The double-edged sword of technological diversity in R&D alliances: Network position and learning speed as moderators

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Abstract

Research on alliances has recognized the bright and dark sides of technological diversity between alliance partners. We extend this line of research by offering a model that examines how network centrality and learning speed shape the relationship between technological diversity and market performance. We tested the model by using a large sample of 769 firm-year observations from U.S. biotech, pharmaceutical, and medical device industries, spanning the period from 1990 to 2006. The results reveal that the degree of technological diversity between alliance partners exhibits an inverted U-shaped relationship with firm performance. In addition, this relationship is positively moderated by network centrality and learning speed.

Keywords:
R&D alliance
Technological diversity
Network centrality
Learning speed

1. Introduction

To address volatile environments, firms leverage research and development (R&D) alliances as a strategic mechanism for exploring new capabilities or technologies, sharing risks, and gaining synergy (Haas & Hansen, 2007; Meuleman, Lockett, Manigart, & Wright, 2010; Shipilov, 2009). R&D alliances have proliferated in technology-intensive industries (Lin, Yang, & Arya, 2009; Meuleman et al., 2010; Mowery, Oxley, & Silverman, 1996), because the resources of interest in interfirm R&D collaborations allow firms to improve their technological development (Rodan & Galunic, 2004). When firms collaborate with partners who are sufficiently differentiated in technological domains from themselves, both parties complement each other in producing or commercializing products (Lin, Yang, & Demirkan, 2007; Park & Zhou, 2005; Yang, Phelps, & Steensma, 2010). Although R&D alliances provide an opportunity to tap into diverse technological capabilities, they do not guarantee superior performances (Luo & Deng, 2009; Sampson, 2007; Wadhwa & Kotha, 2006).

Scholars have recognized the ramifications of technological diversity between allied firms on firm performance. In a study on the telecommunications equipment industry, Sampson (2007) indicated that the relationship between technological diversity and innovative performance is curvilinear. Considering the complex nature of a curvilinear relationship, Miller (2006) suggested that researchers should explore whether this relationship is contingent on certain organizational characteristics (Schilke & Goerzen, 2010). In particular, we focus on two characteristics that are crucial in coping with technological diversity (Lai & Weng, 2013). Given that firms differ in their learning capability based on prior experience with different technological knowledge, they vary with respect to the costs of understanding and assimilating new technological knowledge (Zander & Kogut, 1995). Moreover, once a firm forms an alliance with another firm, it is embedded in a network of interfirm relations (Galunic, 2004). The resources available to a firm is a function of its position within the network structure (Tsai & Ghoshal, 1998), and an advantageous position will allow the firm to mobilize and tap into potentially useful resources in absorbing new knowledge (Gilsing, Nooteboom, Vanhaverbeke, Duysters, & van den Oord, 2008; Lee, Lee, & Pennings, 2001). Accordingly, we theorize that a firm’s network and learning characteristics may alter the effect of technological diversity on firm performance. To elucidate the moderating roles of these characteristics, we use social capital theory and absorptive capacity theory as a theoretical lens.

Social capital theory emphasizes the benefits derived by actors...
2. Theoretical foundation and hypotheses

Firms that form R&D alliances typically aim for substantial technological advances and product innovations through the acquisition of knowledge and capabilities from partner firms (Hagedoorn, 1993; Hamel, 1991; Mowery et al., 1996). The reason behind R&D alliance formation is supported by the heterogeneous knowledge bases that characterize firms and the fact that this heterogeneity originates from a process of cumulative learning (Dosi, Nelson, & Winter, 2000). The resource-based view (RBV) of a firm suggests that such heterogeneity is a source of competitive advantage (Barney, 1991; Conner & Prahalad, 1996; Wernerfelt, 1995). The traditional RBV tends to focus on resources within the firm, but this perspective can be extended to the alliance context. Das and Teng (2000) employed the RBV to provide a comprehensive overview of strategic alliances. The RBV rationale of alliance management emphasizes value maximization rather than cost minimization. The specific firm’s resources involved in collaboration include financial resources, market power, technological assets (e.g., Ahuja, 2000), and social position. Research focuses on resource exchange, in which firms exchange complementary resources (Burgers, Hill, & Kim, 1993), especially knowledge (Roper & Crone, 2003; Teece, 1998).

Certain pioneering contributions facilitated the burgeoning research on interfirm knowledge transfer (e.g., Kogut, 1988; Teece, 1986). Subsequent studies have addressed the subject of knowledge transfer between alliances, including aspects such as governance modes (Aggarwal, Siggelkow, & Singh, 2011), partner selection (Lin et al., 2009; Meuleman et al., 2010), and knowledge-transfer mechanisms (Inkpen, 2008; McEvily & Marcus, 2005). Partner-selection studies have recently given rise to a stream of research that considers a firm’s alliances to be a portfolio, with a focus on the diversity of alliance partners (Jiang, Tao, & Santoro, 2010; Sampson, 2007). Similar to the examination of network diversity conducted by Goerzen and Beamish (2005), this notion of alliance-partner diversity is reflective of the degree of variance in partners’ resources, capabilities, knowledge, and technological bases (Jiang et al., 2010).

