, 2002). A firm hence can gain more opportunities to access and process new technology developments, which may help to create unique recombination and exploratory innovation (Costantino & Pellegrino, 2010; Sharma et al., 2020). Moreover, the focal firm may also encourage multiple competing suppliers to collaborate with each other, therefore providing for unique knowledge resources (Choi & Hong, 2002; Wu, Choi, & Rungtusanatham, 2010). In this way, firms may enter novel technological domains that are broader at the industry level.

With firms increasingly exposed to various technological advancements and related new opportunities through multiple suppliers, we hence expect that a firm with a high indegree centrality in supply network is more likely to enter into NTDs. Therefore, we hypothesize that:

Hypothesis 1a: A firm's indegree centrality in its supply network is positively associated with the likelihood of the firm's entry into NTDs.

Indegree centrality in supply network and firms' technological exit. To maintain in OTDs, a firm needs to search and exploit its technological opportunities in existing domains (Narasimhan & Narayanan, 2013). When firms have low indegree centrality in their supply network, they tend to innovate exploitatively in the existing domains, leading to maintenance in OTDs. There are many good reasons why firms should exploit a narrow set of supplier relationships, for instance because of lower search costs, more easily established trustworthiness, and better monitoring suppliers that accumulate accurate and timely information (Costantino & Pellegrino, 2010; Lu & Shang, 2017). Controversially, engaging with limited suppliers runs the risk of locking the firms into prior mental models, which results in a drift into exploitation at the expense of exploration (Crossan & Berdrow, 2003; Luger et al., 2018). The opportunity set for further exploitative search reveals diminishing returns over time until a new technology is invented and adopted (Chang, 1996; Sharma et al., 2020).

As the number of suppliers increases, the focal firm faces more external technology opportunities to avoid lock-in dynamics in times of competence-destroying technological change. The increased supplier partners may provide additional ways to obtain comparable knowledge and resources that make an existing partner substitutable. In this regard, firms need to address the fundamental tension of strategic renewal – the tension between technology exploration and exploitation (Agarwal & Helfat, 2009; Crossan & Berdrow, 2003). Firms may renew their knowledge base through the refreshment or replacement of existing technology elements that has the potential to substantially affect its long-term prospects, thus breaking away from the status quo of technology exploitation (Agarwal & Helfat, 2009; Barr, Stimpert, & Huff, 1992). In this regard, firms are more likely to exit existing technology domains to effectively fit the technology development of the increased connected suppliers or even the whole industry.

In sum, we posit that possessing multiple suppliers gives a firm wider reach and access to knowledge and information in the supply networks, which will enhance the likelihood of exiting from OTDs. We hence hypothesize:

Hypothesis 1b: A firm's indegree centrality in its supply network is positively associated with the likelihood of the firm's exit from OTDs.

The Moderating Role of Board Interlock Networks

While being connected to an array of suppliers might benefit buyer firms' entry into NTDs and exit from OTDs, as argued under Hypothesis 1a/b, not all firms equally gain these potential benefits. The decisions to leverage supplier relations into technological entry and exit are finalized by corporate leadership who are embedded in the board interlock network (Li, 2019; Mahmood et al., 2011). Thus, as a firm concurrently positions itself in its supply network next to its board interlock position, the two networks are likely to interact and jointly influence a firm's technological entry and exit.

Based on the prior work of Mahmood et al. (2011) and Mazzola, Perrone, and Kamuriwo (2016), we argue that board interlocks can provide two resource advantages in particular, namely complementary generic knowledge and credible information, which affects firms' accessing and assimilating technology knowledge deriving from supply networks. Through board interlock networks, firms could access a plurality of strategic-oriented generic knowledge, which may well complement specific knowledge provided by their operational-oriented supplier ties (Mahmood et al., 2011). Moreover, board interlocks can provide more credible information about ongoing and foreseen innovative practices due to the higher level of trust between interlocked directors (Li, 2021), thus allowing the firm to better evaluate the reliability, accuracy, and quality of information from its supply networks (Mazzola et al., 2016; Mizruchi, 1996).

The moderating effect of board interlocks on technological entry. While having a large number of suppliers in the supply network allows the focal firm to acquire specific knowledge related to operational product development (Lawson et al., 2015; Potter & Wilhelm, 2020), board interlocks may provide complementary generic and strategic knowledge that determines how efficiently available resources can be combined with administrative arrangements in a firm to achieve its innovative goals (Mahmood et al., 2011; Shropshire, 2010). Generic knowledge exchange via board interlocks tends to be more macro oriented in nature, thus encompassing an understanding of broad technological paradigms, best practices, and external market opportunities (Mahmood et al., 2011; Shropshire, 2010). Access to generic knowledge via this relational route provides firms an opportunity to integrate, build, and efficiently reconfigure their knowledge base when responding to changing supply networks. Thus, board interlocks facilitate the exchange of fine-grained information of a strategic caliber that would be of benefit to firms considering whether to enter into NTDs through their suppliers or not (Mahmood et al., 2011; Mazzola et al., 2016).

Moreover, board interlock ties can facilitate coordination and reduce uncertainty about the availability of resources when these ties occur with suppliers (Mazzola et al., 2016; Mizruchi, 1996). Due to the higher level of trust between interlocked directors, board interlock ties tend to provide richer and more credible

strategic information for firms, compared with firms that lack such strategic embeddedness. As a consequence, board directors can help the management of the firm reducing the cost of finding useful information, filtering redundant information, and certifying incoming knowledge as legitimate and potentially useful for technology exploration (Mazzola et al., 2016). Thus, firms with a higher number of interlocking partners would have a better chance of making sound strategic decisions, enabling firms to successfully leverage advanced knowledge and novel ideas obtained from their suppliers to enter into NTDs.

In sum, the advantage of supplier partners in firms' entry into NTDs can be more effectively realized when accompanied by the presence of multiple board interlock ties. Hence, we posit the following hypothesis:

Hypothesis 2a: A firm's degree centrality in its board interlock network strengthens the positive effect of indegree centrality in its supply network on the firm's entry into NTDs.

The moderating effect of board interlocks on technological exit. When deciding whether to sustain innovation activities in an existing technology domain, firms need to consider the benefits and costs of exploiting technology opportunities in that domain. As the degree centrality in board interlock network increases, the enhanced exchange of information on novel technology opportunities among interlocking firms could partially offset the focal firm's reliance on supplier partners to dig deeper into the pre-existing technology domains (Mazzola et al., 2016). Although the costs and uncertainty of tapping into technology opportunities from suppliers in established technology domains may be low, firms with more interlocking partners also tend to underestimate the corresponding benefits, especially as external industry-level technology opportunities continue to emerge (Li, 2019; Mahmood et al., 2011). A well-connected board can substantially shift the firm's attention to timely and effectively identifying technology opportunities in new areas rather than existing ones (Li, 2021).

Additionally, when the focal firm is connected with multiple board interlock partners, this will enable the firm to more accurately identify and efficiently leverage its suppliers to explore technology opportunities in NTDs, when the strategic relevance is deemed (Li, 2019; Mahmood et al., 2011; Mazzola et al., 2016). Accordingly, the focal firm will be more empowered to allocate needed resources and furnish supportive systems for exploration rather than exploitation, thus shifting their capabilities away from established technology domains familiar to their suppliers (Chang, 1996; Li, 2021). By doing so, a firm is more likely to be proactive in updating its technology portfolios by exiting old technology domains and entering new ones.

Taken together, as a firm's degree centrality in the board interlock network increases, both the motivation and the ability of the firm to sustain innovation in the existing technology domains derived from its supply networks tend to be weakened, making the positive effect of the supply network on its exit from OTDs more prominent. As such we hypothesize:

Hypothesis 2b: A firm's degree centrality in its board interlock network strengthens the positive effect of indegree centrality in supply network on the firm's exit from OTDs.

METHODS

Empirical Context and Data

To test our hypotheses, we used the Chinese automotive industry as empirical setting, which remains the world's largest automotive production and market since 2009.^[1] We selected it for three reasons that are consistent with our study. First, the automotive industry is characterized by a high degree of value added by multiple suppliers in manufacturing as well as in the engineering of car components (Quesada, Syamil, & Doll, 2006). Interfirm networks along the automotive supply chain have been proved effective ways to create competitive advantages (Narasimhan & Narayanan, 2013; Zhou, Zhang, Sheng, Xie, & Bao, 2014). Second, in the economic and political transition in China, a historical country in which networks (i.e., *guanxi*) are traditionally valued, interorganizational ties play particularly important roles in determining firms' actions and outcomes (Zhou et al., 2014). Third, the automotive industry is a highly patent-intensive industry, which features strong motives to develop and commercialize the patented inventions to defend their particular market niche (Faria & Andersen, 2017). Thus, Chinese automotive provides an ideal context to examine the impacts of interfirm networks on firms' technological entry and exit.

We center on the set of automotive companies listed in the Chinese A-share Shanghai or Shenzhen Stock Exchanges during the period 2011–2015 as our sample. We chose the five-year period of 2011–2015 as the time window for our study. In the *Outline of the Twelfth Five-Year (2011–2015) Plan for National Economic and Social Development of the People's Republic of China*, the Chinese government has proposed that the automotive industry should strengthen the research and development capabilities of the entire vehicle and increase the autonomy of key components technologies, which provides a specific timeframe for our observation of firms' technological upgrade.

