Near is more: learning efficiency in research and development innovation among interlocking firms

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article

Abstract

Research question/issue: This study examines whether geographic proximity produces a proximity preference as interlocking firms observe each other and learn innovative behaviors through information transmission among interlocking directors.

Research findings/insights: We study the performance of A-share-listed companies in China from 2007 to 2017 on the basis of resource dependence theory, agglomeration effect theory, and Porter's competitive theory. When target firms learn about research and development–related innovation behaviors from interlocking firms closer to them, they experience more efficient learning effects and have improved convergent traits. Moreover, this proximity advantage increases the willingness of the target firm to communicate with and learn from interlocking firms closer to them. Highly developed areas and research and development–intensive industries positively affect the learning efficiency of interlocking firms.

Theoretical/academic implications: Our conclusion is consistent with resource dependence theory; target firms in highly developed areas are more willing to imitate and study nearby interlocking firms to maintain their peer relations, innovation potential, and competitiveness. Our conclusion is also consistent with competition theory, which states that the exchange of information between target firms in highly research and development–intensive industries and distant interlocking firms increases innovation differentiation, innovation potential, and competitiveness, even when such exchange has a high cost.

Practitioner/policy implications: The results support resource dependence theory and peers' effects. The information obtained by interlocking directorates through external social relations guides firm decision-making, and closer distances reveal more obvious effects.

Keywords: Geographical distance, Interlocking directorates, R&D, Learning efficiency

JEL Classification: G20, G32, G34

"While the grass grows the horse starves".

Introduction

Studies on peer effects have indicated that the nature of social interaction enables firms to conduct observational learning related to the behavior of peer firms (Leary and Roberts 2014; Hope and Zhao 2018). The premise of this phenomenon is that because firms are competitive, they assess the strengths and weaknesses of competitors by carefully observing their behavior and decision-making (Porter 1980). For example, some firms determine executive salaries on the basis of those at peer firms (Bizjak et al. 2008). Bouwman (2011) reveals that firms that share a director exhibit similar behavior in terms of corporate governance and practices, and the peer effect originates from close connections among interlocking directorates. According to resource dependence theory (Pfeffer and Salancik 1978), director sharing can be an external resource for a firm to enhance information exchange among target and interlocking firms (Chuluun et al. 2014). The peer effect may occur when a firm observes and understands the behavior of similar firms through interlocking directorates rather than through social relations that result from competition among firms (Kaustia and Rantala 2015). Therefore, in this study, it is hypothesized that the functions of interlocking directorates can be described as follows: Interlocking directorates possess confidential information on interlocking firms and are permitted to speak in several firms; therefore, they perform dual roles of messengers and decision-makers. In observational learning, interlocking directorates serve as communication channels as well as decision-makers regarding received information. They obtain information through interpersonal relationships and provide firms with knowledge and skills, which increase social capital for a firm's board of directors (Hillman and Dalziel 2003; Vaccaro et al. 2010; Yu 2013), thereby enabling the firm to produce effective research and development (R&D) plans or motivating the firm to conduct R&D (Chen 2014).

However, geographic proximity has not been carefully evaluated in terms of the aforementioned methods by which interlocking directorates access information. A compact geographic distribution pattern enables firms to experience the combined effects of economies of scale, knowledge spillover, and competitive markets. However, a wide geographic dispersion can lead to substantial problems in terms of investment and financial decisions (Brown et al. 2008; Hong et al. 2008; Kedia and Rajgopal 2009; Baik et al. 2010; John 2011; García and Øyvind 2012; Shi et al. 2015). Firms located near each other have more opportunities to communicate, and effective information sharing can reduce information asymmetry (Pagano and Jappelli 1993; Hong et al. 2005; Gao et al. 2008; Baschieri et al. 2012; Doblas-Madrid and Minetti 2013). Geographic proximity among firms affects the efficiency of information exchange among directors, thereby substantially affecting a firm's economic activity. Von Hippel (1994) proposes that knowledge spillover always occurs through frequent contact between economic individuals and that the geographic proximity of firms improves information transmission in neighboring regions, thus enhancing the R&D of local firms (Carosi 2016). Geographically isolated firms invest more financial resources in information exchange between firm executives (Engelberg et al. 2013). Firms with the advantage of geographic proximity conduct efficient and inexpensive information transmission. After long-term development, this

proximity effect in a firm develops into a proximity preference or home bias (Coval and Moskowitz 1999; Hong et al. 2008). On the basis of this concept, Baran and Wilson (2018) explore the geographic locations of interlocking directorate networks and reveal that firms in remote areas allow directors to hold concurrent positions in different companies in metropolitan statistical areas (MSAs) to obtain the benefits of combined effects. In the present study, it is posited that areas with high commercial activity and combined effects increase the efficiency of information transmission among firms, enabling them to obtain innovative advantages in competitive markets and increasing the willingness of directors in remote areas to work in MSAs. In summary, this study focuses on whether geographic proximity produces a proximity preference as interlocking firms observe each other and learn innovative behaviors through information transmission among interlocking directorates.

Specifically, this study seeks to determine (1) whether the distance between the target and interlocking firms affects the efficiency of mutual R&D innovation and (2) whether a target firm is more inclined to exchange innovation-related information with geographically closer interlocking firms. The answers obtained from the empirical analysis affirm these two questions; a target firm learns innovative behaviors more efficiently from geographically closer interlocking firms and is more inclined to communicate with closer interlocking firms. The results pass the robustness test by which the interaction term of distance and the average R&D expenditures of all interlocking firms were established. Recent studies on the relationship between interlocking directorates and R&D are in agreement that the interlocking network formed by directors is the social capital of a firm and is conducive to information transmission and improved R&D. However, these studies do not consider proximity, which affects the efficiency of information exchange and transmission among directors, thereby affecting the efficiency of learning innovation among firms. This study fills a research gap in this respect.

To meet the research objectives, this study uses the geographic distance between a target firm and interlocking directorates to conduct a quantitative analysis. Rather than employing the level of geographic dispersion (degree of distribution or spatial dispersion index; Gao et al. 2008; Baschieri et al. 2012; Shi et al. 2015) or spatial statistical methods (Grinblatt and Keloharju 2001; Ayers et al. 2011; Eckel et al. 2011; Chhaochharia et al. 2012), geographically weighted regression (GWR; Carosi 2016) was used to define interlocking firms' level of R&D related to distance. Distance represents the cost of communication, and the advantage of the GWR method is that it uses distance rather than spatial orientation to analyze target and interlocking firms. This study employs a method in which (1) a focal firm is not required[1] and (2) the distances between the target and interlocking firms accurately reflect those required for information transmission.

Subsequently, we examined the regulatory role of the highly developed regions, the intensity of R&D in the industry, and the legal institutions that can affect learning efficiency between target firms and interlocking firms. The establishment of highly developed regions relies on the marketization index of China's provinces (Kong et al. 2020).
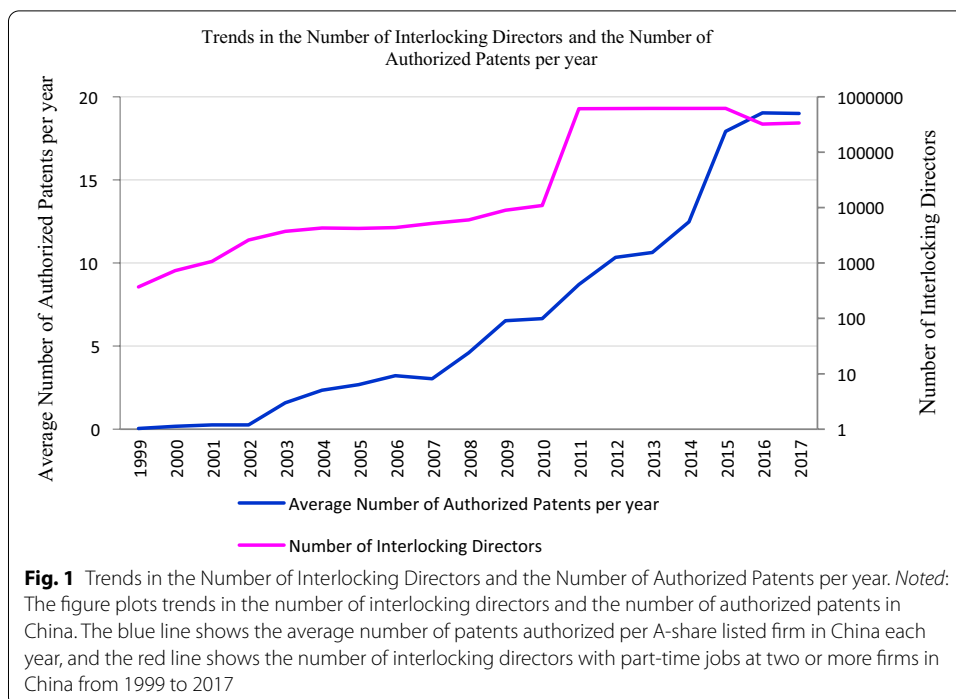
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[1] It is assumed that an executive concurrently serves as a director at firms A, B, and C. If the research object is company A, then A is the target firm and B and C are interlocking firms. If the research object is firm B, then B is the target firm and A and C are interlocking firms. No fixed principal company was studied.