Following previous research (e.g., Mowery et al., 1996; Sinkula, Baker, & Noordewier, 1997), this study extends organizational learning into an alliance setting. Organizational learning theorists have argued that alliances provide a platform whereby firms can learn new skills and capabilities that considerably enhance their capability to innovate, take risks, and develop new revenue streams (Huber, 1991; Lyles & Salk, 1996). Collectively, inter-organizational learning facilitates synergistic and superior performance because it enables firms to develop new in-house capabilities while acquiring novel capabilities externally. One aspect of interfirm learning that has received attention in the alliance literature is absorptive capacity, particularly a firm’s absorptive capacity for learning from its alliance partners (Mowery et al., 1996). As previously discussed, absorptive capacity theory inspires this study to identify learning speed as a moderator of the technological diversity–performance relationship. Moreover, based on the social capital theory and network research by Gulati (1999) and Lechner et al. (2010) that associated network location with organizational learning, we argue that a firm’s network centrality is another moderator.

The “bright side” of alliance-partner diversity has been acknowledged in the literature (Jiang et al., 2010; Park & Zhou, 2005). The risks and costs that accompany increased
technological diversity have also been recognized in prior studies (Miller, 2006; Oerlemans, Knoben, & Pretoriosi, 2013). By considering both sides of technological diversity, we followed Sampson’s (2007) view of the curvilinear relationship between such diversity and firm performance. We then extended her analysis by suggesting that learning speed and network centrality are key moderators.

2.1. Technological diversity and firm performance

Technological diversity captures the difference in technological capabilities between a focal firm and its alliance partners. The curvilinear relationship between alliance-partner diversity and firm performance found in previous research (Sampson, 2007; Wuyts & Dutta, 2014) has been explained by two partially overlapping theories, namely the RBV (e.g., de Leeuw, Lokshin, & Duysters, 2014) and organizational economics (e.g., Belderbos, Carree, & Lokshin, 2006). This study adopts the RBV that technological diversity enables firms to tap into diverse and non-redundant knowledge bases that complement their innovation efforts (Park & Zhou, 2005; Wuyts & Dutta, 2014). Thus, superior performance can be achieved by combining the knowledge of alliance partners and exploiting possible complementarities and synergies (de Leeuw et al., 2019). Low levels of technological diversity suggest that two partners are the same kinds of firms that possess similar knowledge bases (Oerlemans et al., 2013). Consequently, they have limited possibilities of profiting from synergies because of the minimal complementary assets and novel knowledge that they can acquire (Faems, Van Looy, & Debackere, 2005). At moderate levels of technological diversity, firms profit the most from the diversity of inflowing knowledge while concurrently being capable of dealing with such diversity (Oerlemans et al., 2013).

Wuyts and Dutta (2014) explicitly highlighted the advantages of such diversity. These advantages include the stimulation of the breadth of perspective and creative thinking and the facilitation of new knowledge assimilation. A wide knowledge base augments the knowledge capabilities of firms, which consequently leads to an expanded approach to problem-solving with new or refined methods (Katila, 2002; Katila & Ahuja, 2002). For example, acquired complementary knowledge enables firms to enhance product functionality and add new features to existing products. In this way, firms are more likely to develop technologically superior and competitive new products that are highly valued by customers (Wadhwa & Kotha, 2006). Indeed, technological diversity provides new opportunities for solving existing and potential problems associated with technologies, products, and market competition (March, 1991). Through recombination across diverse technological fields, firms gain advantages in terms of knowledge creation and innovation, which in turn contribute to their future value.

When the levels of technological diversity further increase, the costs associated with such diversity may outweigh the benefits. Collaborating with a highly disparate partner substantially increases the costs of coordination, monitoring, and communication, as well as the likelihood of opportunism, which may result in unintended knowledge spillovers (Combs & Ketchen, 1999; Oerlemans et al., 2013). Sampson (2007) cautioned that the additional costs that accompany high levels of technological diversity are detrimental to performance. For example, the over-absorption of diverse knowledge is likely to increase collaborative costs in alliance activities. Generally, firms can only manipulate and assimilate knowledge that is sufficiently similar to their own (Luo & Deng, 2009; Sampson, 2007). As knowledge possessed by partners is so tacit and context-specific that it is difficult to transfer and integrate (Nelson & Winter, 1982; Simonin, 1999), firms may need to invest in new capabilities for assimilating the extramural knowledge. In other words, when diversity is high, the recombination of knowledge becomes excessively difficult (Wuyts & Dutta, 2014), which minimizes the contributions of diverse knowledge to firm value.