Moreover, the Chinese automotive listed companies were identified according to the Industry Classification Guide of Listed Companies issued by the China Securities Regulatory Commission. We specifically searched from the China Stock Market & Accounting Research (CSMAR) Database, which offers reasonably consistent and complete data on China's listed companies (Han, Bose, Hu, Qi, & Tian, 2015). On November 8, 2018, we searched CSMAR for all listed companies in the automotive manufacturing industry that went public before 2015. Then, we removed four firms in our sample that were delisted or changed the industry of their main business after 2015. Thus, the number of our sample firms increases year by year due to newly listed companies. Furthermore, considering that there could exist systematic correlations between

firms' financial performance and technological innovation, we did not exclude the samples that belong to ST (Special Treatment) firms during 2011–2015 to avoid the possible selection bias. There are three firms in our sample that had been labeled as ST firms because of two continuous years of financial loss, including Hunan Tyen Machinery, Dongan Auto Engine, and Xiyi. The sample selection process resulted in 86 distinct sample firms in the Chinese automotive. Our final sample contained both major Chinese automakers (e.g., FAW Group, SAIC Group, Dongfeng Motor, BYD Company, Beijing Automotive Industry Group, Changan Automobile Group, and Guangzhou Automobile Group) and major Chinese components manufacturers (e.g., Weichai Power, Wanxiang Group, VIE Group, Dongan Power, Joyson electronics), which makes our samples fully representative for the Chinese automotive industry.

Unlike most existing research that focuses on international technology transfer in the Chinese automotive industry (Zhao & Anand, 2009), our study centers on the technological entry and exit decisions via local network relationships among the Chinese automotive firms. We employed multiple data sources to construct our data set on interfirm network relationships. First, we collected the board of directors of the aforementioned 86 sample firms during 2011–2015 from the CSMAR database, which was also checked with the 'Profile of Directors and Senior Managers' section of these firms' annual reports. Second, we collected the supplier information of all sample firms during 2011–2015 from the yearbooks of '*China Automotive Industry Enterprises & Administrative Organizations*' compiled by the China Association of Automobile Manufacturers (CAAM) approved by the Ministry of Civil Affairs of the People's Republic of China. Specifically, the yearbook contains information on more than 10,000 Chinese automakers and component manufacturers, making it the most authoritative and comprehensive yearbook for the Chinese automotive industry. It lists all the Chinese suppliers of each automotive manufacturer and also all the Chinese buyers of each automotive component manufacturer, enabling us to match our set of sample firms.

Subsequently, we used patent data that are most commonly used in innovation literature to measure a firm's technological invention activities (Guan & Liu, 2016; Leten et al., 2016). In line with previous research, we used invention patent application data to construct indicators of firms' technological entry and exit choices (Leten et al., 2016; Malerba & Orsenigo, 1999). The invention patent application data are used for the following reasons. First, the quality of invention patents is much higher than that of utility models and designs patents in the China National Intellectual Property Administration (CNIPA), and hence can better portray the technological innovation. Second, we chose the patent application data rather than grant data because the application date represents the time at which the patent was actually completed and materialized (Gilsing et al., 2008; Li, 2021). Third, although a patent application in a specific technology domain may not subsequently be granted, it provides a clear indication that a firm is pursuing technology development in the domain. Thus, the patent

Table 1. Profiles of the sample companies ($N=86$)

<i>Sample characteristics</i>	<i>Frequency</i>	<i>%</i>
Firm type (2015)		
Vehicle firm	22	25.58
Component firm	64	74.42
Average ratio of state ownership (2011–2015)		
0	50	58.14
0–5%	19	22.09
5%–20%	11	12.79
20%–50%	5	5.81
>50%	1	1.16
Number of employees (2015)		
<1,000	8	9.30
1,000–5,000	45	52.33
5,000–10,000	17	19.77
>10,000	16	18.60
Number of invention patents (2011–2015)		
0	7	8.14
1–50	54	62.79
50–500	14	16.28
>500	11	12.79

application is a closer indicator of technology development efforts than a patent grant (Leten et al., 2016). All firms' patent information between 2011 and 2015 was collected from the CNIPA.

Finally, information regarding characteristics of firm type, board members, firms' R&D expenditure, the number of employees, export revenue, state ownership, and performance (Return on Assets) were all obtained from the CSMAR database and were checked based on firms' annual reports (Aalbers & Ma, 2023). The profiles of our sample firms are shown in Table 1. Our final sample includes 22 vehicle manufacturers and 64 auto components manufacturers. Among these listed firms, 50 of them have no state ownership, only one has an average of more than 50% state ownership. Most firms have 1,000–5,000 employees, accounting for 52.33% of the sample. In particular, 18.6% of the companies have more than 10,000 employees. Furthermore, only seven firms in the sample did not apply for any invention patents during 2011–2015, while 62.79% of the sample applied for 1–50 invention patents.

Variables and Measures

Dependent variables: Technological entry and exit. Our dependent variables are the firm's technological entry and exit. We constructed two dependent variables, 'Technological Entry' and 'Technological Exit', from technology class information in patent documents. In innovation literature, patent classes are commonly considered to be valid proxies for technology domains (e.g., Guan & Liu, 2016; Leten

et al., 2016). The CNIPA uses the IPC System to classify all patents in at least one eight-digit technology class. Technology classes can be aggregated into 131 broader three-digit IPC classes^[2], which we use to indicate technology domains in our study.^[3]

Then, we examine entry into *new-to-the-firm* and exit from *old-to-the-firm* technology domains by the 86 sample firms during the period 2011–2015. A technology domain is defined as *new-to-a-firm* in year t , if the firm did not patent in that domain during the prior five years. A technology domain is defined as *old-to-a-firm* in year t , if the firm had applied for patents in that domain during the prior five years. The assumption is that a domain presents an old (new) technology to the firm if the firm has (not) been active in it for a considerable time (Leten et al., 2016). A firm's knowledge stock in a technology domain depreciates and becomes obsolete when a firm is inactive in the domain for an extended period of time (Li, 2021). Scholars have argued that a moving window of five years is an appropriate timeframe for assessing the technological impact of prior inventions (Gilsing et al., 2008), because the knowledge capital depreciates sharply and loses most of its economic value within five years. Therefore, we used a five-year moving window to characterize the change in the firm's technology domains, which are 2007–2011, 2008–2012, 2009–2013, 2010–2014, and 2011–2015.

As a final data aggregation step to examine firms' entry into and exit from technology domains, we considered firms' knowledge creation in different technology domains as a two-mode network to represent the association between firms and their patents' technology domains. We searched the 86 sample firms in the CNIPA during 2007–2015 to obtain 22,487 invention patents, which have been assigned to 106 technology classes. Then, we constructed five binary two-mode matrices of size 86×106 for each five-year moving window. The row in each matrix represents the firms, and the column represents the technology domains. In the intersection cells, 1 indicates that the row firm has at least one patent application in the column technology domain, and 0 otherwise. Then, comparing firm-technology domain networks as represented by the five matrices enabled us to track network evolution: which ties were formed, maintained, or terminated. Specifically, we can recognize four tie change patterns between two consecutive time windows (i.e., 2007–2011 and 2008–2012): the maintenance of previously not existing ties ($0 \rightarrow 0$), the creation of previously not existing ties ($0 \rightarrow 1$), the maintenance of existing ties ($1 \rightarrow 1$), and the termination of existing ties ($1 \rightarrow 0$). Here, *Technological Entry*, a firm's entry into a *new-to-the-firm* technology domain, is defined as the creation of previously not existing ties ($0 \rightarrow 1$). *Technological Exit*, a firm's exit from an *old-to-the-firm* technology domain, is defined as the termination of existing ties ($1 \rightarrow 0$).

Independent variable: Indegree centrality in supply network. A focal firm's position in the supply network characterizes our independent variable. In this study, we pay attention to the number of suppliers a firm has in the automotive industry, which was

measured by firms' indegree centrality in the supply network (*SN indegree*). Meanwhile, we control the number of buyers a firm has in the automotive industry, which was measured by firms' outdegree centrality in the supply network (*SN outdegree*).

By collecting all supplier information of our 86 sample firms from the year-books of 'China Automotive Industry Enterprises & Administrative Organizations' between 2011 and 2015, we get information on the dyadic relations defined in terms of a firm's suppliers among all the 86 firms within the automotive industry. We constructed five interfirm buyer–supplier matrices of size 86×86 from 2011 to 2015. These matrices are binary and asymmetric matrices. Each matrix contains in each row (column) the supplier (buyer) firms, and the intersection cells value 1 if there is supplier relation from the row to the column firm, and 0 otherwise. The network indegree centrality thus represents the number of suppliers a focal firm has, and the network outdegree centrality represents the number of buyers a focal firm has.

Moderating variable: Degree centrality in board interlock networks. As our moderating variable, we consider a firm's position in its board interlock network. Specifically, we use a firm's degree centrality in the board interlock network (*BI degree*) to indicate the number of board interlock partners a firm has. First of all, we considered two firms with at least one common board member as a board interlock relationship. Based on the information on dyadic relations defined in terms of board interlocks among all the 86 firms within the automotive industry, we constructed five interfirm board interlock matrices of size 86×86 from 2011 to 2015. These matrices are binary and symmetric matrices and the intersection cells value 1 if there is a board interlock relation between the row and the column firm, and 0 otherwise. Subsequently, we can calculate the degree centrality of each firm in the board interlock network.