The results reveal that R&D innovation behavior is more efficient for target firms in highly developed regions that are closer to interlocking firms. However, no proximity preference is observed in the industry R&D intensity test and legal institutionalization test. Specifically, industry R&D intensity relies on firms' past nonzero capitalized R&D expenditures, and the extent of legal institutionalization relies on the development of market intermediary organizations and the legal environment index of China's provinces (He and Wintoki 2016). Industry R&D intensity and level of legal institution negatively affect learning efficiency.

For the robustness test, we replace the explained variable R&D and the explanatory variable with dummy variables related to distance. Our results are demonstrated to be consistent. The results indicate that if a target firm is close to interlocking firms, its learning efficiency for R&D innovation remains high. In addition, target firms prefer to communicate with distant interlocking firms. Baran and Wilson (2018) demonstrate that geographically remote firms benefit from connections with firms in MSAs because of their high commercial density and that firms in MSAs reduce the adverse effects of intensive business by connecting with firms in remote areas.

This study makes the following contributions: First, the concept of geographical distance is introduced to interlocking directorate networks. The results expand the scope of research on interlocking directorates and R&D. Specifically, geographic proximity among firms enhances information transmission among interlocking directorates; therefore, close interlocking firms affect R&D in the target firm. Second, in this study, the geographic bias concept proposed by Coval and Moskowitz (1999) and Hong et al. (2008) is applied to information transmission among interlocking directorates, and the results demonstrate that firms develop proximity preferences based on the advantage of geographic proximity. The results support resource dependence theory and its combined effects. The information obtained by interlocking directorates through external social relations helps guide firm decision-making, and shorter distances reveal more obvious effects.

Kono et al. (1998) indicated the effects of interlocking directors and their spatial structure on corporate behavior by studying large industrial firms. In the United States, the geographical location of a parent company and its subsidiary companies and the geographical distribution of production facilities are the determinants of interlocking director network relations. Two types of interlocking director networks exist: the cohesive network, based on the concentration of strength, and the decentralized and dispersed network (Cárdenas 2012). The interlocking director networks in Mexico, Chile, and Peru are highly cohesive, whereas those in Brazil and Colombia are not, which is caused by the complementarity of state-owned enterprise relations and market openings in economies with high trade openness (Cárdenas 2016, 2019). Barros et al. (2020) indicated that in Brazil, the highly centralized interlocking director network could increase information asymmetry in mergers and acquisitions. The interlocking director networks in Europe are highly overlapping, with both domestic and transnational interlocking relationships, whereas the interlocking director networks of large firms tend to be more transnational (Heemskerk 2013). Over time, the interlocking director network density has increased in Brazil, Mexico, and Taiwan but decreased in Chile, Israel, and South Korea. Countries that have neither liberalized

Fig. 1 Trends in the Number of Interlocking Directors and the Number of Authorized Patents per year. *Noted*: The figure plots trends in the number of interlocking directors and the number of authorized patents in China. The blue line shows the average number of patents authorized per A-share listed firm in China each year, and the red line shows the number of interlocking directors with part-time jobs at two or more firms in China from 1999 to 2017

nor rapidly privatized, such as China, were the last to develop a small group of interlocking directors (Mizruchi 2015). In China, the effect of interlocking director networks on firms is caused by the resource dependence of interlocking director relations as social capital. From the perspective of resource dependence theory, the core of interlocking director networks is the spatial structure that enables firms to obtain resources. Through this interlocking director network, interlocking firms replace cash holdings with bank loans or acquire valuable strategic information and innovation resources through interlocking directors (Li et al. 2020). In China, the crucial role of interlocking directors for firms is reflected by their exchange of information and access to resources. We collected data and experiences regarding the number of interlocking directors and company patents in China to determine the role of interlocking directors. Figure 1 presents the number of interlocking directors in China and the average number of invention patents granted annually to China's A-share listed firms. Before 2001, few directors served as interlocking directors in more than two companies. In 2010, the number of directors in China increased considerably, and the number of interlocking directors has remained stable at more than 100,000 since 2011. The number of invention patents granted annually has increased steadily over time; this is related to China's legal protection index (Li et al. 2017). Chen (2014) revealed that the number of interlocking directors increasing rapidly indicates a positive relationship between directors and R&D and that interlocking directors' information exchange positively affects their company's R&D.

This study is divided into six sections. The second section summarizes relevant literature and proposes research assumptions. The third section introduces the research methods. The fourth section presents the empirical results. The fifth section presents the additional test, and the sixth section provides conclusions, insights, and implications.

Literature

This study focuses on whether a target firm's learning of R&D innovation behavior from interlocking firms through information transmission among interlocking directorates is affected by geographic distance among the firms. Therefore, the literature review is based on the influence of information exchange and the combined effects of interlocking directorates on R&D.

Effect of information exchange among interlocking directorates

Interlocking director networks share the characteristics of small-world networks: strong coordination and high clustering (Newman et al. 2001; Battiston and Catanzaro 2004; Conyon and Muldoon 2006; Caldarelli 2013; Prem Sankar et al. 2015; Sankowska and Siudak 2016). Clusters tend to have clear centers and short channels. The remote connection of high-level, two-part clusters comes at a cost (Robins and Alexander 2004). The network of companies and boards of directors exhibit a regular proportion, and the complexity, board size, and the number of directors in interlocking director networks often have a power-law distribution (Siudak and Sankowska 2016). These characteristics make interlocking director networks closely related to the decision-making process of companies, societies, and nations. Interlocking director networks are nodes of enterprise societies, and the system connects the nodes together to form a framework for the operation of enterprise societies (Caldarelli 2013). Conyon and Muldoon (2006) noted that board networks in the United States, the United Kingdom, and Germany have small-world characteristics in addition to random distribution characteristics, which increase the connectivity of the board of directors. Newman et al. (2001) revealed that board networks have a vertex distribution structure that can be analyzed to accurately predict the status of a company. Robins and Alexander (2004) studied the number and density of interlocking director network nodes and discovered that companies are more likely to be influenced by boards of directors than by a group of individual directors and that the sharing of remote connections among board members (i.e., interlocking directors) is costly. Boards of directors and directors of large companies form an intensive two-way network through which large companies participate in national macroeconomic decisions (Battiston and Catanzaro 2004). Durbach and Parker (2009) demonstrated that the establishment of interlocking director networks is crucial both for small emerging economies such as that of South Africa and for highly developed countries. Interlocking directors also play a key role in the corporate governance system, and the performance of companies and directors who participate in basic interlocking director networks differs considerably from that of those who do not (Prem Sankar et al. 2015).

In resource dependence theory (Pfeffer and Salancik 1978), the survival of an organization depends on its environment and its ability to continually absorb resources and experience from the environment. Competition theory (Porter 1980) posits that to secure a competitive position in the market, an organization must surpass other organizations in terms of cost or product heterogeneity. Both theories emphasize continual information exchange with other organizations during business management. However, the two theories differ in that competition theory focuses more on observation and learning among organizations, and it considers the acquisition of confidential information to

be the fundamental driving force of business communication among enterprises. Firm managers typically invest substantial resources to obtain innovative strategic advantages by collecting confidential information (Aghion and Tirole 1997; Stein 2002; Abeka 2017). The two theories and studies on peer effects indicate that a firm exchanges more information with its peers than with other firms, and financial policies are often established in accordance with those of peer firms. For example, Bizjak et al. (2008) report that the executive salary in a firm is generally similar to those of its peer firms to ensure stable human resources. Leary and Roberts (2014) discover that the external influence of a peer firm causes a firm to maintain similar costs of capital, which contributes to the similarity in the capital structure. Bouwman (2011) proposes that the relationship between common directorates of peer firms generates a peer effect. Kaustia and Rantala (2015) note that the peer effect is more likely to be caused by firms observing and learning from their peers rather than relying on the social relationships resulting from competition alone. According to resource dependence theory, relationships among directorates can provide key knowledge that a firm cannot generate internally, and the purpose of interlocking directorates is to improve information exchange between a target firm and other firms. Engelberg et al. (2012) argue that relationships among directorates contribute to convenience in firm financing. Cai and Sevilir (2012) report that interlocking directorates are essential in information transmission during mergers and acquisitions. Chuluun et al. (2014) argue that the social capital of directors increases the bond yield spread. The spillover effect caused by information transmission also influences the R&D level of an enterprise. As the core of firm competitiveness, innovation is often the primary target for firm observation and learning. Chen (2014) argues that the knowledge and skills that interlocking directorates contribute can increase the R&D capabilities of a firm. The small-world network attribute of interlocking director networks also affects information exchange and business practice diffusion. System networks consisting of boards of directors can be divided into company networks and director networks, and these two networks exchange information and influence each other (Caldarelli and Catanzaro 2004). Interlocking directors play a crucial role in corporate behavior and corporate governance (Kogut 2012; Prem Sankar et al. 2015).