Hence, this study proposes that firm performance initially increases with technological diversity because of the advantages of technological complementarity. Subsequently, the increasing collaborative costs resulting from technological diversity can reach a point at which they outweigh any potential benefits of collaboration, thus undermining firm performance.

**Hypothesis 1.** The degree of technological diversity between the focal firm and its partners has an inverted U-shaped relationship with its firm performance.

2.2. The moderating role of network centrality

As discussed earlier, although technological diversity has some benefits, it weakens a firm’s capacity to learn from its partners. Firms can translate technological diversity into firm outcomes only when interfirm learning is effective. However, high technological diversity complicates the problems pertaining to exchange hazards. As highlighted by Reuer and Zollo (2005), exchange hazards in R&D alliances can reduce cooperation and knowledge sharing between firms, thereby hindering firms’ knowledge recombination efforts. Alliance partners have the incentive to compete, which elevates the risk of opportunism. Gulati and Singh (1998) noted that partners face the risk of withholding effort and resources needed to achieve alliance goals, involuntary knowledge leakage, and misrepresentation of newly created knowledge—all of which pose barriers to transferring tacit knowledge developed in partnerships. We expect that network centrality will promote interfirm learning in R&D alliances by alleviating the above problems.

A central position in the network facilitates trust and reciprocity among networked firms, which reduce exchange hazards in alliances and increase cooperation among partners. Trust reduces the extent to which alliance partners protect knowledge, increases partners’ willingness to share knowledge, and enhances interfirm learning (Kale, Singh, & Perlmutter, 2000; Larson, 1992). Reciprocity norms reinforce this motivation to share, since firms can be confident that partners will reciprocate (Dyer & Nobbeoka, 2000). Network centrality promotes trust by increasing the costs of opportunism. Firms that sustain a central network position are recognized as industry leaders, making them more visible and trustworthy to potential resource providers (Stam & Elfring, 2008). Since a central firm’s behavior is more visible in a network, an act of opportunism can damage its reputation, jeopardize its existing alliances, and decrease future alliance opportunities (Gulati, 1998). Considering the costs of opportunism outweigh its benefits, firms refrain from opportunistic behavior. Thus, central firms are generally regarded as more trustworthy than peripheral ones (Stam & Elfring, 2008).

Moreover, high centrality indicates the quality and status of a venture as an exchange partner (Podolny, 2001). Central firms are able to verify and triangulate the information received externally, thereby enhancing their access to high-quality information that facilitates the pursuit of innovative opportunities (Stam & Elfring, 2008). Highly central firms also have superior access to valuable resources because they are more capable of attracting resource providers (Tsai, 2001; Zaheer & Bell, 2005). Network centrality may stimulate reciprocity exchanges where partners share privileged resources because they expect highly central recipients to be more likely to repay them with resources of equivalent or even higher value (Coleman, 1988). In particular, the resultant trust and reciprocity benefits also improve partners’ joint problem-solving efforts and stimulate experimentation with different knowledge.

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combinations, thereby improving knowledge detection and transfer from diverse partners (Dyer & Noboea, 2000; Uzzi, 1997). Trust and reciprocity can increase a partner’s motivation to “teach” (Szulanski, 1996). This is crucial for student firms when partner diversity increases, because they would find it difficult to learn if they are not aided by dissimilar partners (Szulanski, 1996). As a result, the knowledge and know-how shared will be less distorted, richer, and of higher quality (Dyer & Noboea, 2000; Uzzi, 1997). Central firms are more likely to efficiently communicate with and learn from diverse partners than peripheral firms.

When accessing high levels of diverse technological knowledge, a firm that has high network centrality is better able to utilize technological knowledge and successfully generate novel technologies that expand the scope of its technology base (Lai & Weng, 2013). In general, such a firm can be viewed as an intermediary in that it can bridge the gap between the partners’ technological knowledge and manipulate knowledge flows within the alliance network. Owing to its central position, the firm acts as a pivot because most knowledge paths, between partners, flow through the firm. This pivot is conducive to screening and interpreting the potential value of technological knowledge to the firm; in turn, it develops a richer understanding and a better evaluation of the diverse technological knowledge it receives (Rowley, Bell, & Krackhardt, 2000). In other words, when encountering difficulties in absorbing dissimilar knowledge from a partner, a central firm has more opportunities to turn to other network members who potentially provide different types of knowledge and interpretations that are beneficial for absorption (Burt, 2005; Gilsing et al., 2008). This increases the likelihood of a firm comprehending dissimilar technological knowledge. As Stam and Elfring (2008) argue that with a deepening of the knowledge bases of the firms, high centrality reinforces their capability to absorb and apply new dissimilar knowledge derived from their partners.