Control variables. Besides controlling the effects of buyers in the supply network, we also control for several factors likely to impact firms' technological entry and exit decisions (Gilsing et al., 2008; Leten et al., 2016; Li, 2021). First, we controlled for the firm's type according to its products (*Type*), which values 1 if the firm is an automaker, 0 is a component producer. Second, we controlled for the firm's R&D expenditure (*R&D*), which reflects the relative R&D investment strength between the firms. Third, while we constructed board interlock networks among the 86 firms within the automotive industry, our sample firms may also have board interlock ties with firms outside the network. For this reason, we controlled for firm's board interlock relations with firms beyond the automotive industry, which is measured by the number of industrial external board interlock relationships (*External B-I ties*). Fourth, we controlled for firm size (*Firm Size*) measured by the log of the number of firm's employees. Fifth, we used the export ratio of the firm (*Export*) to control for the potential effects of learning from international

buyers. Sixth, we used the percentage of state-owned shares in all shareholders (*State*) to control for the potential impact of the Chinese government. Seventh, we control the performance of firms with the Return on Assets (*ROA*). Eighth, we control the possible impact of the firm's technological knowledge base, measured by the number of all invention patent applications before the sample year (*Patent*). Ninth, we use the number of inventors at the firm before the sample year (*Inventor*) to control the firm's absorptive capacity. Finally, we control the board size of the firm (*Board Size*) which is measured by the number of all directors on the board, and the average number of boards on which each board member of the firm serves (*Board Number*).

Stochastic Actor-Oriented Models: RSIENA

Analytical procedure. Our empirical analysis is conducted using stochastic actor-based modeling for multilevel network dynamics, methodologically known as SAOM (Snijders, Lomi, & Torló, 2013; Snijders, Van de Bunt, & Steglich, 2010), a network analytical approach is particularly suitable for handling longitudinal network data in a manner that accounts for network endogeneity.

The stochastic actor-oriented modeling advantage. To test our hypotheses, we were faced with multiple challenges using the ordinary regression-based approaches. First, the firm's technological entry and exit decisions may occur simultaneously, but the regression-based approaches rarely examine multiple dependent variables (e.g., entry into NTDs and exit from OTDs) at the same time. Second, there exists endogeneity concerns when investigating the impact of interfirm networks on a firm's technology strategy (Gao et al., 2015). We aim to reveal the effects of board interlocks and supply networks on firm's technology choices, however, the technology choices may also affect the subsequent interfirm network ties creation. Third, the supply networks and board interlocks might be correlated and influence each other, thus it is important to account for their mutual dependencies when examining their interaction effects.

To address these challenges, we used stochastic actor-oriented modeling, based on the RSIENA package version 1.3.0 in R (R based Simulation Investigation for Empirical Network Analysis). This SAOM method was originally developed by Snijders and his colleagues (Ripley, Snijders, Boda, Vörös, & Preciado, 2021; Snijders et al., 2010). It uses Markov Chain Monte Carlo Maximum Likelihood Estimation (MCMC-MLE) to model network evolution (Snijders et al., 2010). The SAOM models the change of network ties from the perspective of the actors which always 'imagine' network evolution as individual actors creating, maintaining, or terminating ties to other actors, which fits our research on the dynamics of interfirm networks and technological entry/exit (Howard, Withers, & Tihanyi, 2017). Recently, Snijders et al. (2013) extended the SAOM for the co-evolution of one-mode and two-mode networks so that dependence mechanisms within and across networks can be specified rigorously, which has

been used in sociology and management (Stadtfeld, Mascia, Pallotti, & Lomi, 2016; Tröster, Parker, Van Knippenberg, & Sahlmüller, 2019). This co-evolution SAOM allows us to properly model tie interdependence across the board interlock network, supply network, and firm-technology domains network, to appropriately capture the time-based nature of network tie change. While providing a detailed description of the logic of SAOM analysis in the Appendix, we refer interested readers to the more detailed *Manual for RSiena*^[4] (Ripley et al., 2021).

The co-evolution SAOM deals with the above challenges in the following ways. First, according to Ripley et al. (2021), network evolution may be modeled in SAOM by three functions: the evaluation (the presence of ties regardless of whether they were newly created or maintained), creation (the creation of previously not existing ties), and endowment (the maintenance of existing ties) functions. The SAOM allows to include one or two of these functions in a single model. In this study, by including the creation and endowment functions into co-evolution SAOMs simultaneously, we can differentiate the effects of networks on tie creation (entry vs. not-entry in NTDs) and endowment (maintenance vs. termination in OTDs), hence responding to the first empirical challenge we pose. Second, in the co-evolution SAOM there are multiple dependent network variables, these can be one-mode networks (e.g., supply networks or board interlocks), two-mode networks (e.g., firm-technology domains networks), or a combination of these. We use this co-evolution model to examine the two-by-two interplay between the supplier network, board interlock network, and firm's technological entry/exit at the same time. In this way, the co-evolution model makes up for the shortcomings of regression-based models that mostly consider one-way effect while ignoring the possible endogeneity problems (Kim, Howard, Cox Pahnke, & Boeker, 2016), hence well dealing with the second and third empirical challenges.

Stochastic actor-oriented model specification. In our co-evolution model, supply network, board interlock network, and firm-technology domain affiliation network are all dependent networks. RSIENA will report results of the dynamics of three networks at the same time. Following prior research (Snijders et al., 2013; Stadtfeld et al., 2016), we set the 'effects' affecting the tie dynamics in each network as follows.

First, we test our hypotheses in the evolution of the two-mode firm-technology domain network by considering between-network effects. Following Stadtfeld et al. (2016), we separate the creation and endowment effects of the supply networks and board interlock networks, including the variables of *SN indegree*, *SN outdegree*, and *BI degree*. Then, we put *SN indegree creation/endowment*, *BI degree creation/endowment*, and their interaction items into the model to test our hypotheses. In the two-mode firm-technology domain network, we also control the within-network structural effects, including the *Rate Parameters* representing the average number of changes in the network between the discrete panels, the *Outdegree (Density)* term serving as an intercept in SAOMs analysis, the *outdegree – activity* representing the preferential attachment through outdegree centrality, and the *four-cycles* effect capturing the

transitivity in two-mode networks. Then, we include all the ego effects of control variables (see [Table 2](#)).

Second, for the one-mode supply network, we also control the within-network structural effects of *Rate Parameters*, *Outdegree (Density)*, and *outdegree – activity*. Moreover, we include the *indegree – popularity* representing the preferential attachment through indegree centrality, the *reciprocity* defined by the number of reciprocated ties, and the *transitive triads* defined by the number of transitive patterns. For the between-network effects, we control the potential impacts of board interlock network degree centrality on firms' outdegree (*BI degree_out*) and indegree (*BI degree_in*) in the supply network. Similarly, we also control the potential impacts of two-mode firm-technology domain network on firms' outdegree (*TD degree_out*) and indegree (*TD degree_in*) in the supply network. All the ego and alter effects of control variables are also included in the model (see [Table 2](#)).

Third, for the one-mode board interlock network, we control the within-network structural effects *Rate Parameters*, *Outdegree (Density)*, *outdegree – activity*, and *the transitive triads*. For the between-network effects, we control the potential impacts of supply network outdegree centrality (*SN outdegree*) and indegree centrality (*SN indegree*) on firms' degree centrality in the board interlock network. Similarly, we also control the impacts of the two-mode firm-technology domain network outdegree centrality (*TD degree_out*). In addition, we include all the ego effects of control variables in the model (see [Table 2](#)).

[Table 2](#) presents the parameters included in our models with a description of the corresponding social processes of tie formation.

RESULTS

Descriptive Results

We present the descriptive statistics and bivariate correlations of the variables in [Table 3](#). Because the SAOM approach models the evolution of tie formation at the network level and does not allow us to calculate bivariate correlations (Howard et al., 2017), we derive the descriptive statistics and correlations from the firm-year data structure. Our sample firms enter in 1.5 NTDs and exit from 0.44 OTDs on average. Firms have on average 2.92 buyers or suppliers in the automotive industry. The firm's average degree centrality in the board interlock network is 0.83, indicating that Chinese automotive firms have only less than 1 board interlock partner. As for other variables, Chinese firms in the automotive industry have patents at 6.72 technology domains on average. 26% of the firms are automotive manufacturers while 74% of them are component manufacturers. The average R&D expenditure of our sample firms is 0.369 billion Yuan, the average number of external board interlocks is 4.51, the average logged number of employees is 8.28, the average ratio of exports to sales revenue is 0.14 and the average ratio of state-owned shares is 0.05. The firms' average ROA is 0.05.