To enable companies to obtain external resources, increase their competitiveness, and utilize the information exchange associated with interlocking directors, the spatial network formed by interlocking directors' human resources must benefit the company's resource acquisition. Transnational interlocking board networks with the financial industry at the core played a vital role in the formation of the European Enterprise Community, made the European Union unique in the field of regional integration, and helped European enterprises overcome economic crises (Carroll et al. 2010; Heemskerk 2011, 2013; Van der Pijl et al. 2011; Van Veen and Kratzer 2011; Heemskerk et al. 2013). A relationship exists between the personal history and geography of directors in the interlocking director networks of American companies. If the personal experience of directors is similar to that of the company, the company will achieve superior performance. National and local boundaries hinder the exchange of corporate information and the flow of knowledge (O'Hagan and Green 2002; O'Hagan 2015). Knowledge transfer depends on the maturity of the system in which an interlocking director network is located. The lower the knowledge threshold of a company is, the more quickly knowledge transfer

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occurs (O'Hagan and Green 2004). In the process of economic globalization, individuals with international experience act as intermediaries connecting domestic enterprises with enterprises in remote areas, increasing profitability for those companies (O'Hagan and Rice 2015).

Combined effects on firm R&D

The geographic location of an enterprise is essential because proximity is conducive to information transmission, which substantially affects economic activity. The effects of geographic location can be roughly categorized into the following situations: (1) In terms of corporate governance, governance structures differ according to their geographic location. Francis et al. (2016) investigated the connections among spatial clusters of enterprises in large and central cities and discovered that the CEOs of urban community firms generally adopt incentive-based compensation strategies. Alam et al. (2011) argue that firms located in information-intensive regions have a higher percentage of nonaffiliated board directors living near firm headquarters. (2) According to agency theory, geographic location affects the monitoring costs of a firm. Coval (1999) demonstrates that investors have a strong preference for purchasing the stocks of geographically proximal firms. Ayers et al. (2011) use the distance between a firm and institutional investors as a proxy variable for the cost of accessing monitoring information. The results indicate that greater distances result in less discretion when financial reports are filed. Chhaochharia et al. (2012) consider local institutional investors to be effective supervisors of enterprise behavior, suggesting that more local institutional investors correspond to more effective supervision. Devos and Rahman (2014) explore the effect of the location of a firm on its operating lease, and the results suggest that the costs of information acquisition and monitoring incurred by firms near cities are lower. Boubakri et al. (2016) conclude that firms located farther from domestic financial centers attract less participation and ownership by foreign investors.

Firms are affected by their geographic locations, and the most prominent effect of geography is the combined effect. The combined effect enables the sharing of key knowledge among specific groups of organizations within certain proximity; these firms exhibit favorable growth potential and innovation competency. Vroom (1994) proposes that the specific spatial arrangement of economic activity affects innovation in an enterprise. Von Hippel (1994) indicates that knowledge spillover must occur through frequent contact and information exchange and that the possibility of contact among firms is largely determined by information transfer among interlocking directorates, which are essential in information transmission and decision-making. Firms are more likely to interact if they have geographic proximity. Chen (2014) verifies that social capital generated by interlocking directorates improves enterprise R&D. Helmers et al. (2017) discovered that interlocking networks of boards of directors have a significant positive effect on R&D and patents. Specifically, some companies reapply for patents abroad for inventions patented in India to expand their patent protection. Chuluun et al. (2017) noted that the characteristics of interlocking director network connections—namely centrality, cohesion, diversity, innovation, and affinity—affect the innovation input and output of enterprises. Howard et al. (2016) revealed that the interlocking director relationships of technology enterprises represent a unique form of external resource dependence. Such

enterprises not only obtain knowledge resources from other enterprises through the R&D alliances formed through interlocking relationships but also defend their intellectual property rights by using this circle. Carosi (2016) proposes that geographic proximity enhances information transmission in neighboring regions, thereby improving the R&D of local firms. By integrating resource dependence theory, Carosi (2016) proposes that a target firm learns the R&D innovation behavior of interlocking firms through information transmission among interlocking directorates. Moreover, the closer interlocking firms are geographical, the higher the learning efficiency is. Competition theory supports this conclusion. Additionally, competition is more intense for firms in a market with a greater number of similar firms, and the proximity of such firms corresponds to a decreased range of market competition but higher competition intensity. Consequently, firms carefully observe the innovative decision-making behaviors of their most prominent competitors.

A target firm with proximity advantages can obtain more information, and its R&D level would be similar to those of interlocking firms. However, Engelberg et al. (2013) prove that geographically isolated firms invest more time, money, and energy in the executive process of establishing an information exchange network. Motivated by reducing costs, a firm generates proximity preferences for communicating with proximal rather than distal interlocking firms. Directors on the boards of firms in remote areas hold concurrent positions in firms in MSAs to avoid the adverse effects of isolation (Baran and Wilson 2018).

Hypothesis development

Considering the aforementioned theories related to interlocking directors and R&D, we propose a competitive hypothesis that the R&D behavior of an interlocking firm can positively or negatively affect the R&D behavior of a target firm.

Resource dependence hypothesis: resource dependence theory dictates that the target firm and the interlocking firm have similar R&D behavior

The first hypothesis is that the R&D level of the interlocking firm positively affects the R&D level of the target firm. This prediction relies on the mutual imitation behavior of enterprises enacted through the peer effect. For example, management social capital reduces the dependence of enterprises on internally generated cash, social capital positively affects the sensitivity of external financing in accordance with Tobin's Q (David et al. 2016), and the political network of directors contributes substantially to the returns on a company's initial public offering (Gounopoulos et al. 2021). Resource dependence theory states that companies use social relationships in the behavior of their peers to observe learning and maximize access to social resources. As external resources of a company, interlocking director relationships make the same voter appear in the board of directors of the target firm and the interlocking firm. This relationship can provide key knowledge that the target firm cannot generate internally, such as the level of compensation in the interlocking firm (Bizjak et al. 2008), whether the company possesses the same level of governance as its peers (Bouwman 2011), or financing from the interlocking firm at a lower cost (Engelberg et al. 2012). The board network is positively related to corporate social responsibility performance, and the ability of independent directors

to collect information and resources from their network can facilitate the transmission of information (Amin et al. 2020). Imitation between companies represents definitive evidence of this phenomenon. Binay and Anup (2018) discovered that a company's payment policies, dividends, and share buybacks are significantly affected by the policies of industry peers and that peer effects more strongly affect payments in companies that face greater competition in product markets and operate in a better information environment. Hence, we speculate that the interlocking director relationship encourages the target firm to share resources with the interlocking firm, rather than compete for resources. On the basis of this idea, the following hypothesis is proposed.

H1a (Resource dependence hypothesis): The R&D level of the interlocking firm positively affects the R&D level of the target firm.

Competition hypothesis: competition theory dictates that the target firm and the interlocking firm have less similar R&D behavior

The second hypothesis is that the R&D level of the interlocking firm negatively affects the R&D level of the target firm. According to competition theory, 1) the more substitutes the company has in the market, the more intense the competition and the closer the company is to the homogenous company and 2) the smaller the scope of market competition, the higher the intensity of the competition (Porter 1980). Competition theory states that enterprise communication emphasizes observation and learning among organizations and that obtaining confidential information is the fundamental driving force of business communication between enterprises. Business managers often invest many resources to gain a strategic advantage in innovation by gathering confidential information (Aghion and Tirole 1997; Stein 2002). Observation and learning must occur through frequent contact and information exchange, and the possibility of contact between enterprises depends greatly on the transmission of information between interlocking directors (Von Hippel 1994). The interlocking director relationship allows the target firm and the interlocking firm to obtain corporate information and trade secrets about other companies. Under the condition of limited market resources, companies with high product homogeneity closely observe and learn from the innovation and decision-making behavior of the most threatening competitors and seek out unique methods to adopt different R&D strategies in the competitive market. Combined effect theory is also consistent with this proposition. The information transmission effect among interlocking directors largely determines how possible it is for the target firm and interlocking firm to obtain information from each other, and the closer the distance, the more likely it is that the interlocking firms can obtain information from each other. Certain spatial arrangements of economic activities and the localization of peer firms strongly affect firms' innovation (Vroom 1994), and geographically isolated firms invest more time, money, and energy into the executive process of establishing an information exchange network (Engelberg et al. 2013).To avoid the adverse effects of geographic isolation, interlocking directors of target firms, such as directors on the boards of firms in remote areas holding concurrent positions in firms in MSAs, must pay the additional cost of observation (Baran and Wilson 2018). We speculate that target firms and interlocking firms differentiate themselves to respond to competition. On the basis of this discussion, the following hypothesis is proposed:

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H1b (Competition hypothesis): The R&D level of the interlocking firm negatively affects the R&D level of the target firm.

H1a and H1b are competitive hypotheses, and we empirically tested which one of the two is supported.