In summary, network centrality mitigates some of the costs and amplifies some of the benefits of increasing technological diversity by increasing the amount and quality of knowledge transferred while simultaneously reducing the need to engage in time-consuming, costly monitoring activities. Based on the above arguments, we formulate the following hypothesis:

**Hypothesis 2.** The degree of network centrality positively moderates the inverted U-shaped relationship between technological diversity and firm performance. Specifically, when the degree of centrality is higher, the rate of performance increase associated with increasing technological diversity is faster, whereas the rate of performance decrease is slower when the degree of centrality is lower.

### 2.3. The moderating role of learning speed

Learning speed refers to the rate at which a firm assimilates new knowledge and applies it to innovations or product development (Gopalakrishnan & Birley, 2006). It reflects the adaptability to state-of-the-art knowledge and the ability to integrate this knowledge with the existing knowledge base (Birley & Chakraborti, 1996). According to Lane and Lubatkin (1998), knowledge similarity, which refers to the similarity between the knowledge bases of two firms, is the main source of a firm’s capacity to absorb knowledge from its partners. Further, Schilt, Keil, and Maula (2012) suggested that successful knowledge acquisition depends on knowledge similarity in the initial as well as later stages. In an R&D alliance, the average learning rate of a firm can be influenced by the manner in which it exploits knowledge similarity.

The organizational capability to acquire external knowledge is dependent on how fast a firm is able to incorporate external knowledge into its knowledge base (Aage, 2003; Zahra & George, 2002). Firms with a high learning speed are characterized by the quick recognition, inventory, synthesis, and use of knowledge gained externally (Zahra, Neubaum, & Huse, 2000). Since such firms typically possess a superior ability to rapidly internalize knowledge, they are able to integrate dissimilar knowledge from their partners into their technology base efficiently (Simonin, 2004). Specifically, firms have large scaffolds on which they build new knowledge structures because they know how to rapidly create new cognitive nodes of knowledge and reinforce the connections between these nodes (Schilling, Vidal, Ployhart, & Marangoni, 2003). By expanding the current knowledge base, firms can increase their knowledge similarity, which, in turn, provides firms with more opportunities to share and expand their understanding of technical issues and establish a shared mode of discourse (Mowery et al., 1996), which allows diverse partners to more effectively communicate with and learn from one another (Kogut & Zander, 1996). That is, as a firm’s personnel gain rich learning experiences, they learn about best practices that expedite the adoption and application of innovative technologies (Zhou & Li, 2012). The speed of learning that is underlined by the learning experience determines the capability to understand and codify novel technological knowledge effectively (Zander & Kogut, 1995). Thus, a firm with a high learning speed may be able to absorb and utilize novel technological knowledge based on fused technologies, and, as a result, integrate diverse external knowledge bases. Likewise, such firms are also more likely to maximize the synergy between knowledge in similar domains.

Compared with slow-learning firms, fast-learning firms are better able to quickly identify and access complementary resources to fill what it currently lacks, and subsequently recombine its resources for actualizing the promised benefits. In brief, the diversity of partner capabilities is a lucrative economic opportunity rather than a time- and cost-consuming problem because firms with a high learning speed are adept at managing the diversity of technologies. This might augment the positive effects and lessen the negative effects of technological diversity on firm performance. Consequently, we propose the following hypothesis:

**Hypothesis 3.** Learning speed positively moderates the inverted U-shaped relationship between technological diversity and firm performance. Specifically, when learning speed is higher, the rate of performance increase associated with increasing technological diversity is faster; whereas the rate of performance decrease is slower when learning speed is lower.

### 3. Method

#### 3.1. Sample and data collection

The hypotheses were tested using a data set on the alliances and patenting activities of U.S. firms in biotech, pharmaceutical, and medical device industries in the period 1990–2006. We chose these industries for two reasons. First, these industries are characterized by frequent collaborations and active alliances, including not only R&D, but also joint production, joint marketing and cross-licensing due to the rapid pace of technology development (Rothaermel & Deeds, 2004, 2006). Second, a critical criterion for sample choice is patents, because some of our key measures are based on patent data. Even with some recent criticisms (Alcácer, Gittelman, & Sampat, 2009; Alcácer & Gittelman, 2006), patent-based measures continue to be among the best ways to gauge knowledge-related constructs in large quantitative studies (e.g., Almeida, 1996; Haupt, Kloyer, & Lange, 2007; Nerkar & Paruchuri, 2005). This study focuses on two major forms of R&D alliances: bilateral contracts and equity joint ventures. Among organization
alternatives for forming R&D alliances, these two are the most widely selected since R&D alliances involve high levels of exchange of technological capabilities (Mowery et al., 1996). A bilateral contract is a contractual arrangement whereby partners pool their capabilities for the purpose of collaborative R&D, but do not form a separate legal identity for the alliance (Sampson, 2007). In an equity joint venture, firms similarly pool their capabilities, but also create a new entity that is jointly owned and operated by two or more collaborating firms (Pisano, Russo, & Teece, 1988).