Table 2. Parameters included in the model

<i>Parameters</i>	<i>Explanation of social process</i>	<i>Model setting</i>
Within-network structural effects		
<i>rate</i>	Average number of changes in the network between the discrete panels	Firm-technology domains network, supply network, board interlock network
<i>outdegree (density)</i>	The intercept representing baseline tendency for tie formation	Firm-technology domains network, supply network, board interlock network
<i>indegree – popularity</i>	Tendency toward variation in the degree to which an actor receives multiple ties	Supply network
<i>outdegree – activity</i>	Tendency toward variation in the degree to which an actor sends multiple ties	Firm-technology domains network, supply network, board interlock network
<i>reciprocity</i>	Tendency toward reciprocity in tie formation	Supply network
<i>transitive triplets</i>	Tendency for the closure of transitive triads	Supply network, board interlock network
<i>four-cycles</i>	Tendency for the closure of transitivity of four nodes	Firm-technology domains network
Between-network effects		
<i>degree popularity</i>	The impact of degree centrality in one network on the indegree centrality in the other network (BI degree_in, TD degree_in)	Firm-technology domains network, supply network, board interlock network
<i>degree activity</i>	The impact of degree centrality in one network on the outdegree centrality in the other network (BI degree_out, TD degree_out)	Firm-technology domains network, supply network, board interlock network
<i>indegree activity</i>	The impact of indegree centrality in one network on the degree centrality in the other network (SN indegree)	Firm-technology domains network, board interlock network
<i>outdegree activity</i>	The impact of outdegree centrality in one network on the degree centrality in the other network (SN outdegree)	Firm-technology domains network, board interlock network
Covariates effects		
<i>ego</i>	Tendency of firms with higher covariate variables (<i>Type, R&D, External B-I ties, Firm Size, Export, State, ROA, Patent, Inventor, Board Size, and Board Number</i>) to form ties with any other firm	Firm-technology domains network, supply network, board interlock network
<i>alter</i>	Tendency of firms to form ties with any other firms with higher covariate variables (<i>Type, R&D, External B-I ties, Firm Size, Export, State, ROA, Patent, Inventor, Board Size, and Board Number</i>)	Firm-technology domains network, supply network, board interlock network

Table 3. Descriptive statistics and correlations for firm-year sample

<i>Variable</i>	<i>Mean</i>	<i>Std. Dev.</i>	<i>Min</i>	<i>Max</i>	<i>1</i>	<i>2</i>	<i>3</i>	<i>4</i>	<i>5</i>	<i>6</i>	<i>7</i>	<i>8</i>	<i>9</i>	<i>10</i>	<i>11</i>	<i>12</i>	<i>13</i>	<i>14</i>	<i>15</i>	<i>16</i>	
1.Technological entry	1.50	2.21	0	14	1																
2.Technological exit	0.44	1.37	0	20	-0.01	1															
3.SN indegree	2.92	6.19	0	28	0.33	0.31	1														
4.BI degree	0.83	1.23	0	5	-0.01	0.12	0.13	1													
5.SN outdegree	2.92	3.48	0	14	-0.04	-0.07	-0.17	0.07	1												
6.TD degree	6.72	10.39	0	61	0.38	0.27	0.69	0.08	-0.14	1											
7.Type	0.26	0.44	0	1	0.36	0.23	0.74	0.12	-0.33	0.56	1										
8.R&D	3.69	8.74	0.01	68.32	0.20	0.20	0.49	0.08	-0.07	0.56	0.42	1									
9.External B-I ties	4.51	3.43	0	21	0.08	0.10	0.23	0.08	0.01	0.22	0.22	0.47	1								
10.Firm Size	8.28	1.19	5.63	12.14	0.34	0.16	0.63	0.16	0.04	0.60	0.59	0.63	0.29	1							
11.Export	0.14	0.18	0	0.96	-0.08	0.04	-0.21	-0.13	-0.25	-0.15	-0.18	-0.14	0.04	-0.14	1						
12.State	0.05	0.12	0	0.70	0.16	0.03	0.17	0.28	-0.01	0.16	0.09	0.17	0.14	0.19	-0.17	1					
13.ROA	0.05	0.05	-0.22	0.21	0.06	-0.09	-0.12	-0.05	0.01	0.02	-0.17	0.14	-0.02	-0.01	-0.01	0.04	1				
14.Patent	2.85	1.93	0	8.50	0.31	0.34	0.58	0.16	0.04	0.79	0.44	0.54	0.29	0.54	-0.09	0.15	-0.03	1			
15.Inventor	1.51	0.85	0.00	3.46	0.41	0.28	0.61	0.18	0.07	0.79	0.48	0.53	0.28	0.55	-0.15	0.23	-0.02	0.91	1		
16.Board Size	10.52	3.09	5	25	0.27	0.05	0.30	0.35	0.03	0.24	0.19	0.26	0.34	0.36	-0.02	0.40	-0.10	0.31	0.36	1	
17.Board Number	1.65	0.40	1	3.11	-0.06	0.12	0.10	0.25	0.04	0.10	0.07	0.28	0.60	0.08	0.00	0.09	0.08	0.07	0.08	0.04	1

Table 4. Descriptive of the changes of network relationships in the periods between subsequent waves

<i>Network</i>	<i>Tie changes</i>	<i>0 ==> 0</i>	<i>0 ==> 1</i>	<i>1 ==> 0</i>	<i>1 ==> 1</i>	<i>Distance</i>	<i>Jaccard</i>
Firm-technology domains network	2011 ==> 2012	8,176	162	31	747	193	0.795
	2012 ==> 2013	8,072	135	25	884	160	0.847
	2013 ==> 2014	7,977	120	38	981	158	0.861
	2014 ==> 2015	7,915	100	58	1,043	158	0.868
Supply network	2011 ==> 2012	7,046	12	13	239	25	0.905
	2012 ==> 2013	7,045	14	23	228	37	0.860
	2013 ==> 2014	7,041	27	10	232	37	0.862
	2014 ==> 2015	7,046	5	16	243	21	0.920
Board interlock network	2011 ==> 2012	3,624	13	0	18	13	0.581
	2012 ==> 2013	3,608	16	6	25	22	0.532
	2013 ==> 2014	3,599	15	4	37	19	0.661
	2014 ==> 2015	3,594	9	16	36	25	0.590

The average logged number of prior invention patent applications is 2.85, and the logged number of prior inventors of the firm is 1.51. The size of the board of directors is 10.52 on average, and the average number of boards on which each board member of the firm serves is 1.65.

To check the assumption that the observed panels represent time slices of a gradually evolving network, we provide information on tie changes of the three networks and the Jaccard coefficients to measure the stability of networks between consecutive observations in Table 4 (Snijders et al., 2013). The Jaccard coefficients of the firm-technology domain networks range between 0.795 and 0.868, showing relatively high network stability. During 2011–2015, 100–162 new ties were created, representing the firm’s entry into NTDs. There are 25–58 existing ties terminated, representing the firm’s exit from OTDs. The stability of the supply networks is highest as revealed by Jaccard coefficients ranging between 0.86 and 0.92, while the stability of the board interlock networks is much lower, with Jaccard coefficients ranging between 0.532 and 0.661. To sum up, the Jaccard index values of the three networks are greater than 0.3, indicating that our data satisfies the assumptions of SAOMs (Snijders et al., 2013).

RSIENA Estimation Results

We conduct the stochastic actor-oriented analysis using the RSiena package Version 1.3.0, following the procedures outlined by Snijders et al. (2010) and Ripley et al. (2021) for model fitting and testing for convergence and goodness of fit. The results of our co-evolution modeling are shown in Table 5–7. The co-evolution analysis reports the results for the dynamics of the three networks at the same time. The results consist of three parts: The first part estimates the firm-technology domain network dynamics, the second estimates the supply

Table 5. SIENA results with the effect of supply network

<i>Model 1</i>	<i>Firm-technology domains network</i>		<i>Supply network (SN)</i>		<i>Board interlock network (BI)</i>	
	<i>Estimate</i>	<i>S.E.</i>	<i>Estimate</i>	<i>S.E.</i>	<i>Estimate</i>	<i>S.E.</i>
Constant rate (period 1)	6.5676	0.6004	0.5901	0.138	0.4313	0.1743
Constant rate (period 2)	4.6251	0.4757	0.8566	0.175	0.4582	0.1389
Constant rate (period 3)	4.2081	0.4363	0.8055	0.1603	0.3627	0.1021
Constant rate (period 4)	4.068	0.3941	0.3769	0.0901	0.5033	0.1145
Outdegree (density)	-2.288***	0.1503	-6.3375***	0.6145	-6.486	5.1536
Indegree – popularity			0.0487**	0.0221		
Outdegree – activity	0.0186***	0.0049	0.0779*	0.0434	0.8671	1.3009
Reciprocity			0.753	1.6289		
Transitive triads			-0.0309	0.2999	4.1821***	1.3005
Four-cycles	0.0116***	0.0006				
Type alter			1.7669***	0.6806		
Type ego	0.3	0.2781	-0.0166	0.0186	-0.3343	3.5495
R&D alter			-0.0252	0.0865		
R&D ego	-0.0089	0.0084	0.3986**	0.1747	-0.0218	0.1895
External B-I ties alter			0.0085	0.0468		
External B-I ties ego	-0.0059	0.0247	-0.0871	0.0595	1.5512	2.4931
Firm Size alter						
Firm Size ego	0.2621***	0.0916	0.5381	0.3495	1.7148	3.9794
Export alter			-2.846*	1.6591		
Export ego	-0.2138	0.356	0.1122	2.7543	-0.6785	5.8953
State alter			2.7012	4.2005		
State ego	0.0589	0.643	-0.6517	1.1314	30.4522	61.694
ROA alter			0.6457	1.5879		
ROA ego	1.917	1.3856			-49.9609	82.6559
Patent alter			-0.3021	0.5839		
Patent ego	-1.5257***	0.3005	0.1291**	0.0553	-0.928	7.1818
Board size alter			2.2165**	0.9757		
Board size ego	0.0345	0.0269	0.9261*	0.5585	-1.6114	2.5631
Inventor alter			-0.0383	0.0746		
Inventor ego	1.2175***	0.2535	0.8729	0.768	0.0372	3.6755
Board Number alter						
Board Number ego	-0.5187**	0.2118	-0.0915	0.6805	-16.7042	27.3958
TD degree_in			-0.1015	0.2033		
TD degree_out			-1.0332***	0.3898	0.2038	2.6898
BI degree_in			-0.0831	0.3218		
BI degree_out			-0.5276	0.4277		
SN outdegree					0.153	1.3328
SN outdegree (endowment)	0.1572	0.1698				
SN outdegree (creation)	-0.0562	0.1413				
SN indegree					0.9192	1.8487
SN indegree (endowment)	-3.1106***	0.1228				
SN indegree (creation)	2.3324***	0.1328				