Methodology

Data

The research sample comprises A-share listed companies in China from 2007 to 2017. After considering the availability and time-sensitivity of key control variables such as market competition,[2] this study selects the observed values of these firms. Corporate operation and governance data were obtained from the China Stock Market and Accounting Research Database, and market value data were obtained from the Stock Trading Database. Geographic distances from the target firm to the interlocking firms are obtained through a manual search and calculation based details of each firm[3] (Huang and Kang 2017). To ensure data reliability and accuracy, the samples are processed as follows: (1) financial firms are excluded because their unique R&D levels make them unsuitable for research; (2) firms with missing financial data are excluded; and (3) except for the dummy variables used in this study, the data are winsorized at 1% in their distribution tails to remove outliers and the most extreme data. After screening, a total of 8,922 valid observed annual values are included in this study.

Variable definitions

R&D expenditure

This study investigates whether the R&D innovation behavior of the target firm is affected by the proximity of interlocking firms. Therefore, the dependent variable is the R&D expenditure level of the firm (*RD1*), which is measured using the R&D sales ratio, R&D asset ratio, and the number of patents the firm has. The number of patents obtained within 5 years is unsuitable for this study because R&D decision-making regarding patent applications is lengthy and thus does not reflect the effect of information. Carosi (2016) uses the ratio of firm R&D expenditure to annual sales revenue as a proxy variable; using the sales income as the denominator produces the proportion that the firm intends to invest in R&D. This represents the opportunity for future growth for the firm. However, this study considers the extent to which the R&D decisions of the target firm are positively affected by interlocking firms. This effect should reflect the capitalization of R&D expenditure. Thus, it is measured using the ratio of R&D expenditure and total assets, and the dependent variables are measured one period later to reflect the delay in information transmission. In the robustness test, the dependent variable is

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[2] To determine the extent of market competition in this study, China's marketization index (Wilson, 2016) is used as a proxy variable. Marketization is scored on the basis of the overall situation of market reform and progress in different aspects in China's provinces, autonomous regions, and municipalities in 2007–2017.

[3] This study collects detailed address information for the A-share-listed firms. The coordinates of the firms are determined according to their addresses, and the geographical distance between two coordinates is calculated using the geographical distance function of SAS.

the R&D expenditure level of the firm (*RD2*), which is measured using the ratio of R&D expenses to annual sales revenue.[4]

Learning efficiency

First, variables are assigned to define the learning efficiency of the target firm *i* in terms of the R&D innovation behavior of interlocking firms. *CoRD* is the average value of R&D expenditures for all interlocking firms of *i*. Specifically, R&D expenditure refers to the ratio of R&D expenditure to total assets. A higher coefficient of correlation between the *CoRD* and *RD* of the target firm corresponds to greater similarity in the R&D behavior of the target and interlocking firms. Target firm *i* has a total of *m* interlocking firms in year *t*. *CoRD* is then defined as follows:

$$CoRD_{i,t} = \frac{\sum\limits_{j=1} RD_{i,j,t}}{m}, \quad i = 1, 2, 3, \ldots, n; j = 1, 2, 3, \ldots m; t = 1, 2, 3, \ldots, T \qquad (1)$$

To investigate whether geographic distance affects learning efficiency in this study, a learning efficiency variable related to distance is assigned. The R&D level of an interlocking firm is weighted according to the distance between the interlocking firm *j* and the target firm *i*. If located farther away, the interlocking firm has a larger weight for the R&D level. Low correlation coefficients between the distance-weighted R&D expenditure of the interlocking firm (*KmRD*) and *RD* indicate similar R&D innovation behavior between the target and interlocking firms. According to geographically weighted regression (GWR) (Carosi 2016), *KmRD* is defined as follows:

For a total of *n* listed firms, $D_{i,j,t}$, is the distance (unit: 1,000 km) between target firm *i* and interlocking firm *j* in year *t*. The distance weight between target firm *i* and its interlocking firm *j* is as follows:

$$W_{i,j,t} = \frac{D_{i,j,t}}{\sum\limits_{j=1} D_{i,j,t}}, \quad i = 1, 2, 3, \cdots, n; j = 1, 2, 3, \cdots m; t = 1, 2, 3, \cdots, T \qquad (2)$$

The weight of the observed values depends on the proximity of the firm to the target firm; a greater distance corresponds to a higher weight. If RD_{ij} is the R&D expenditure of interlocking firm *j* of target firm *i* in year *t*, then the distance-weighted R&D expenditure of the interlocking firms of firm *i* is as follows:

$$KmRD_{i,t} = \sum\limits_{j=1} \left(\frac{RD_{i,j,t}}{W_{i,j,t}} \right), \quad i = 1, 2, 3, \cdots, n; j = 1, 2, 3, \cdots m; t = 1, 2, 3, \cdots, T \qquad (3)$$

Average distance

In this study, the average distance between the target firm and an interlocking firm (unit: 1,000 km) was used as a moderator in the robustness test. On the basis of

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[4] We also tested Patent1 (the natural logarithm of the number of patents a firm apply each year), Patent2 (the natural logarithm of the number of patents a firm is granted each year), and Patent3 (the natural logarithm of the number of patents cited annually by a company) as explanatory variables. The tests for the explained variables of the patent are contained in the appendix.

precise geographic coordinate data of the parent firms of the listed firms, the precise distances between each target firm and all interlocking firms were obtained for each year, and the average value was used as the proxy variable (*Distance*). The specific measurement method is described as follows:

In addition, target firm *i* has a total of *m* interlocking firms in year *t*, and the average distance between target firm *i* and all interlocking firms is as follows:

$$Distance_{i,t} = \frac{\sum\limits_{j=1} D_{i,j,t}}{m}, \quad i = 1, 2, 3, \ldots, n; j = 1, 2, 3, \ldots, m; t = 1, 2, 3, \ldots, T \quad (4)$$

Proxy variable $Distance_{i,t}$ is the average distance between target firm *i* and all interlocking firms in year *t*. We also include a dummy variable for target firms that are both far from and close to interlocking firms to determine the learning efficiency of the R&D innovation behavior of the two target firms. We use the dummy variable *D_Distance*, which is equal to 1 when the distance between the target firm and the interlocking firm is lower than the industry average and 0 otherwise.

Marketization index

Interlocking directors in highly developed regions tend to have convenient transportation methods, which may increase the learning efficiency of interlocking firms. Kong et al. (2020) take the same method as Fan et al. (2011) to calculate the marketization index of China's provinces. So we take the same method as Kong et al. (2020) to measure the marketization index (*Area*).

R&D intensity

According to Porter's competition theory (Porter 1980), R&D-intensive firms are likely to be highly competitive, which may result in high learning efficiency. R&D stock is a measure of past capital R&D expenditures calculated using the perpetual inventory method (He and Wintoki 2016). So we measure R&D stock by R&D stock.

Control variables

This study makes reference to relevant literature (Chen 2014; Carosi 2016; Husted et al. 2016; Wilson 2016) and considered factors such as operation scale, profitability, and firm growth to select control variables, namely firm size (*Size*), return on assets (*ROA*), total debt to total assets (*LEV*), book to market ratio (*BM*), Dividend per share (*Div*), state-owned enterprise (*Soe*), ratio of advertising expenditure and total assets (*AD*), Herfindahl–Hirschman Index (*HHI*), Sales growth rate (*Sales_g*), the cash growth ratio *Cash*, and average industry R&D level *RD_ind* of each year are included ("Appendix A").

Research design

To verify the effect of geographic distance and variables related to interlocking directorates on enterprise R&D, the following regression is established:

$$
\begin{aligned}
RD_{i,t+1} = {} & \alpha + \beta_1 X_{i,t} + \beta_2 Size_{i,t} + \beta_3 ROA_{i,t} + \beta_4 LEV_{i,t} + \beta_5 BM_{i,t} + \beta_6 Sales\_g_{i,t} \\
& + \beta_7 Soe_{i,t} + \beta_8 RD\_ind_{i,t} + \beta_9 AD_{i,t} + \beta_{10} HHI_{i,t} + \beta_{11} Div_{i,t} + \beta_{12} Cash_{i,t} \\
& + \Sigma Year + \Sigma Firm + \varepsilon
\end{aligned}
\quad (5)
$$

In regression (5), *RD* is the dependent variable and *X* is the independent variable. In the variable design, *X* is separately regarded as *CoRD* and *KmRD*. Additionally, *X* is considered *Copatent* and *Kmpatent* in subsequent tests. $\beta_1 \ldots \beta_{12}$ are variable parameter estimates, and ε is a random error term.