The data set was constructed from three main sources: the Compustat database, the United States Patent and Trade Office (USPTO), and the Securities Data Company (SDC) database on Joint Ventures and Alliances. The SDC database contains information on all types of alliances, and was compiled from publicly available sources (e.g., Securities and Exchange Commission (SEC) filings, industry and trade journals, and news reports). To increase the reliability of the SDC data, all deals for which an alliance announcement date was set were verified against the Lexis-Nexis database. The main source for the patent data was the United States Patent and Trademark Office (USPTO) Database. However, a weakness of this source is that many patents are granted to large firms under the names of subsidiaries that differ from those of their parent companies (Katila, 2002; Patel & Sung, 2012; Roijakkers, and Van Kranenburg, 2006). We estimated Tobin’s Q by the ratio of the market value of assets divided by the replacement value of assets. Tobin’s Q ratio reflects investors’ and other stakeholders’ perceptions of a firm’s value creation (Laitner & Stolyarov, 2003). We estimated Tobin’s Q by the ratio of the market value of equity plus the book value of debts to the book value of the firm’s assets (Chung & Pruitt, 1994). The data for Tobin’s Q were obtained from the Compustat database.

3.3. Independent variables

3.3.1. Technological diversity

Based on Jaffe (1986), Sampson (2007) measures the diversity of partner technological capabilities by examining the extent to which partner patents are in the same technology class. We employed Sampson’s (2007) formula which can capture the technological position of a focal firm relative to its alliance partner. This formula involves measuring the distribution of each firm’s patents across technology classes, year by year. The distribution is captured by a multi-dimensional vector: \( F_i = [F_{i1} \cdots F_{in}] \), where \( F_{ij} \) represents the number of patents assigned to partner firm \( i \) in patent class \( j \). Patents are categorized in accordance with the US Patent Classification (UPC). According to Argote (1999), the significant value of new technological knowledge is lost within approximately five years; therefore, firm technological characteristics are typically gauged in the five-year period \( (t-5\ldots t-1) \) before the focal year \( t \) (Lin et al., 2012; Lee, Wu, & Liu, 2013). Specifically, the focal year was not included in the five-year assessment period because not only would the R&D alliances not be announced identically at the end of the focal year but because firm technological fields do not vary in the short term. Therefore, it is reasonable to use the preceding year \( (t-1) \) as the start year to observe the technological fields in which the firms specialize. The range of technological diversity varies from 0 to 1. A value of 1 indicates the greatest possible technological diversity between alliance partners. Diversity of partner capabilities is as follows:

\[
\text{Technological diversity} = 1 - \frac{F_i F_j}{\sqrt{(F_{i1} \cdots F_{in})(F_{j1} \cdots F_{jn})}}, \quad \text{where } i \neq j
\]

3.3.2. Network centrality

To measure the centrality of firms in a network, we created a network of alliances and calculated the positions of the firms in this structure. In this network, 751 R&D alliances involving 202 firms were identified from 1993 to 2006 (inclusive). Overall, 769 firm-year observations were included in calculating network centrality.

In the examination of network centrality at the firm level in our research context, a network is a single-mode firm–firm alliance network with firms as nodes and alliances as ties. When two firms have an R&D alliance, they are linked by a tie in the network. The network structure changes with the formation of new ties and the...
dissolution of old ties over time. However, information about the dissolution of these ties is not disclosed in most circumstances. Generally, researchers take a conservative approach, assuming that alliance relationships last for three years (Schilling & Phelps, 2007; Stuart, 2000). Following this approach and using the moving three-year window analysis, we considered alliance ties older than 3 years as dissolved.

We updated this measure annually because new ties are formed and old ties are dissolved every year. Hence, we created an R&D alliance network for each year. We incorporated all alliance ties formed by firms during the previous three-year period. For example, when the dependent variable was measured for year \( t \), we constructed an alliance network by calculating ties among firms during year \( t-1 \) to \( t-3 \). Ties before year \( t-3 \) were considered dissolved.

Network centrality is gauged by eigenvector centrality. Unlike other centrality measures that treat all ties equally, eigenvector centrality weights partners by their own centrality (Bonacich, 1987). Thus, it involves counting both direct and indirect connections of every firm (Bonacich, 2007). A high eigenvector centrality score means that a firm is associated with a relatively large number of powerful partners in terms of their centrality in the network (Hagedoorn & Duysters, 2002). We calculated eigenvector centrality by using UCINET VI software based on the formula described below (Bonacich, 1987, 2007; Borgatti, Everett, & Freeman, 2002):

\[
C_i = \alpha \sum_{j=1}^{n} A_{ij} C_j, \quad i = 1, \ldots, n
\]

This formula calculates the eigenvector of the largest positive eigenvalue as a measure of centrality for an adjacency matrix \( A \). \( A_{ij} \) is the adjacency matrix of the alliance network, \( C_i \) is the eigenvector centrality of firm \( i \), and \( \alpha \) is a parameter used to scale the measure (selected automatically by UCINET VI).