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 6. SIENA results with the direct effect of board interlock network

<i>Model 2</i>	<i>Firm-technology domains network</i>		<i>Supply network (SN)</i>		<i>Board interlock network (BI)</i>	
	<i>Estimate</i>	<i>S.E.</i>	<i>Estimate</i>	<i>S.E.</i>	<i>Estimate</i>	<i>S.E.</i>
Constant rate (period 1)	6.3245	0.585	0.5902	0.1357	0.4371	0.1754
Constant rate (period 2)	4.6194	0.4999	0.8575	0.1516	0.464	0.1405
Constant rate (period 3)	4.3144	0.424	0.8078	0.1466	0.3629	0.0914
Constant rate (period 4)	4.0727	0.4144	0.375	0.0907	0.5027	0.1246
Outdegree (density)	-2.2857***	0.1551	-6.3913***	0.5623	-6.515*	3.8072
Indegree – popularity			0.049**	0.0213		
Outdegree – activity	0.0121**	0.0053	0.0783*	0.042	0.8889	1.1646
Reciprocity			0.7365	1.4168		
Transitive triads			-0.0234	0.2522	4.1727***	0.9498
Four-cycles	0.0117***	0.0006				
Type alter			1.7757***	0.6551		
Type ego	0.5576*	0.2955	-3.2454***	1.1603	-0.4365	3.8671
R&D alter			-0.0166	0.0184		
R&D ego	-0.0101	0.0089	0.0075	0.049	-0.0213	0.1571
External B-I ties alter			-0.0871	0.0605		
External B-I ties ego	-0.0572**	0.0289	-0.0345	0.0881	1.5348	1.5767
Firm Size alter			0.398**	0.1883		
Firm Size ego	0.2874***	0.0932	0.5406	0.3473	1.6573	2.6776
Export alter			-2.4393	1.5434		
Export ego	-0.4049	0.3689	-2.8762*	1.7037	-0.7483	6.5545
State alter			-0.6322	1.1919		
State ego	0.7207	0.7313	0.7761	1.6346	28.9023	70.0251
ROA alter			0.1095	2.4054		
ROA ego	1.5113	1.487	2.5855	4.1669	-49.8773	62.7877
Patent alter			-0.292	0.6096		
Patent ego	-1.2837***	0.3223	0.062	0.7559	-1.1058	5.8878
Board size alter			0.1288**	0.0577		
Board size ego	0.0874***	0.0306	-0.0282	0.0725	-1.6027	2.0356
Inventor alter			0.874	0.8369		
Inventor ego	1.2237***	0.2859	2.2381**	0.9899	0.1495	3.3764
Board Number alter			0.9196*	0.5487		
Board Number ego	-0.0144	0.2283	0.0081	0.6318	-16.4629	18.8808
TD degree_in			-0.106	0.218		
TD degree_out			-1.0696***	0.4012	0.2561	2.5046
BI degree_in			-0.0865	0.3128		
BI degree_out			-0.6482*	0.3869		
SN outdegree					0.0921	1.6206
SN outdegree (endowment)	0.1772	0.1939				
SN outdegree (creation)	-0.0282	0.1532				
SN indegree					0.9603	1.7137
SN indegree (endowment)	-3.2394***	0.1461				
SN indegree (creation)	2.3894***	0.1355				
BI degree (endowment)	-0.1187	0.3535				
BI degree (creation)	-0.9713***	0.3062				

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 7. SIENA results with the moderating effects of board interlock network

<i>Model 3</i>	<i>Firm-technology domains network</i>		<i>Supply network (SN)</i>		<i>Board interlock network (BI)</i>	
	<i>Estimate</i>	<i>S.E.</i>	<i>Estimate</i>	<i>S.E.</i>	<i>Estimate</i>	<i>S.E.</i>
Constant rate (period 1)	6.176	0.6208	0.5907	0.142	0.4335	0.1749
Constant rate (period 2)	4.6558	0.521	0.8588	0.1881	0.4658	0.1547
Constant rate (period 3)	4.5257	0.5065	0.8116	0.1649	0.364	0.0939
Constant rate (period 4)	4.318	0.5222	0.3759	0.0976	0.5063	0.1354
Outdegree (density)	-1.9301***	0.2039	-6.4***	0.5855	-6.3651	4.8639
Indegree – popularity			0.0493**	0.0234		
Outdegree – activity	0.0057	0.0061	0.0776*	0.0419	0.8462	1.4369
Reciprocity			0.7248	1.5817		
Transitive triads			-0.0246	0.2858	4.1366***	1.173
Four-cycles	0.0118***	0.0006				
Type alter			1.7713***	0.6249		
Type ego	0.5783*	0.3264	-3.2561***	1.1363	-0.3735	4.2074
R&D alter			-0.0166	0.0183		
R&D ego	-0.0116	0.0084	0.0072	0.046	-0.0234	0.2277
External B-I ties alter			-0.0874	0.0607		
External B-I ties ego	-0.1064***	0.0348	-0.0375	0.0957	1.4836	2.677
Firm Size alter			0.3979**	0.1925		
Firm Size ego	0.2692***	0.0917	0.5395	0.3519	1.5733	3.4326
Export alter			-2.4233	1.6822		
Export ego	-0.6436*	0.3886	-2.8701*	1.7037	-0.6922	6.9221
State alter			-0.6325	1.2375		
State ego	1.2678	0.8941	0.7652	1.7809	28.658	72.2738
ROA alter			0.0812	2.4952		
ROA ego	2.0757	1.697	2.6815	3.8353	-47.4188	72.8091
Patent alter			-0.3077	0.5731		
Patent ego	-0.9232**	0.3711	0.0826	0.7522	-1.0241	6.4983
Board size alter			0.1293**	0.0543		
Board size ego	0.1368***	0.0387	-0.0278	0.0749	-1.542	2.7726
Inventor alter			0.8872	0.8156		
Inventor ego	1.0987***	0.3125	2.2854**	1.0142	0.2543	3.439
Board Number alter			0.926	0.5686		
Board Number ego	0.351	0.2508	0.0448	0.6931	-15.8139	28.2666
TD degree_in			-0.1043	0.2236		
TD degree_out			-1.0907**	0.4238	0.1676	2.9059
BI degree_in			-0.0974	0.2989		
BI degree_out			-0.6312	0.393		
SN outdegree					0.1122	1.5878
SN outdegree (endowment)	0.2934	0.2376				
SN outdegree (creation)	-0.1629	0.1709				
SN indegree					0.9422	2.0912
SN indegree (endowment)	-2.5047***	0.1918				
SN indegree (creation)	1.6905***	0.1489				
BI degree (endowment)	-4.9105***	0.9851				
BI degree (creation)	3.6164***	0.9046				
BI degree × SN indegree (endowment)	-2.1821***	0.4684				
BI degree × SN indegree (creation)	1.7849***	0.4269				

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

network dynamics, and the third part estimates the board interlock network dynamics. The variable coefficients and standard errors are reported, along with significance levels corresponding to two-tailed tests. Specifically, Model 1 in Table 5 is used to test the impacts of supply network (*SN indegree*, *SN outdegree*) with the consideration of the creation and endowment effects. Model 2 in Table 6 further includes the effects of the board interlock network (*BI degree*). Finally, Model 3 in Table 7 adds the interaction terms of *SN indegree* and *BI degree* in the model, where we report centralized variables before building the interaction terms.

The overall maximum convergence ratios of our SAOM Models 1–3 in Tables 5–7 are 0.2995, 0.3169, and 0.3014, respectively, which is within the accepted range of less than 0.35. The convergence *t*-ratios of all estimation parameters are less than 0.1 in absolute value, meeting the requirements for convergence (Ripley et al., 2021). We further use the *sienaGOF* function to assess the goodness of fit for our actor-oriented models.^[5] The goodness-of-fit analysis of the outdegree distribution for firm-technological domain network suggests that Model 3 reflects the observed data and shows better fit than Model 1 and Model 2. In Figure 1, we examine violin plots created based on the results of the *sienaGOF* function (Ripley et al., 2021). Compared with the plots based on Model 1 and Model 2, the plots for outdegree distribution based on Model 3 show that the observed values stay closely within the simulated values. The Monte Carlo Mahalanobis Distance Test^[6] shows that the *p*-values for three models are 0.015, 0.051, and 0.066, respectively, suggesting that the simulated values based on Model 3 reasonably fit the observed networks. Of course, we admit that the equivalence of the unexplained variance that the stochastic actor-oriented analysis is not capturing is quite large because the *p*-values are so far away from 1. Thus, there are many opportunities for future research to further explore the dynamic mechanism of technological entry/exit in addition to the interaction between board interlock and supply networks, which will further be discussed in the limitation section.