To determine the effect of the marketization index and R&D intensity on the mechanism, *M* is used for a moderator. The regression model is as follows:

$$
\begin{aligned}
RD_{i,t+1} = {} & \alpha + \beta_1 X_{i,t} + \beta_2 X_{i,t} \cdot M_{i,t} + \beta_3 M_{i,t} + \beta_4 Size_{i,t} + \beta_5 ROA_{i,t} \\
& + \beta_6 LEV_{i,t} + \beta_7 BM_{i,t} + \beta_8 Sales\_g_{i,t} + \beta_9 Soe_{i,t} + \beta_{10} RD\_ind_{i,t} \\
& + \beta_{11} AD_{i,t} + \beta_{12} HHI_{i,t} + \beta_{13} Div_{i,t} + \beta_{14} Cash_{i,t} + \sum Year + \sum Firm + \varepsilon
\end{aligned}
\quad (6)
$$

In regression (6), *M* represents *Tech* and *Area*, and *X* represents *CoRD* and *KmRD*, both of which are subject to regression. In the regression, α is a constant, $\beta_1 \ldots \beta_{14}$ are variable parameter estimates, and ε is a random error term.

Results

Descriptive statistics

Table 1 lists the overall sample population, which contains 8,922 observed values. The mean *RD1* is 0.0089, and the median *RD1* is 0.0016 after winsorization. These results indicate that the majority of the companies in our observed sample have a low ratio of R&D to total assets. The HHI of 0.0426 and the Sale_g of 20.51% indicate a high degree of competition and high growth in the product market.

Table 2 presents the distribution of the 8,922 observed values and the 1,977 sample firms by industry and region. Panel A presents the distribution of the samples in nine industries (excluding finance). The data indicate that because of the development of the industrial economy and the service industry, the samples were mainly from materials, industrial, and unnecessary consumption. Panel B presents the distribution of the samples in 30 provinces and autonomous regions. The data indicate an imbalance among China's regional economies. The sample of listed firms is densely concentrated in the developed coastal cities (Beijing, Shanghai, Zhejiang, Jiangsu, and Guangdong) and less concentrated in remote areas.

Table 3 presents the characteristics of R&D intensity and the classification of the development area, especially in terms of the differences in R&D level.

Panel A indicates that target firms with a high level of R&D intensity have higher R&D levels (*RD1*). In addition, interlocking firms have a higher level of R&D because they are affected by the target firm's R&D intensity (*CoRD1* and *KmRD1*). The t-test value for RD1 in column (2−1) is −6.12. The t-test value for *CoRD1* and *KmRD1* are −4.01 and −3.46, respectively, and the absolute value of the differential coefficient of *CoRD1* (−0.0014) is smaller than that of *KmRD1* (−0.0288). This indicates that after distance weighting, the difference in R&D level of the interlocking firms gradually increases and that the significance decreases. All differences in mean values (column 2−1) are statistically significant at p = 0.05.

Table 1 Descriptive statistics

Variable	MEAN	STD	MIN	Q1	MEDIAN	Q3	MAX
Panel A: Total Samples							
RD1	0.0089	0.0130	0.0000	0.0000	0.0016	0.0147	0.0712
RD2	0.0175	0.0280	0.0000	0.0000	0.0027	0.0284	0.1827
CoRD1	0.0095	0.0085	0.0000	0.0034	0.0078	0.0135	0.0636
CoRD2	0.0186	0.0174	0.0000	0.0062	0.0147	0.0258	0.1143
KmRD1	0.62988	1.50285	0.10765	0.0021	12.69415	0.62988	1.50285
KmRD2	1.19567	2.84377	0.19846	0.0015	22.07759	1.19567	2.84377
RD_ind1	0.0088	0.0069	0.0000	0.0037	0.0081	0.0105	0.0292
RD_ind2	0.0170	0.0153	0.0000	0.0057	0.0145	0.0230	0.0567
Size	21.8715	1.1397	19.2315	21.0379	21.7448	22.5439	26.5727
ROA	0.0491	0.0548	− 0.1793	0.0178	0.0435	0.0766	0.2644
LEV	0.4178	0.2113	0.0272	0.2470	0.4087	0.5839	0.9884
Soe	0.3995	0.4898	0.0000	0.0000	0.0000	1.0000	1.0000
BM	0.6692	0.3553	0.0749	0.4070	0.6159	0.8596	2.1469
Div	0.0094	0.0562	0.0000	0.0000	0.0000	0.0000	0.5000
AD	0.0092	0.0229	0.0000	0.0004	0.0015	0.0060	0.1881
HHI	0.0426	0.0495	0.0129	0.0257	0.0385	0.0437	0.9736
Sales_g	0.2051	0.8918	− 0.9814	− 0.0505	0.0955	0.2598	13.9749
Cash	0.0247	0.1653	− 2.0827	− 0.039	0.002	0.0533	1.5639

This table presents the mean, standard deviation (STD), minimum (MIN), maximum (MAX), 25 percentiles (Q1), 50 percentiles (MEDIAN), and 75 percentiles (Q3) for all the variables used in the main tests

Panel B indicates that target firms with a higher level of regional development have higher R&D levels (*RD1*) and that their interlocking firms have higher R&D levels (*CoRD1* and *KmRD1*). The t-test value of *CoRD1* in column (2−1) is − 12.26, and the t-test value of *KmRD2* is − 9.18. The absolute value of the differential coefficient of *CoRD1* (− 0.0029) is smaller than that of *KmRD1* (− 0.3890), which indicates that the interlocking firms of the target firm have differences among regions. After distance weighting, the differences in the R&D level of interlocking firms gradually increase. Distance negatively affects the differences among the samples. Panels C and D present the results of robustness tests for *RD2*, which lead to the same conclusions.

Table 4 indicates that both the *CoRD* and *KmRD* of interlocking firms are significantly and positively correlated with the target firm's *RD*, suggesting that there is a high positive correlation between interlocking firm's R&D behavior and target firm's R&D behavior. This finding preliminarily validates our hypothesis. The regression calculated in the subsequent section validates the effect of specific variables on R&D expenditure.

Multiple regression analysis
Overall sample regression
Table 5 indicates that both the average *CoRD* and *KmRD* are positively correlated with *RD* at the 0.1% significance level. The results are consistent with those of the present study, indicating that the R&D innovation behavior of the target firm is consistent with and affected by that of interlocking firms.

Table 2 Distribution of firms by industry and region

	Industry	Nfirms	Nobs	% of firms	% of obs
Panel A: Distribution of firms by industry					
1	Energy	37	155	1.8715	1.7372
2	Materials	327	1405	16.5402	15.7475
3	industrial	498	2214	25.1896	24.815
4	Unnecessary Consume	394	1915	19.9291	21.4637
5	Necessary Consume	147	745	7.4355	8.3501
6	Medical & Health	192	950	9.7116	10.6478
7	Information technology	323	1296	16.3378	14.5258
8	Telecom	5	28	0.2529	0.3138
9	Utilities	54	214	2.7314	2.3985
Total		1977	8922	100.0000	100.0000
	Location (Province)	Nfirms	Nobs	% of firms	% of obs
Panel B: Distribution of firms by region					
1	Beijing	155	675	7.8402	7.5656
2	Tianjin	27	126	1.3657	1.4122
3	Hebei	38	167	1.9221	1.8718
4	Shanxi	20	93	1.0116	1.0424
5	Inner Mongolia	14	61	0.7081	0.6837
6	Liaoning	58	261	2.9337	2.9254
7	Jilin	30	128	1.5175	1.4347
8	Heilongjiang	20	84	1.0116	0.9415
9	Shanghai	125	516	6.3227	5.7835
10	Jiangsu	217	922	10.9762	10.3340
11	Zhejiang	212	1030	10.7233	11.5445
12	Anhui	58	299	2.9337	3.3513
13	Fujian	69	340	3.4901	3.8108
14	Jiangxi	31	177	1.5680	1.9839
15	Shandong	130	552	6.5756	6.1870
16	Henan	59	308	2.9843	3.4521
17	Hubei	68	312	3.4396	3.4970
18	Hunan	64	339	3.2372	3.7996
19	Guangdong	298	1230	15.0733	13.7861
20	Guangxi	25	106	1.2645	1.1881
21	Hainan	19	69	0.9611	0.7734
22	Chongqing	25	120	1.2645	1.3450
23	Sichuan	88	392	4.4512	4.3936
24	Guizhou	16	90	0.8093	1.0087
25	Yunnan	24	111	1.2140	1.2441
26	Tibet	9	36	0.4552	0.4035
27	Shaanxi	33	147	1.6692	1.6476
28	Gansu	26	133	1.3151	1.4907
29	Qinghai	8	38	0.4047	0.4259
30	Ningxia Hui Autonomous Region	11	60	0.5564	0.6725
Total		1977	8922	100.0000	100.0000

This table presents the distribution of sample firms by industry/region. Panel A describes the distribution of firms by industry, and panel B describes the distribution of firms by region. Nfirms (Nobs.) is the number of firms (observations) in each industry/region. % of firms(obs.) is the percentage of firms (observations) represented by each industry

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Table 3 Characteristics of R&D intensity and development area classification