### 3.3.3. Learning speed

This variable is used to capture a firm’s capability of acquiring and utilizing new technologies. According to Gopalakrishnan and Bierly (2006), Katila (2002) and Wu et al. (2014), learning speed is measured as technology cycle time, the average age of a firm’s patents. High technology cycle time means that a firm takes a long time to incorporate new technologies into its new products or processes. Thus, low technology cycle time is indicative of high learning speed (Gopalakrishnan & Bierly, 2006). Herein, we calculated learning speed by transferring it into multiplicative inverse, as shown in the following formula. The range of learning speed varies from 0 to 1. A value of 1 indicates the greatest learning speed of the firm. For example, if Firm A’s technology cycle time vale is 20 and Firm B’s technology cycle time vale is 5, then Firm A’s learning speed is 1/20 and Firm B’s learning speed is 1/5, i.e. Firm B has a greater learning speed than Firm A.

\[
\text{Learning speed} = n / \sum_{i=1}^{n} (\text{the issue year of patent}_i - \text{the average issue year of patent's cited patents})
\]

where \( n \) means a firm’s total patents.

### 3.4. Control variables

We controlled for several variables, which fall outside the purview of our theory, but may affect firm performance.

1. **Firm size and firm age:** We measured firm size as the total number of employees, and firm age as the number of years since the firm was founded. Research generally considers firm size and age as control variables because they are predictors of market-based performance (He & Wong, 2004).
2. **R&D intensity and R&D intensity \( t-1 \):** R&D intensity was controlled form because it has been shown to be an important antecedent of performance (Scherer, 1984). Besides, R&D intensity is often seen as proxy measure of absorptive capacity that could influence a firm’s knowledge acquisition and exploitation (Cohen & Levinthal, 1990; Lin et al., 2012) and thus has to be controlled in this study. This control variable was measured by the ratio of R&D expenditure to annual sales.
3. **Past return on assets \( t-1 \), past return on equity \( t-1 \), and past return on investment \( t-1 \):** In the alliance literature, the profitability of firms is captured through the previous year’s ROA \( t-1 \), ROE \( t-1 \), and ROI \( t-1 \) (Ahuja, 2000; Alcacer & Gittelman, 2006). Successful past performance provides firms with relatively rich resources to explore new technologies and market opportunities (Baum, Calabrese, & Silverman, 2000; Zahra et al., 2000). We thus controlled for these profitability indicators to lessen the influence of past profitability on current-period firm performance.
4. **Joint venture:** The ownership difference at the founding of a strategic alliance influences organizational performance (Baum et al., 2000). If firms founded the joint venture, more opportunities may accrue from the complementary assets of other network firms (Shenkar & Li, 1999). Additionally, the motivations for firms to enter into alliances are reflected in the types of alliances they form (Mowery et al., 1996; Sammarra & Biggiero, 2008). We thus accounted for such possibilities by including dummy variables, using code 1 if firms founded the joint venture and 0 otherwise.
5. **Alliance experience:** As Sampson (2005) suggests, a firm’s prior alliance experience exerts a greater effect on collaborative returns in R&D alliances because such experience can be turned into the ability to manage alliances and partnerships. In order to obtain unbiased results, alliance experience thus has to be controlled for in an empirical analysis. To measure prior alliance experience, we used the cumulative counts of prior research alliances. Research suggests that the number of alliances that a firm has entered into can be used as a proxy for alliance experience (Heimeriks & Duysters, 2007; Schilke & Goerzen, 2010; Tzabbar, Aharonson, & Amburgey, 2013). Following this approach and in line with the period over which we measured network centrality, we measured alliance experience as the number of R&D alliances formed by firm \( i \) in the three years before year \( t \).
6. **Network density:** Network density is the ratio of all ties within an alliance network at a particular period of time to the possible number of ties in the network. The ratio is equal to \( N \times (N-1) \), where \( N \) is the number of firms in the alliance network (Shipilov, 2009). High network density may decrease organizational performance because its interlocked effect diminishes opportunities for firms to access and broker heterogeneous information from out-boundary-connecting (Burt, 2007).
7. **Industry:** Different industrial segments represent systematic differences between innovation and financial factors of firms (Molina-Morales & Martinez-Fernandez, 2009). We classified our sample firms into three industrial segments: biotech, pharmaceutical, and medical device. The dummy for medical device industry was omitted.
8. **Year effect:** Since the sample period is from 1990 to 2006, year dummies were added to control for year effect. This allows us to account for year-specific characteristics.
4. Results

Table 1 presents the descriptive statistics and correlations. We conducted OLS hierarchical regression analyses to test the hypotheses. First, we entered the controls in Model 1 and subsequently estimated the effect of technological diversity on firm performance in Model 2. In Model 3, we tested the main effects of the moderating variables, network centrality and alliance experience. In Model 4, we added the interaction terms between technological diversity squared and these two moderating variables. The results are presented in Table 2.