From Table 5, we find that in the results for firm-technology domains network evolution, the network structural terms *outdegree – activity* and *four-cycles* are significant in predicting changes in firms' technological entry and maintenance, supporting the use of network-level SAOM analysis in the evolution of ties rather than the conventional regression techniques that would fail to account for these structural factors. In the results for supply network evolution, the impact of *TD degree_out* is negative and significant, indicating that firms patenting in more technology domains are more likely to have high outdegree centrality in the supply networks. By contrast, the impact of *TD degree_in* is not significant, suggesting that the firm's expansion in technology domains does not help attract more suppliers. However, the impacts of both *BI degree_in* and *BI degree_out* are not significant, suggesting that the board interlocks have no significant effects on the creation and maintenance of buyer–supplier ties. In the results for board interlock network evolution, the impact

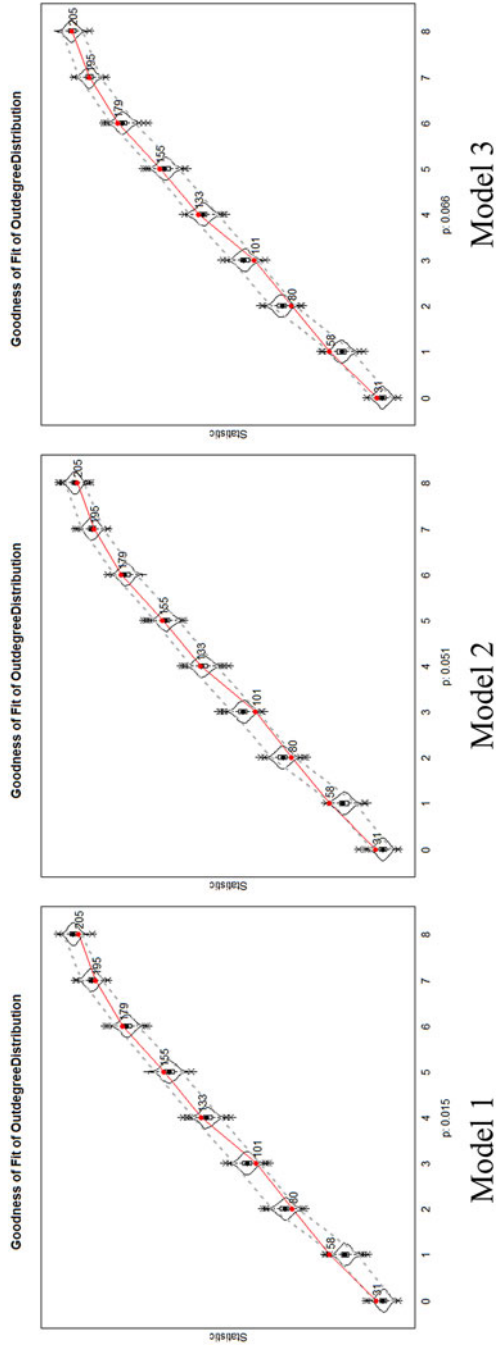


Figure 1. Goodness of fit of outdegree distribution for firm-technology domains network in three models

of *TD degree_out* is not significant, so the firms' expansion in technology domains is not helpful in attracting more board interlock partners. The impacts of both *SN outdegree* and *SN indegree* are also not significant, indicating that the supply network ties have no significant effects on the board interlock ties creation and maintenance. In this way, we use the network co-evolution model to control the possible interplay between different networks when analyzing the impact of one network on the evolution of ties in another network, thus dealing with the possible endogeneity problems.

Then, we test our hypotheses based on the dynamics results of co-evolution models in Tables 5–7. Our first set of hypotheses proposes that the indegree centrality a focal firm has in supply network is positively associated with the likelihood of the firm's entry into NTDs (H1a) and also the likelihood of the firm's exit from OTDs (H1b). We separated the main effect of supplier partners into two effects: *SN indegree (creation)* examines how the suppliers drive the creation of ties in NTDs, while *SN indegree (endowment)* examines how the suppliers drive the maintenance of ties in OTDs. The results in the firm-technology domain network dynamics model of Table 5 show that, the coefficient for the creation effect of indegree centrality in supply network (*SN indegree (creation)*) is positive and significant ($\beta = 2.3324$, $p < 0.01$). Thus, the focal firm with more supplier partners is more likely to enter into NTDs, supporting Hypothesis 1a. Meanwhile, the coefficient for the endowment effect of indegree centrality in supply network (*SN indegree (endowment)*) is negative and significant ($\beta = -3.1106$, $p < 0.01$), which means that as the number of suppliers increases, the focal firm is more likely to exit from rather than maintain in OTDs, supporting our Hypothesis 1b. The results in the firm-technology domain network dynamics model of Table 6 show that after including the variable of board interlock network (*BI degree*), the coefficient for the *SN indegree (creation)* is still positive and significant ($\beta = 2.3894$, $p < 0.01$) and the coefficient for the *SN indegree (endowment)* is still negative and significant ($\beta = -3.2394$, $p < 0.01$), additionally confirming Hypotheses 1a and 1b.

Our second set of hypotheses predicts that the degree centrality in a firm's board interlock network strengthens not only the positive effect of the number of suppliers on the firm's entry into NTDs (H2a), but also the positive effect of the number of suppliers on the firm's exit from OTDs (H2b). From Table 7, we find that the coefficient for the creation effect of the interaction term of *BI degree* and *SN indegree (BI degree \times SN indegree (creation))* is positive and significant ($\beta = 1.7849$, $p < 0.01$), indicating that the focal firm with higher degree centrality in the board interlock networks can benefit more from their suppliers to enter into more NTDs. Hypothesis 3a is thus supported. The coefficient for the endowment effect of the interaction term of *BI degree* and *SN indegree (BI degree \times SN indegree (endowment))* is negative and significant ($\beta = -2.1821$, $p < 0.01$), which reflects that as the degree centrality in the board interlock networks increases, the focal firm benefits more from their suppliers to exit from rather than maintain in OTDs. Thus, Hypothesis 3b is also supported.

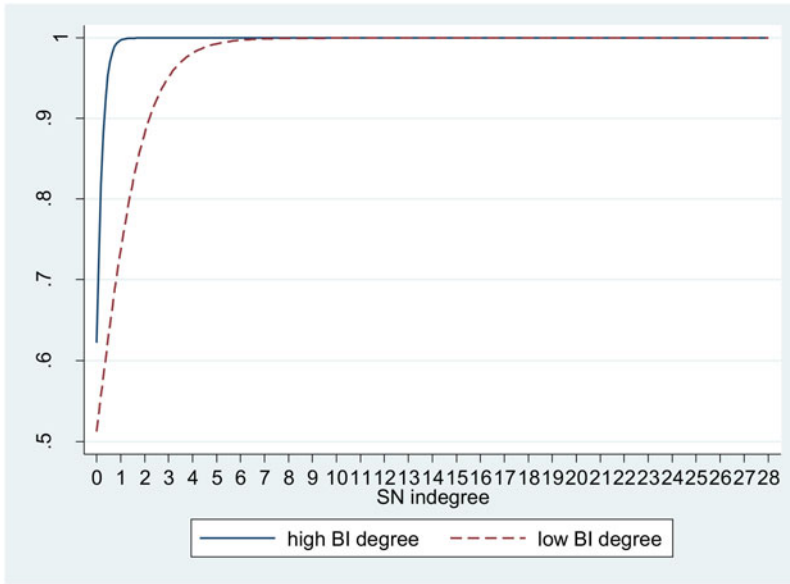


Figure 2. The moderating role of centrality in the board interlocks on the effects of supplier partners on firms' entry in NTDs

The analytical procedure with SAOMs did not provide the plotting of interaction patterns, as this is not the common protocol for the RSIENA module we applied. Therefore, we used the alternative and commonly applied method for plotting interactions from binary logistic regression to illustrate the interaction patterns. As shown in Figures 2 and 3, the relationship between supplier partners and firms' entry in NTDs is more positive for firms with high degree centrality in the board interlocks than for those with a low degree centrality. Also, the negative relationship between supplier partners and firms' maintenance in OTDs is stronger for firms with high degree centrality in the board interlocks, indicating that firms benefit more from their suppliers to exit from OTDs when they occupy the central position in the board interlocks.

Robustness Tests

We performed a number of robustness tests. First, we estimated models with two different moving time windows for constructing the firm-technology domains networks: 'three years' and 'four years' (see Models 4 and 5 in Table 8). The results basically keep consistent with the 'five years', although the results are less significant for 'three years' time windows.

Second, we re-constructed the binary firm-technology domains networks, where 1 in the matrices indicates that the row firm has at least two patent applications in the column technology domain, hence eliminating the possible noise caused by the accidental patent invention. The re-run model is shown in Model 6 of Table 8 and the results are also consistent.