	(1)	(2)	(2–1)	
Panel A: High R&D intensity and Low R&D intensity (RD1)				
RD1	0.0120	0.0087	− 0.0034	***
			(− 6.12)	
CoRD1	0.0109	0.0095	− 0.0014	***
			(− 4.01)	
KmRD1	0.6571	0.6283	− 0.0288	***
			(− 3.46)	
Panel B: Highly developed area and Low development area (RD1)				
RD1	0.0096	0.0056	− 0.0039	***
			(− 10.17)	
CoRD1	0.0100	0.0071	− 0.0029	***
			(− 12.26)	
KmRD1	0.6947	0.3057	− 0.3890	***
			(− 9.18)	
Panel C: High R&D intensity and Low R&D intensity (RD2)				
RD2	0.0254	0.0169	− 0.0084	***
			(− 7.18)	
CoRD2	0.0210	0.0184	− 0.0026	***
			(− 3.50)	
KmRD2	1.2472	1.1930	− 0.0542	
			(− 0.45)	
Panel D: Highly developed area and Low development area (RD2)				
RD2	0.0188	0.0112	− 0.0076	***
			(− 9.64)	
CoRD2	0.0194	0.0144	− 0.0050	***
			(− 10.21)	
KmRD2	1.3142	0.6022	− 0.7120	***
			(− 8.88)	

This table presents the Classified Characteristics of RD1, CoRD1, KmRD1, RD2, CoRD2, and KmRD2. Panel A shows the characteristics of high R&D intensity and low R&D intensity. Panel B shows the characteristics of highly developed areas and Low development areas. Panel C shows the characteristics of high R&D intensity and low R&D intensity. Panel D shows the characteristics of highly developed areas and Low development areas. Column (1) presents firms that are in the highly area, column (2) presents firms that are in Low area, column (2–1) presents the difference between the two. *, **, and *** mean statistical significance at 0.1%, 1%, and 5%, respectively

Columns 1 and 2 reveal a significant positive coefficient of regression between *CoRD1* and *KmRD1. CoRD1* (regression coefficient: 0.1837) and *KmRD1* (regression coefficient: 0.0005) are positively correlated with *RD1* at the 0.1% significance level, which indicates that the R&D expenditure level of interlocking firms is synergistic with the target firm and that interlocking firms imitate and learn from target firms' R&D behavior. The positive correlation between *KmRD1* and *RD1* is also highly significant. This indicates that the level of R&D expenditure of interlocking firms remains synergistic with the target firm when the distance weight of interlocking firms' R&D level is inversely proportional to actual distance. This means that interlocking firms close to the target firm are likely to learn from the target firm's R&D behavior.

Table 4 Correlation coefficient

VARIABLE	RD1	CoRD1	KmRD1	RD2	CoRD2	KmRD2	RD_ind1	RD_ind2	Size	ROA	LEV	SOE	BM	Div	Ad	HHI	Sales_g	Cash
RD1	1.00																	
CoRD1	0.19	1.00																
KmRD1	0.05	0.24	1.00															
RD2	0.84	0.17	0.03	1.00														
CoRD2	0.14	0.85	0.20	0.14	1.00													
KmRD2	0.05	0.21	0.94	0.02	0.24	1.00												
RD_ind1	0.46	0.11	−0.01	0.49	0.07	−0.02	1.00											
RD_ind2	0.47	0.14	0.01	0.51	0.11	0.01	0.96	1.00										
Size	−0.19	−0.05	0.08	−0.24	−0.05	0.09	−0.15	−0.14	1.00									
ROA	0.17	0.08	0.04	0.13	0.08	0.03	0.04	0.04	−0.01	1.00								
LEV	−0.23	−0.13	−0.01	−0.31	−0.15	−0.01	−0.12	−0.14	0.48	−0.41	1.00							
SOE	−0.13	−0.11	−0.03	−0.19	−0.12	−0.04	−0.06	−0.08	0.31	−0.14	0.34	1.00						
BM	−0.01	−0.02	−0.02	−0.01	−0.06	−0.03	0.04	−0.02	0.24	−0.07	0.01	−0.02	1.00					
Div	0.03	−0.01	0.02	0.02	0.01	0.02	0.02	0.01	0.05	0.12	0.01	0.01	−0.06	1.00				
Ad	0.04	0.01	0.05	−0.02	0.01	0.04	−0.06	−0.05	0.01	0.24	−0.11	−0.06	−0.12	0.02	1.00			
HHI	−0.04	−0.04	−0.04	−0.01	−0.03	−0.03	−0.06	−0.03	0.05	−0.01	−0.01	0.03	0.03	0.01	−0.03	1.00		
Sales_g	−0.02	−0.01	0.01	−0.05	0.01	0.01	0.01	0.01	0.10	0.14	0.07	−0.03	−0.01	0.01	0.04	0.01	1.00	
Cash	−0.05	−0.02	0.01	−0.06	0.01	0.01	−0.04	−0.03	0.12	0.13	0.04	−0.2	−0.01	0.02	0.03	−0.01	0.43	1.00

This table presents the Pearson correlations for the sample observations for all the main variables used. The bold font represents statistical significance at the 5% level

Table 5 Regression results of the overall sample

	$Y = RD1_{t+1}$	
	$X = CoRD1_t$	$X = KmRD1_t$
	(1)	(2)
Intercept	0.0209***	0.0225***
	(8.16)	(8.64)
X_t	0.1837***	0.0005***
	(11.28)	(6.21)
RD_ind_t	0.8016***	0.8248***
	(35.28)	(35.97)
$Size_t$	− 0.0009***	− 0.0009***
	(− 7.52)	(− 7.36)
ROA_t	0.0281***	0.0286***
	(9.67)	(9.79)
LEV_t	− 0.0034***	− 0.0042***
	(− 4.78)	(− 5.78)
SOE_t	− 0.0007**	− 0.0009***
	(− 3.13)	(− 3.81)
BM_t	0.0006	0.0005
	(1.71)	(1.49)
Div_t	0.0032	0.0025
	(1.34)	(1.08)
AD_t	0.0179**	0.0162*
	(2.81)	(2.54)
HHI_t	0.0005	0.0001
	(0.27)	(0.07)
$Sales\_g_t$	− 0.0002	− 0.0002
	(− 1.56)	(− 1.47)
$Cash_t$	− 0.0024876**	− 0.0026***
	(− 3.19)	(− 3.43)
Firm & Year FE	YES	YES
Adj R^2	28.12%	27.00%
Obs	8922	8922

This table presents the regression results of the overall sample in regression (5). Column (1) and (2) respectively shows the regression results of two explanatory variables on dependent variable *RD1*. Firm fixed effects and year fixed effects are controlled in the regression. The T statistic is in parentheses under the coefficient. *, **, and *** mean statistical significance at 5%, 1%, and 0.1% respectively

Robustness test

In Table 6, *RD1* is replaced by *RD2*, and the overall sample is used for regression (5). The explanatory variables *CoRD2* and *KmRD2* are also calculated using *RD2*. The results indicate that the direction of the regression coefficients between *X* and *RD* are positive. In addition, the results indicate a large difference in the explained variables between target firms and interlocking firms when sales revenue is used as the denominator to measure RD expenditure. *CoRD2* (regression coefficient: 0.0852) and *KmRD2* (regression coefficient: 0.0003) are positively correlated with *RD1* at the 0.1% significance level, which leads to the same conclusion as the one derived from Table 5.

In Table 7, a dummy is used for the distance between the target firm and the interlocking firm. The results in the table indicate whether learning efficiency is affected by

Table 6 Robustness test of alternative measures of RD2

	$Y=RD2_{t+1}$	
	$X=CoRD2_t$	$X=KmRD2_t$
	(1)	(2)
Intercept	0.0523***	0.0538***
	(11.15)	(11.29)
X_t	0.0852***	0.0003***
	(5.26)	(3.6)
RD_ind_t	0.8559***	0.8642***
	(35.39)	(35.74)
$Size_t$	−0.0019***	−0.0019***
	(−8.19)	(−8.04)
ROA_t	0.0187**	0.0186**
	(3.03)	(3.02)
LEV_t	−0.0219***	−0.0228***
	(−13.68)	(−14.29)
SOE_t	−0.0035***	−0.0036***
	(−7.41)	(−7.8)
BM_t	0.0027**	0.0025**
	(3.23)	(2.98)
Div_t	0.0048	0.0045
	(1.12)	(1.04)
AD_t	−0.0218*	−0.0242*
	(−2.11)	(−2.33)
HHI_t	0.0028	0.0025
	(0.55)	(0.49)
$Sales\_g_t$	−0.0011**	−0.0010**
	(−3.03)	(−2.95)
$Cash_t$	−0.0024	−0.0025
	(−1.36)	(−1.45)
Firm & Year FE	YES	YES
Adj R^2	34.02%	33.85%
Obs	8922	8922

This table presents the regression results of the overall sample in regression (5). Column (1) and (2) respectively shows the regression results of two explanatory variables on dependent variable *RD2*. Firm fixed effects and year fixed effects are controlled in the regression. The T statistic is in parentheses under the coefficient. *, **, and *** mean statistical significance at 5%, 1%, and 0.1%respectively

the distance between the target firm and the interlocking firms. With the effect of distance, *CoRD1* had a strong positive effect on *RD1*. The closer the distance between the target firms and interlocking firms is, the more homogeneous is their R&D behavior. The robustness test support resource dependence theory, which states that learning efficiency is higher at shorter distances.