Before presenting the regression results, we used the variance inflation factor (VIF) to assess multicollinearity among all of the regressors. The VIF of some control variables are quite high, i.e. ROA and ROI. However, these two indicators have been proved highly correlated (e.g., Song, Xie, & Dyer, 2000). In order to confirm whether the multicollinearity of these control variables distorts our findings, we thus compared the directions and significance levels of variables of interest in the models that alternatively included and excluded these control variables. The results show that the directions and significance levels of the main variables did not markedly change. Expect for the abovementioned two control variables, the VIF of other variables are less than 2.4. The above examinations suggest that multicollinearity was not a concern among the main variables.

Hypothesis 1 posits that the relationship between technological diversity and firm performance is an inverted U-shaped pattern. Model 2 shows that the coefficient for technological diversity is positive and significant ($\beta = .655, p < .001$) while the coefficient for the squared term of technological diversity is negative and significant ($\beta = -.629, p < .001$), indicating the inverted U-shaped relationship between technological diversity and firm performance. Following Aiken and West’s (1991) suggestion, we also plotted a graph (see Fig. 2). As expected, the relationship between technological diversity and firm performance formed an inverted-U pattern. Thus, Hypothesis 1 is supported.

Hypotheses 2 and 3 explore whether network centrality and learning speed will moderate the relationship between technological diversity and firm performance. In Table 2, Model 3 is to estimate the direct effects of network centrality and learning speed on firm performance. The results reveal that the direct effect of network centrality is significantly negatively associated with performance ($\beta = -0.777, p < .01$). Although the majority of studies suggest that firms can achieve superior performance by being highly central in a network, some evidence shows that high centrality may not always benefit profitability but is context-dependent (e.g., Stam & Elfring, 2008). The significant performance effect of learning speed echoes the early studies and reveals that firms in a dynamic industry can enhance competence through a fast learning speed (Gopalakrishnan & Biely, 2006).

Model 4 shows the coefficients for the two moderating effects. The interaction between network centrality and the linear term of technological diversity is significantly positive ($\beta = .349, p < .01$), whereas the interaction between network centrality and the squared technological diversity term is negative and significant ($\beta = -.400, p < .01$). The results provide initial support to Hypothesis 2. Moreover, compared to the negative effect of network centrality, the positive moderating effect further demonstrates that the merit of network centrality could be demonstrated when firms attempt to integrate their existing knowledge with transferred knowledge from their alliance partners. Regarding learning speed, the regression results also show that its interaction terms with technological diversity is positively significant ($\beta = -290, p < .05$) and technological diversity squared ($\beta = -294, p < .05$) are negatively significant. Hypothesis 3 thus is tentatively supported.
in both sides of the curve are steeper. That is, the perfor-
effects of the moderators.

The nuanced differences between the groups can demonstrate the
moderator variable and reran Model 2 for each of the two groups;
high learning speed vs. low learning speed) by the mean of the
subgroups (high network centrality vs. low network centrality and
Barnett, Dwyer, and Chadwick (2004). Figs. 3 and 4 present the
moderating effects following the approach proposed by Richard,

Two-sided tests.

Inverted U-shaped relationship between technological diversity and
performance.

To increase the robustness of our results, we plotted the
moderating effects following the approach proposed by Richard,
Barnett, Dwyer, and Chadwick (2004). Figs. 3 and 4 present the
results graphs. Specifically, we divided the entire sample two
subgroups (high network centrality vs. low network centrality and
high learning speed vs. low learning speed) by the mean of the
moderator variable and reran Model 2 for each of the two groups;
the nuanced differences between the groups can demonstrate the
effects of the moderators.

Fig. 3 shows that, in the firm with low network centrality, there
is a definite inverted U-shaped relationship between technological
diversity and firm performance (Tobin’s Q). In the firms with low
network centrality, this inverted U-shaped curve changes; the
slopes for both sides of the curve are steeper. That is, the perfor-
manence effect of high/low technological diversity decreases sharply
in firms having low network centrality. Compared to the firms with
a lower level of network centrality, the negative effects of high/low

5. Discussion and conclusions

Our study makes several concrete contributions to the extant
research on alliances and networks. The primary contribution is
made to an emerging line of alliance research which recognizes
that technological diversity has both enriching and impeding ef-
fects on knowledge acquisition. The results complement recent
work, such as Sampson’s (2007) and Wuys and Dutta (2014),
which consolidate and reconcile seemingly conflicting arguments
by suggesting a curvilinear effect of alliance partner diversity on
innovation performances. Extending this line of research, we
examined how technological diversity influences market-based
performance and validated this relationship. Thus, this study