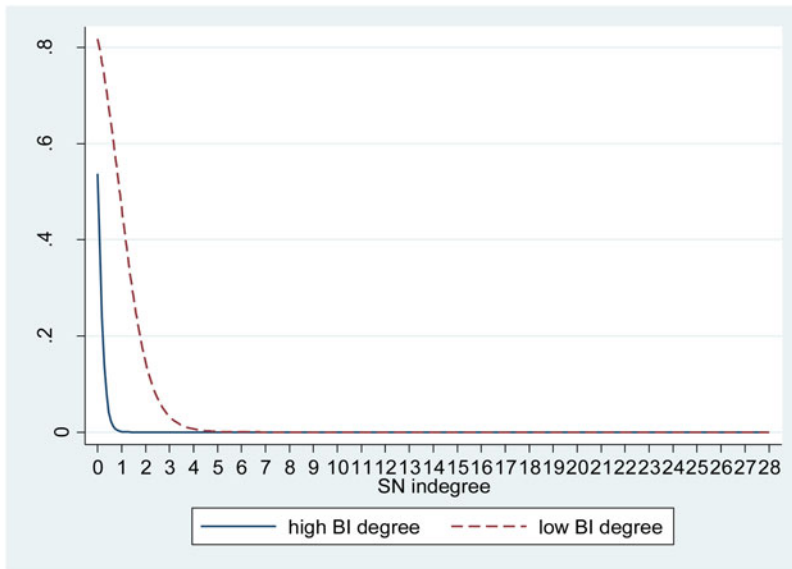


Figure 3. The moderating role of centrality in the board interlocks on the effects of supplier partners on firms' exit from OTDs

Third, we add the interaction item of the number of buyers (*SN outdegree*) and the degree centrality in the board interlocks (*BI degree*) into the full model, the result in Model 7 of Table 8 shows that the interaction of buyer partners with board interlocks is not significant, but the interaction of suppliers with board interlocks kept significant and consistent result.

Fourth, we consider the possible impact of the Burt-type constraint measure of board interlock network, and put the interaction item of the *SN indegree* and the constraints in board interlocks (*BI constraint*) into the model. The results are shown in Models 8 and 9 of Table 8. When examining the *BI constraint* alone, its moderating effect on suppliers is all significant, and the sign of the moderating effect is the opposite of the *BI degree*. However, when examining both the centrality and constraint in the board interlocks, only the moderating effect of *BI degree* is significant, further confirming the robustness of our prior results.

Fifth, the independent variable in this article only focuses on the number of suppliers of the focal firm, we further construct a variable *Supplier Diversity* to measure the technological diversity of suppliers of the focal firm, which is captured by the number of three-digit IPCs in the patent applications of all supplier partners during the last five years. We find that the correlation coefficient between *SN indegree* and *Supplier Diversity* is as high as 0.93, implying that an increase in the number of suppliers of a firm does bring about an increase in the diversity of suppliers' technological knowledge. Then, we further control *Supplier Diversity* in the model and find consistent results with the main model (see Model 10 in Table 8).

Finally, this article focuses on the impact of the number of supplier partners on firms' technology exploration/exploitation decisions through direct and

Table 8. Robustness test results in firm-technology domain network dynamics

<i>Firm-technology domain network</i>	<i>Model 4 Estimate</i>	<i>Model 5 Estimate</i>	<i>Model 6 Estimate</i>	<i>Model 7 Estimate</i>	<i>Model 8 Estimate</i>	<i>Model 9 Estimate</i>	<i>Model 10 Estimate</i>	<i>Model 11 Estimate</i>
Constant rate (periods 1–4)	Included	Included	Included	Included	Included	Included	Included	Included
Outdegree (density)	Included	Included	Included	Included	Included	Included	Included	Included
Outdegree – activity	Included	Included	Included	Included	Included	Included	Included	Included
Four-cycles	Included	Included	Included	Included	Included	Included	Included	Included
Control variables (<i>Type, R&D, External B-I ties, Firm Size, Export, State, ROA, Patent, Inventor, Board Size, and Board Number</i>)	Included	Included	Included	Included	Included	Included	Included	Included
SN outdegree								–0.6626***
SN outdegree (endowment)	–0.0242	0.3618*	–0.0935	0.3454	0.2218	0.2657	0.2614	
SN outdegree (creation)	0.1461	–0.1347	0.0088	–0.2559	–0.0789	–0.143	–0.1985	
SN indegree								0.0148
SN indegree (endowment)	–2.3531***	–2.3202***	–3.1004***	–2.5411***	–3.2666***	–2.091***	–2.8281***	
SN indegree (creation)	1.7749***	1.619***	2.1161***	1.7415***	2.3327***	1.2239***	1.3402***	
BI degree (endowment)	–2.7963	–5.0789***	–5.3856***	–4.5881***	–0.7623	–6.5585***	–5.0497***	–0.9013
BI degree (creation)	2.1158	3.8836***	3.7421***	3.5812***	–0.7459	5.4569***	3.5117***	–1.5590
BI degree × SN indegree (endowment)	–1.0612	–2.1457***	–2.8047***	–2.2266***		–2.1048***	–2.1799***	
BI degree × SN indegree (creation)	1.0006	1.838***	2.0076***	1.8338***		1.6277***	1.7805***	
BI degree × SN outdegree (endowment)				0.4308				
BI degree × SN outdegree (creation)				–0.253				
BI constraint (endowment)					–10.2764***	4.1182		
BI constraint (creation)					11.0248***	–4.05		
BI constraint × SN indegree (endowment)					–6.8355***	0.9344		
BI constraint × SN indegree (creation)					6.9753***	–0.1411		

Table 8. Continued

	<i>Model 4</i>	<i>Model 5</i>	<i>Model 6</i>	<i>Model 7</i>	<i>Model 8</i>	<i>Model 9</i>	<i>Model 10</i>	<i>Model 11</i>
<i>Firm-technology domain network</i>	<i>Estimate</i>	<i>Estimate</i>	<i>Estimate</i>	<i>Estimate</i>	<i>Estimate</i>	<i>Estimate</i>	<i>Estimate</i>	<i>Estimate</i>
Supplier diversity ego							0.9034***	
SN MixedInWX (endowment)								-0.8448**
SN MixedInWX (creation)								0.2193**
SN to (endowment)								0.8246***
SN to (creation)								0.1412***

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. For simplicity, we only put brief results for the estimates of key variables in firm-technology domain network dynamics. Detailed results are available upon request. Model 1 to Model 8 are explained as follows:

Model 1: Robustness test (three-year moving window of firm-technology domains network);

Model 2: Robustness test (four-year moving window of firm-technology domains network);

Model 3: Robustness test (the re-constructed firm-technology domains network);

Model 4: Robustness test (the interaction effects of the number of buyers and board interlocks);

Model 5: Robustness test (the individual moderating effects of the Burt-type constraint in the board interlocks);

Model 6: Robustness test (the combined moderating effects of the degree and Burt-type constraint in the board interlocks);

Model 7: Robustness test (model with an additional control variable: Supplier Diversity);

Model 8: Robustness test (the direct knowledge spillover mechanism from supplier/buyer partners).

indirect knowledge spillover. In fact, SAOMs allow us to test the direct knowledge spillover mechanism from supplier/buyer partners to the focal firm. The ‘*MixedInWX*’ effect can be used to test whether a firm will explore or exploit technologies in domains where its suppliers have applied for patents, while the ‘*to*’ effect can control the direct knowledge spillover from the firms’ buyer partners (see Ripley et al., 2021). Then, we put *SN MixedInWX (creation)*, *SN MixedInWX (endowment)*, *SN to (creation)*, and *SN to (endowment)* into the model (see Model 11 in Table 8). The coefficient of *SN MixedInWX (creation)* is positive and significant ($\beta = 0.2193$, $p < 0.05$), and the coefficient of *SN MixedInWX (endowment)* is still negative and significant ($\beta = -0.8448$, $p < 0.05$). Thus, our results confirm the direct knowledge spillover from suppliers to the focal firm in technology exploration and exploitation choices, further showing the robustness of our main findings.

DISCUSSION

Where a substantial body of research has suggested both supply networks and board interlocks as separate networks to relate to technological entry and exit, a network pluralism perspective highlights the relevance of the interdependency between different types of networks. Drawing on extant insights from the supply network and board interlock literature, this study examines the joint roles of supply network and board interlock network in firms’ decisions on technological entry and exit in the Chinese automotive context. Using a longitudinal dataset of 86 firms active in the Chinese automotive during 2011–2015, we find that the number of suppliers is positively related to both firms’ entry into NTDs and exit from OTDs, suggesting that supplier relations allow for network advantage as an engine for the renewal of the firms’ knowledge base. Moreover, by highlighting the interplay between board interlock networks and supply networks from the network pluralism perspective, we reveal that the focal firm’s degree centrality in the board interlock network plays significant moderating role in the innovation benefits of firms’ supply networks. Specifically, when firms occupy a central position by having many partners in terms of board interlock ties, they are more likely to benefit from their suppliers to enter in NTDs and exit from OTDs. Our findings hence suggest that supply networks cannot be seen separately from a firm’s board interlock networks, which act as governing body that scouts and pushes forwards accessing and assimilating external technology opportunities on the highest corporate agenda.