Additional tests
Marketization index
Interlocking directors in highly developed regions tend to have access to more convenient modes of transportation, which may cause interlocking firms to have higher learning efficiency. Kong et al. (2020) take the same method as Fan et al. (2011) to calculate the

Table 7 Robustness test of distance

	$Y = RD1_{t+1}$ (1)
Intercept	0.02103***
	(8.16)
$CoRD1_t$	0.1565***
	(5.95)
$CoRD1_t*D\_Distance_t$	0.0466*
	(2.40)
$D\_Distance_t$	− 0.0003
	(− 0.92)
Control variables	YES
Industry & Year FE	YES
Adj R^2	28.03%
Obs	8922

This table presents the robustness test of the overall sample in regression (5). Column (1) shows the regression results of the interaction term of *Distance* and *CoRD1* on *RD1*. Year and firm fixed effects are controlled in the regression. The T statistic is in parentheses under the coefficient. *, **, and *** mean statistical significance at 5%, 1%, and 0.1% respectively

marketization index of China's provinces. Therefore, we take the same method as Kong et al. (2020) and measure the marketization index (*Area*) by the marketization index of China's provinces.

In Table 8, the regression coefficients of *X*Area* and *RD1* are all positive. In addition, the marketization index has a synergistic effect on *CoRD1* and *KmRD1*. In other words, the higher the marketization index in a region is, the more likely a firm is to learn from the R&D behavior of its interlocking firms (Columns 1 and 2). According to resource dependence theory, interlocking directorates can facilitate the exchange of information between a target firm and other firms, and the peer effect enables target firms and interlocking firms to imitate each other's decision-making practice after they obtain information (Bizjak et al. 2008; Leary and Roberts 2014). Knowledge and skills contributed by interlocking directorates can increase the R&D capabilities of a firm (Chen 2014), and the convenience of highly developed areas allows interlocking directorates to utilize their communication skills to increase learning efficiency. Therefore, when situated in highly developed regions, firms may rely on their geographical advantage to imitate the R&D behavior of their peers.[5]

R&D intensity

According to Porter's theory of competitive advantage (Porter 1980), R&D-intensive firms are likely to be more competitive, which may afford them superior learning efficiency. R&D stock is measured by calculating past capitalized R&D expenditures through the perpetual inventory method (He and Wintoki 2016). Therefore, we measure R&D intensity by R&D stock in the same manner as He and Wintoki did (2016).

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[5] Because developed areas often have superior and modern means of communication, this concept is more convincing after the endogeneity problem of Internet communications is tested and excluded.

Table 8 Influence of highly developed regions on learning efficiency

	$Y = RD1_{t+1}$	
	$X = CoRD1_t$	$X = KmRD1_t$
	(1)	**(2)**
Intercept	0.0153***	0.0154***
	(5.53)	(5.67)
X_t	0.0375	−0.0014
	(0.33)	(−1.82)
X_t*Area_t	0.0587**	0.0008*
	(3.08)	(2.32)
$Area_t$	0.0024***	0.0029***
	(4.23)	(6.97)
Control variables	YES	YES
Firm & Year FE	YES	YES
Adj R^2	28.28%	27.37%
Obs	8922	8922

This table present shows how highly developed regions impact the learning efficiency of interlocking firms in regression (6). Column (1) and (2) respectively shows the regression results of two explanatory variables on the dependent variable RD. Firm fixed effects and year fixed effects are controlled in the regression. The T statistic is in parentheses under the coefficient.*, **, and *** mean statistical significance at 5%, 1%, and 0.1% respectively

Table 9 Influence of R&D-intensive to learning efficiency

	$Y = RD1_{t+1}$	
	$X = CoRD1_t$	$X = KmRD1_t$
	(1)	**(2)**
Intercept	0.0219***	0.0238***
	(8.43)	(8.99)
X_t	0.1969***	0.0005***
	(11.52)	(6.53)
X_t*Tech_t	−0.1630**	−0.0006**
	(−3.12)	(−2.88)
$Tech_t$	0.0033***	0.0022***
	(4.48)	(3.81)
Control variables	YES	YES
Firm & Year FE	YES	YES
Adj R^2	27.28%	27.43%
Obs	8922	8922

This table present shows R&D intensive firms impact the learning efficiency of interlocking firms in regression (6). Column (1) and (2) respectively shows the regression results of two explanatory variables on the dependent variable RD. Firm fixed effects and year fixed effects are controlled in the regression. The T statistic is in parentheses under the coefficient. *, **, and *** mean statistical significance at 5%, 1%, and 0.1% respectively

As shown in Table 9, the regression coefficients of *X* and *RD1* are positive, whereas the cross-product regression coefficients of *X*Tech* and *RD1* are negative. The marketization index exhibits a substitution effect on *CoRD1* and *KmRD1*. For companies with a higher R&D intensity, learning between the target firm and the interlocking firm is highly inefficient. In other words, the R&D behavior of the target firm with a higher R&D intensity differs greatly from that of the interlocking firm. This substitution effect allows target

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Table 10 Regression results of the overall sample: Apply for patent

	$Y = Patent1_{t+1}$	
	$X = CoPatent1_t$	$X = KmPatent1_t$
	(1)	(2)
Intercept	− 8.8441***	− 8.7973***
	(− 15.55)	(− 15.36)
X_t	0.0425*	0.0193**
	(2.30)	(2.97)
Control variables	YES	YES
Firm & Year FE	YES	YES
Adj R^2	19.24%	18.13%
Obs	3246	3246

This table presents the regression results of the overall sample in regression (5). We have replaced *RD1* for *Patent1*. Column (1) and (2) respectively shows the regression results of two explanatory variables on the dependent variable. Firm fixed effects and year fixed effects are controlled in the regression. The T statistic is in parentheses under the coefficient.*, **, and *** mean statistical significance at 5%, 1%, and 0.1% respectively

firms with high R&D intensities to not rely on their partners. These results are consistent with what competition theory (Porter 1980) states regarding the securing of a competitive position in the market. R&D-intensive companies have an incentive to compete with their peers. Companies with higher R&D intensity have a certain degree of inherent competitiveness. Therefore, they have greater confidentiality and independence and do not rely on the R&D learning behavior of their peers.

Additional tests on patents

In the additional tests, we provide alternatives by patent filing, grants, and citations to firm R&D spending to determine the robustness of our conclusions.

Patent applications

We refer to the number of patent applications, as in Biggerstaff et al. (2019), to determine the robustness of the results regarding R&D learning behavior among target and interlocking firms. The number of patent applications represents the number of patents expected to be licensed for which firms invest cash flow for R&D expenses each year. In Table 10, *RD1* is replaced by *Patent1*, and the sample is used for regression (5). The results indicate that the coefficients of regression between *X* and *Patent1* are positive. The conclusion is unchanged after variable substitution; interlocking firms imitate and learn from the innovation behaviors of target firms in terms of patent applications.

Authorized patents

The number of patents a firm is granted represents the effectiveness of its R&D expenses each year. Becker-Blease (2011) measured the intensity of enterprises' pursuit of new products and the enhancement of their knowledge by using R&D expenditure and patent data. We refer to Becker-Blease (2011) to define the number of patents granted. In Table 11, *RD1* is replaced by *Patent2*, and the sample is used for regression (5). The

Table 11 Regression results of the overall sample: Authorized patent

	$Y = Patent2_{t+1}$	
	$X = CoPatent2_t$	$X = KmPatent2_t$
	(1)	(2)
Intercept	− 9.6360***	− 9.6774***
	(− 17.95)	(− 17.82)
X_t	0.0305**	0.0050*
	(2.77)	(2.39)
Control variables	YES	YES
Firm & Year FE	YES	YES
Adj R^2	19.18%	18.30%
Obs	3246	3246

This table presents the regression results of the overall sample in regression (5). We have replaced *RD1* for *Patent2*. Column (1) and (2) respectively shows the regression results of two explanatory variables on the dependent variable. Firm fixed effects and year fixed effects are controlled in the regression. The T statistic is in parentheses under the coefficient. *, **, and *** mean statistical significance at 5%, 1%, and 0.1% respectively

Table 12 Regression results of the overall sample: Patents are cited

	$Y = Patent3_{t+1}$	
	$X = CoPatent3_t$	$X = KmPatent3_t$
	(1)	(2)
Intercept	− 12.3367***	− 12.3161***
	(− 20.60)	(− 20.49)
X_t	0.1595***	0.0824***
	(7.96)	(8.12)
Control variables	YES	YES
Firm & Year FE	YES	YES
Adj R^2	28.37%	27.12%
Obs	3246	3246

This table presents the regression results of the overall sample in regression (5). We have replaced *RD1* for *Patent3*. Column (1) and (2) respectively shows the regression results of two explanatory variables on the dependent variable. Firm fixed effects and year fixed effects are controlled in the regression. The T statistic is in parentheses under the coefficient. *, **, and *** mean statistical significance at 5%, 1%, and 0.1% respectively

results indicate that the coefficients of regression between *X* and *Patent2* are positive; thus, the conclusions are unchanged.