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5.1. Managerial implications

More important, this study provides a good starting point for systematically examining potential moderators of the technological diversity-performance relationship. Notably, this study adds value to network research by identifying network centrality as a key moderator. This resonates with the suggestion of Zaheer and Bell (2005) that it is prudent to consider firm capabilities while simultaneously adopting a network structuralist approach in explicating variance in firm performance. As predicted, network centrality was found to positively moderate the inverted U-shaped relationship between technological diversity and firm performance. The resultant pattern of the moderation effect of network centrality shows that high network centrality does neutralize the negative influence of high technological diversity on firm performance (see Fig. 3). In other words, this finding implies that network centrality is instrumental to the development of absorptive capacity, which gives support to the network-enabled capabilities of firms (Bell, 2005; Zaheer & Bell, 2005) that organizational internal capabilities are enhanced by network structure. Specifically, firms occupying preferred network positions are better able to reap the benefits of diverse technological capabilities than other firms because the beneficial positions enable superior absorptive capacity.

Our finding also echoes those from prior studies that suggest the interactive effects of network characteristics and technological diversity on performance outcomes. For example, Gilsing et al. (2008) proposed that technological distance between alliance partners is conducive to innovation when network density is great enough. Likewise, Phelps (2010) verified the complementarities between network density and the technological diversity of an alliance network in facilitating innovation. Accordingly, we conclude that network centrality and technological diversity act synergistically in the improvement of market performance.

As expected, learning speed was found to moderate the inverted U-shaped relationship between technological diversity and firm performance. This finding lends support to the view that firms with a greater learning speed are better able to manage broad sets of knowledge (Wu et al., 2014). However, the positive effect of technological diversity on firm performance was significantly nullified by learning speed, at high levels of learning speed (see Fig. 4). This finding can be explained by the contention of “vicarious learning” (McEvily & Marcus, 2005). In other words, those firms with a great learning speed might actively learn from other network contacts that were not their R&D alliance partners. Therefore, R&D alliances may merely reflect some of the effects of firms’ learning from their overall networks.

5.2. Limitations and directions for future research

As with any study that seeks to expose theoretical propositions to empirical falsification (Popper, 1959), this study contains several limitations, which could provide the basis for future research. First, the performance of alliance firms is affected by their alliance history. A firm’s performance may depend on the distinctive capabilities and complementary resources not only from existing alliance partners, but also from prior alliance partners (Heimeriks & Duysters, 2007; Kale et al., 2000). This study only investigated the effect of the former because of our restriction regarding secondary data from the SDC Database. Future research should consider the effect of the latter. Moreover, the use of the SDC database is not without limitations. Although the SDC database has been generally regarded as the most comprehensive database and widely used in a number of empirical research on alliances and inter-firm networks (e.g., Diestre & Rajagopalan, 2012; Lin et al., 2009; Oxley & Sampson, 2004; Sampson, 2007), it is still far from perfect (Hoehn-Weiss & Karim, 2014). Future research can replicate and extend this study by applying and combining different databases, such as Securities and Exchange Commission’s EDGAR...
Third, we used patent data to measure technological diversity. We consider patents an appropriate databank to construct information on technological diversity because patents demonstrate knowledge and R&D capacity pertinent to developing technologies (Aluja & Katila, 2001; Katila, 2002). However, technological portfolios do not exclusively contain patents (Aluja, 2000; Sampson, 2007). Patenting is a strategic choice. To prevent technology diffusion, firms may not patent all of their technological innovations (Aluja, 2000). Moreover, the USPTO has no standard format for assignees’ names, and typographical errors and mis-spellings are virtually inevitable in the USPTO’s dossiers. Although we searched for variations of names and key character substrings to reduce such noise, and scanned all patent assignees visually to catch incorrect assignees, exclusion of relevant patents or inclusion of irrelevant ones might have occurred. In addition, patents do not always provide tacit knowledge (Almeida & Phene, 2004). Thus, the degree of technological diversity between aligning partners may be underestimated by using patent data alone. Similarly, the instrument used to measure learning speed may also be subject to the constraints of patent data. The sample size is inevitably restricted using the abovementioned limitations of patent data due to the firms without patents being excluded in this study. Future research could assess technological diversity and learning speed in different ways, such as by using a multiple-item measure. In this manner, future studies can replicate and expand this study to examine the robustness of our findings. Last but not least, R&D collaboration in the biotechnology and information technology industries mainly involves the transfer of tacit knowledge. Nevertheless, in some industries such as the primary industries where knowledge exchanged tends to be explicit, the collaboration may be different. Future research can explore if the findings of this study can be applied to these industries. Notwithstanding these limitations, this study yields several important theoretical and managerial implications, and we hope it will trigger future research.

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