Theoretical Contributions

Our insertion of relational pluralism to examine the complexities of organizational relationships as antecedents to a firms’ technological entry and exit, allows us to contribute to the extant literature in plural ways.

First and foremost, we contribute to the literature on interorganizational networks as we examine two distinct networks together by echoing and advancing the emerging network pluralism research (Beckman et al., 2014; Zhang et al., 2019). By revealing the positive interaction effects of supply networks and board interlocks on firms' technological entry and exit, we show that there is a complementary rather than a substitute relationship between the two networks. As a consequence, a firms' strategic decisions in the technological entry and exit arena are shaped by the heterogeneous but complementary effects of their positions in both supply and board interlocks networks. By confirming the effects of supply networks are contingent upon the centrality in the board interlocks, our findings also contribute to the literature on supply chain and board interlock networks. We advance the understanding of the effectiveness of the underlying supplier relations in the innovation context by incorporating other parallel networks (e.g., board interlocks) as the contingency, highlighting the necessity and value of configuring the multiplexity of different types of networks efficiently (Mazzola et al., 2016; Zhang et al., 2019). Moreover, our research extends our understanding about the role of board interlock network in firms' technological entry and exit by emphasizing its moderating effects on other types of networks (e.g., supply network) instead of the often-studied alliance network (Beckman et al., 2014; Mazzola et al., 2016). As such, the current study contributes to the network literature by advancing network pluralism as a valuable way to study the joint role of different types of networks in determining a firm's decision on technological entry and exit.

Second, directly benefiting from the innovative and collaborative Chinese automotive industry as our empirical context to test our theoretical arguments, we capture entry in NTDs and exit from OTDs as central theoretical notions that partially capture firms' explorative and exploitative behavior. Our findings indicate that a firm stands to benefit from plurality in suppliers to enter in NTDs and exit from OTDs, as such renewing their technology portfolio. Firms more exposed to various technological advancements and related new opportunities through multiple suppliers, by means of maintaining a larger number of supplier ties, are more likely to initiate new technology entry and old technology exit. In this regard, we enrich the understanding about the roles of supply networks in the dynamics of firms' technological innovation strategy. By doing so, we call on future network research to focus more on firm innovative behavior (e.g., entry in NTDs and exit from OTDs) than innovative performance (e.g., patent counts or citations), in a manner that considers the non-independent dimensions of interorganizational collaboration as firms simultaneously at various network levels.

Finally, as a modest methodological advancement to our field, we introduce the stochastic actor-based model for multilevel network dynamics as a novel method to the field of supply chain management, which was increasingly used in sociology and management research (Stadtfeld et al., 2016; Tröster et al., 2019). This model allows us to study the co-evolution of buyer–supplier, board interlocks, and firms' technological entry and exit, to reveal how the interdependencies

among different levels of networks influence network evolution and firms' technological innovation behavior. By doing this, we respond to the prior calls for more attention to the dynamics of multiplex ties in strategic management research (Howard et al., 2017; Kim et al., 2016).

Practical Implications

Our study has implications for firms' technology renewal strategy through entering in NTDs and exiting from OTDs. According to our findings, firms with more supplier partners tend to be motivated to move in new technology domains and move out old technology domains, especially those who occupied a central position in the board interlock network. Following this logic, a firm can advance successful upgrading of technology base by leveraging the knowledge resources in different types of interorganizational networks at the same time.

Our study also provides useful practical implications for firms' management on multiplex network partners. Our findings show that a central position in the board interlock network can enhance the embeddedness benefits derived from broad supply networks, so firms can adjust and optimize the benefits of their supply networks on the basis of managing the knowledge and resource flow at the managerial board level.

Limitations and Future Research

Our work has several limitations, especially the quite large unexplained variance in our models, which identify promising areas for future research. First, although patent-based indicators have the advantages to be extensively used in innovation research, it still has limitations in fully portraying firms' technological activities. Thus, our findings need to be understood in the context of industries and firms with a high propensity to patent. Second, we analyze supply networks and board interlock networks as the two are particularly important networks for firms to enter into NTDs and exit from OTDs. However, we believe that the interplay between other various networks provides fertile grounds for further research in operations and innovation management. It would be interesting and worthwhile for future research to examine these contingencies in other types of interorganizational (e.g., R&D alliances) and interpersonal relationships (e.g., R&D staff mobility). Third, we focus on the role of supplier partners alone in the supply network. Although we emphasized the greater value of studying suppliers in the context of automotive manufacturing and controlled for buyers' influence in the model, future research could still explore the direct and indirect roles of buyers in the innovation of focal firms. In addition, we only examined the impact of the number of suppliers on the technology renewal decisions of the focal firm, without considering the role of suppliers' technology diversity. Although we point out that the two variables are very highly correlated, future research still could delve into the mechanism of supplier diversity's influence on the focal firm's technology innovation decision from a heterogeneity perspective.

NOTES

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[1] <https://www.statista.com/topics/1050/automobile-manufacturing-in-china/>

[2] https://www.wipo.int/ipc/itos4ipc/ITSupport_and_download_area/20210101/pdf/scheme/full_ipc/en/index.html

[3] When a patent contains multiple IPC three-digit technology codes, it is assigned to each of the technology domains.

[4] This manual is frequently updated, mostly only in a minor way. The updated version is available from the following URL: http://www.stats.ox.ac.uk/~snijders/siena/R Siena_Manual.pdf

[5] For linear regression models, the coefficient of determination, usually denoted R^2 , is used to indicate the proportion of variance that is explained by the model. In contrast, RSIENA provides some measures that have the same purpose through function `sienaRI()` to reflect the effect sizes, which includes measures for *relative importance of effects* together with *the (non-relative) importance of effects* (Ripley et al., 2021). However, unfortunately, the current version of RSIENA still does not allow two-mode (bipartite) networks as dependent variables (firm-technology domains network in our study) and does not yet work for endowment or creation effects used in our models. Thus, we can only use the `sienaGOF` function to assess the goodness of fit for SAOM models.

[6] The null hypothesis for this test is that the auxiliary statistics for the observed data are distributed according to the cloud of points formed by the simulated data sets shown in the plot. The larger the p -value, the more likely the simulated values for the estimated model fit the observed network. The lower the p -value, the more significant the differences between the observed network and the simulated network.

DATA AVAILABILITY STATEMENT

The data and statistical code that support the findings of this study are openly available in the Open Science Framework (OSF), an open-source cloud-based project management platform that enables users to replicate the code and can be viewed at Aalbers and Ma (2023) at <https://osf.io/hxtdc/>

APPENDIX I

The Stochastic Actor-Oriented Model

The stochastic actor-oriented modeling (SAOM) method was originally developed by Snijders and his colleagues (Ripley et al., 2021; Snijders et al., 2010). According to Ripley et al. (2021), ‘When thinking about network dynamics, researchers usually assume that these decisions (conscious or subconscious) of actors are influenced by the structure of the network itself and the characteristics and behaviors of the focal actor (ego) who is making a decision and those of other actors in the network (alters). SAOMs provide a means to quantify the ways, the extent and the uncertainty with which these factors are associated with network evolution between observations’.

SAOM permits the analysis of multiple, simultaneous social processes of network tie evolution at the actor, dyadic, and broader network levels. The stochastic approach observes sequential changes in the status of actor-level ties from period to period across panels of the observed network data. The network actor behaves according to preferences and constraints that comprise short-term objectives in the choice of whether/how to change its network state (e.g., form new ties, abandon existing ties, etc.). RSIENA (R based Simulation Investigation for Empirical Network Analysis) is a statistical tool developed for the analysis of longitudinal network data, collected in a network panel study with two or more ‘waves’ of observations. RSIENA simulates the change between observed time points through a series of unobserved small changes and calculates the most likely sequence of changes (Snijders et al., 2010). The

transition matrix of the process describes the probability of each possible change, conditional on the node that has the opportunity to make the change. These probabilities are defined by a multinomial logit model.

In the simulation model, where all network changes are decomposed into very small steps, so-called ministeps, in which one actor can choose to add, drop, or keep a tie. This simulation process is repeated until our modeling finds weights (parameters) for the actor preferences that best explain the observed networks (i.e., that minimize the deviations between generated and observed values of the statistics). Within each micro-step, a randomly selected actor evaluates all possibilities to add, drop, or maintain an outgoing tie, or otherwise do nothing. Actors make changes in an effort to maximize the following objective function:

$$f_i(\beta, x) = \sum_i \beta_k s_{ki}(x)$$

where $f_i(\beta, x)$ is the value of the objective function for an actor i . x represents the network state in terms of both network tie structure and values of actor covariates. $s_{ki}(x)$ represents the effects potentially impacting the goals of actor i in changing its network state, which may be based on endogenous structural effects, actor attributes (ego, alter, and similarity effects), or some attributes of pairs of actors (i.e., dyadic covariates) (Snijders et al., 2010). β_k is the statistical parameters associated with the effects. When $\beta_k > 0$, there is a higher probability of network evolution moving in the direction where the effect is higher.

The software package in R, RSIENA (R based Simulation Investigation for Empirical Network Analysis), is developed to carry out the statistical estimation of SAOMs. It provides the outcome of an SAOM with a set of parameters (and standard errors) associated with effects that link network ties and actor attributes, and also the statistics for model fitting, testing for convergence and for goodness of fit.

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