Patents cited

Byun et al. (2021) discovered that enterprises could convert patents into new services and products by registering new trademarks, thereby utilizing the social benefit of patents. We also measure the output of patents of enterprises by cited patents. The number of patents cited annually by a company represents the economic benefit of a company's R&D investment each year. In Table 12, *RD1* is replaced by *Patent3*, and the sample is used for regression (5). The results indicate that the coefficients of regression between *X* and *Patent3* are positive; thus, the conclusions are unchanged.

Conclusion

Relevant studies indicate that the social capital networks formed by connections among firm directors are conducive to information transmission and improve enterprise R&D. Therefore, many studies focus on how the heterogeneity of interlocking directorates affects enterprise R&D (e.g., Chen 2014). After reference to numerous studies and theories related to the effects of a firm's geographic location, it is proposed that the distance between the target firm and interlocking firms affects the efficiency of information transmission among interlocking directorates. As the distance decreases, the degree of competition between firms changes, and the combined effect gradually becomes prominent. The proximity advantage among interlocking firms enhances the efficiency of learning R&D innovation behavior. Therefore, this study proposed answers to two essential questions: (1) whether the distance between the target firm and interlocking firms affects the efficiency of mutual learning to develop innovation behavior, and (2) whether the target firm is more inclined to exchange innovation information with closer interlocking firms.

This study investigates A-share firms listed from 2007 to 2017, except those receiving special treatment and those in the finance industry, and demonstrates that a target firm can achieve optimal learning efficiency by learning innovative behavior from nearby interlocking firms. The proximity advantage increases the learning efficiency of the R&D behavior of the target firm and interlocking firms. In addition, R&D innovation behavior is more efficient for target firms in highly developed regions that are nearby interlocking firms. This result is consistent with resource dependence theory, the concept of combined effects, and Porter's theory of competitive advantage. Target firms in highly developed areas are more willing to imitate and study nearby interlocking firms to maintain peer relations and hone their innovation potential and competitiveness; this finding is consistent with resource dependence theory. The exchange of information between target firms in formal institutions or high-intensity industries and distant interlocking firms increases innovation differentiation, innovation potential, and competitiveness, even at high costs, which is consistent with competition theory.

The results of the endogenous test indicate that when an interlocking CEO or chairperson of a target company leaves, the learning efficiency of the target company and the interlocking company decreases. This study eliminates the endogeneity caused by Internet communication and verifies that although interlocking directors can communicate through the Internet, improving the R&D-related decision-making process requires the exchange and acquisition of information, knowledge, and experience through formal channels, such as board meetings.

The results of this study have several implications for policy-making. First, in the process of forming interlocking director networks, listed firms should recruit interlocking directors who hold positions in remote areas. Interlocking directors help interlocking firms learn from target firms' R&D behavior, especially interlocking directors who are close to target firms. Second, firms with cost-competitive advantages should differentiate themselves to promote R&D and innovation and utilize the information exchange function of interlocking directors in R&D-intensive industries. Third, interlocking boards in highly developed regions increase interlocking firms'

learning efficiency, giving firms a reference when they are determining the costs of certain sites and benefits of aggregation.

Our findings apply to numerous areas of the economy. By using competition theory, we demonstrate that in industries with differing R&D intensity and in regions with different degrees of marketization, interlocking directors imitate and learn the R&D behaviors of target enterprises at differing frequencies; this finding can be applied to behavioral finance through analysis of the psychology and emotions of managers. For example, a hometown complex in directors affects their companies' R&D and innovation decisions (Ren et al. 2020). In addition, we demonstrate the difference in information exchange efficiency between developed and undeveloped regions. For example, if direct flights are introduced to increase travel between two locations, the cost of information exchange decreases (Chi et al. 2021). Given the cost of communication, our findings have implications in terms of the economics of transportation.

Several topics warrant further investigation. First, although this study examines whether the transmission of information through interlocking directors generates homogeneity between target and interlocking firms, competition is not always generated by interlocking firms that are geographically close to target firms. The effect of non-interlocking firms being close to target firms warrants further investigation. Second, this study considers the unique R&D innovation methods of enterprises in R&D-intensive industries but does not identify specific details regarding these industries. Studies have demonstrated that highly competitive industries and industries with high R&D intensity, such as the electronic information industry, involve unique R&D innovation behaviors. Companies in highly competitive industries have a higher level of transaction secrecy, R&D, and a lower level of voluntary disclosure by management, and internal managers will actively engage in rent-seeking activities (Rahman et al. 2021). The influence of internal factors related to corporate governance on the learning efficiency of innovation R&D in certain industries warrants further investigation. Companies in R&D-intensive industries are also subjected to more investor pressure and disclosure than those in other industries. Mohamed and Schwienbacher (2016) discovered that high-tech companies investing heavily in internal R&D face numerous information asymmetry problems and that parent companies that face information asymmetry problems have the highest abnormal returns on announcements. Whether efficient information transmission prompts investors to accept low information disclosure ratings and high required returns should also be explored.

Appendix A: Definition of variables

Variable	Definition
Dependent variable	
RD1	*RD1* is the ratio of R&D expenditure and total assets, which is one interval ahead
RD2	*RD2* is the ratio of R&D expenditure and sales revenue which is one interval ahead
Patent1	*Patent1* is the natural logarithm of the number of patents a firm apply each year
Patent2	*Patent2* is the natural logarithm of the number of patents a firm is granted each year

Variable	Definition
Patent3	*Patent3* is the natural logarithm of the number of patents cited annually by a company
Independent variables	
CoRD1	*CoRD1* is the average value of *RD1* of all interlocking firms, where *RD1* is defined as the ratio of R&D expenditure and total assets
CoRD2	*CoRD2* is the average value of *RD2* of all interlocking firms, where *RD2* is defined as the ratio of R&D expenditure and sales
KmRD1	Weighted according to the reciprocal of the distance between the interlocking firm j and the target firm i, *KmRD1* is the weighted average value of *RD1* of all interlocking firms. *RD1* is defined as the ratio of R&D expenditure and total assets
KmRD2	Weighted according to the reciprocal of the distance between the interlocking firm j and the target firm i, *KmRD2* is the weighted average value of *RD2* of all interlocking firms. *RD2* is defined as the ratio of R&D expenditure and sales
CoPatent1	*CoPatent1* is the average value of *Patent1* of all interlocking firms, where *Patent1* is defined as the natural logarithm of the number of patents a firm apply each year
CoPatent2	*CoPatent2* is the average value of *Patent2* of all interlocking firms, where *Patent2* is defined as the natural logarithm of the number of patents a firm is granted each year
CoPatent3	*CoPatent3* is the average value of *Patent3* of all interlocking firms, where *Patent3* is defined as the natural logarithm of the number of patents cited annually by a company
KmPatent1	Weighted according to the reciprocal of the distance between the interlocking firm j and the target firm i, *KmPatent1* is the weighted average value of *Patent1* of all interlocking firms. *Patent1* is defined as the natural logarithm of the number of patents a firm apply each year
KmPatent2	Weighted according to the reciprocal of the distance between the interlocking firm j and the target firm i, *KmPatent2* is the weighted average value of *Patent2* of all interlocking firms. *Patent2* is defined as the natural logarithm of the number of patents a firm is granted each year
KmPatent3	Weighted according to the reciprocal of the distance between the interlocking firm j and the target firm i, *KmPatent3* is the weighted average value of *Patent3* of all interlocking firms. *Patent3* is defined as the natural logarithm of the number of patents cited annually by a company
Tech	*Tech* is non-zero Capitalized past R&D expenditures in a given period (He and Wintoki 2016)
Area	*Area* is the total marketization index of China's provinces (Kong et al. 2020)
Distance	*Distance* is the average distance between the target firm and the interlocking firm
D_Distance	*D_Distance* describes whether the target firm is far from the interlocking firms. Dummy $= 1$ if the distance between the target firm and the interlocking firm is lower than the industry average, Dummy $= 0$ otherwise
Control variables	
SIZE	*SIZE* is the natural logarithm of the firm's assets
ROA	*ROA* is the return on Assets
LEV	*LEV* is the total debt to total assets
BM	*BM* is the book to market ratio
Div	*Div* is the dividend per share (the dividend paid divided by the total number of shares)
SOE	The value of a state-owned holding firm is 1, and that of a non-state-owned holding firm is 0
AD	*AD* is the ratio of advertising expenditure and total assets
RD_ind1	*RD_ind1* is the average industry ratio of R&D expenditure and total assets
RD_ind2	*RD_ind2* is the average industry ratio of R&D expenditure and sales
HHI	*HHI* is Herfindahl–Hirschman Index
Sales_g	*Sales_g* is the difference between the amount of year-end sales revenue for the previous year divided by the sales revenue at the end of the previous year
Cash	*Cash* is the difference between the amount of year-end cash and cash equivalents for the previous year divided by the total assets at the end of the previous year

Declarations

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