The double-edged sword of technological diversity in R&D alliances: Moderators of the relationship between technological diversity and firm performance

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ABSTRACT

While the benefits of the technological diversity between alliance partners have been widely recognized, some scholars remain skeptical and warn of the potential negative consequences of such diversity. This study integrates these two contrary views to explore the notion of a nonlinear relationship between technological diversity and firm performance. We identify learning speed and network centrality as two critical moderators of this relationship. The results show that the degree of technological diversity between alliance partners exhibits an inverted U-shaped relationship with firm performance. Furthermore, this relationship is moderated by learning speed and network centrality.

Keywords: R&D alliance, technological diversity, network centrality, learning speed

1. Introduction

To address ever-changing environments, firms leverage R&D alliances as a strategic mechanism of exploring new capabilities or technologies, sharing risks, and gaining synergy (Haas and Hansen, 2007; Meuleman et al., 2010; Shipilov, 2009; Steensma and Corley, 2000; Takayama, 2002; Tomlinson, 2010). Researchers who subscribe to the knowledge-based view (KBV) argue that the resources of interest in inter-firm R&D collaborations provide opportunities for firms to improve their technological development (Rodan and Galunic, 2004). Collaborating with partners who are sufficiently differentiated in technological domains can help generate synergies because it allows firms to acquire missing resources and complementary capabilities that can be applied to value-creation activities (Caloghirou et al., 2004; Kim and Song, 2007; Lin et al., 2007; Osborn and Hagedoorn, 1997; Park and Zhou, 2005; Yang et al., 2010). Although R&D alliances are prevalent in technology-intensive industries (Li et al., 2008; Lin et al., 2009; Meuleman et al., 2010), their contribution to performance outcomes does not always meet expectations (Luo and Deng, 2009). In other words, R&D collaboration with partners to tap into diverse technologies cannot guarantee that a firm will enjoy superior performance (Lin et al., 2009; Sampson, 2007; Wadhwa and Kotha, 2006).

The discussion above implies that the relationship between technological diversity of partners and performance is more complex than previous models have suggested. To more completely understand the relationship, it is prudent to investigate whether this relationship varies depending on certain conditions. Evidence suggests that there are systematic differences in the organizational characteristics possessed by firms, and these characteristics determine how effectively they manage their R&D alliances to attain their expected performance (Schilke and Goerzen, 2010). Prior research also indicates that the effects of acquired knowledge-based resources on performance can be fully realized only if a firm can internalize them and integrate them into its knowledge base (Arikan, 2009; Conner and Prahalad, 1996; Makri et al., 2010). To extract value from R&D alliances, firms should be able to effectively absorb and exploit the knowledge-based resources of their partners. However, the firm-specific and tacit nature of knowledge-based resources may hinder the assimilation of this knowledge (Kogut and Zander, 1992; Simonin, 1999). This problem is exacerbated in R&D alliances because they involve the exchange of much tacit and complex knowledge (Inkpen, 2008). In summary, the difference between two firms' technology domains in an R&D alliance can influence their performance. Nevertheless, the strength of this influence is contingent on the firm's capabilities pertinent to knowledge absorption and utilization.

Accordingly, this study aims to examine the technological diversity between R&D alliance firms and its implications for market-based performance. Specifically, this analysis extends beyond simple linear relationships and to investigate potential curvilinear and contingency relationships. We postulate that the degree of technological diversity between the focal firm and its R&D alliance partners has a curvilinear relationship with its market-based performance. In addition, we identify learning speed and network centrality as firms' learning and network capabilities, respectively, which may moderate this relationship. Hence, this research develops the conceptual model shown in Fig. 1 and formulates related research hypotheses. To validate the proposed model, this study uses a large sample of 808 R&D alliances from U.S. industries over a span of 17 years (1990-2006).

Insert Fig. 1 about here

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2. Theoretical background and hypotheses development

In the knowledge-based view, a firm's most strategically significant resource is the view's namesake, knowledge (DeCarolis and Deeds, 1999; Grant, 1996; Kogut and Zander, 1992). A key assumption of this view is that the determinants of performance differences among firms are heterogeneous knowledge bases and capabilities. The underlying knowledge bases of firms can either be developed internally or acquired externally (DeCarolis and Deeds, 1999). In other words, a firm can enhance its existing capabilities and garner a new competitive advantage with differential access to externally generated knowledge (Grant, 1996). As Lin et al. (2009) argued, since each firm possesses heterogeneous resources and idiosyncratic capabilities, the critical resources of firms can be acquired from external resources through the following: alliances, mergers and acquisitions, joint ventures, and other inter-firm relationships. Through alliance activities, firms may gain access to complementary resource endowments they currently lack, such as technical resources, market reputation, distribution channels in markets, strategic position in the industrial environment, or financial capital (Haeussler et al., 2010; Li et al., 2008; Luo and Deng, 2009; Souitaris, 2001). In summary, acquiring and absorbing necessary and valuable knowledge from alliance partners provide firms an opportunity to achieve synergistic performance.

Burgeoning research has addressed the issue of knowledge transfer between alliances, including governance modes (Aggarwal et al., 2011; Sampson, 2004), partner selection (Li et al., 2008; Lin et al., 2009; Luo and Deng, 2009; Meuleman et al., 2010; Park and Zhou, 2005), and knowledge transfer mechanisms (Inkpen, 2008; McEvily and Marcus, 2005; Zhao and Anand, 2009). Originating from the research on partner selection, one recently emerging stream of research views a firm's alliances as a portfolio with a focus on the diversity of alliance partners (e.g., Jiang et al., 2010; Lin, 2012; Sampson, 2007). Similar to Goerzen and Beamish's (2005) network diversity, this notion of alliance partner diversity denotes the degree of variance in partners' resources, capabilities, knowledge, and technological bases (Jiang et al., 2010). In light of this notion, the heterogeneity between alliance firms' technological capabilities appears to have both bright and dark sides. The diversity of technological capabilities between partners increases the possible number of new recombinations of the firm’s resources (Jiang et al., 2010; Park and Zhou, 2005). Conversely, firms are limited in their capabilities. Thus, increased technological diversity may restrict the absorption and utilization of acquired knowledge (Sampson, 2007). By synthesizing the positive and negative views of technological diversity, we punctuate these opposing arguments and elaborate on the conception of nonlinear relationship between technological diversity and firm performance.

2.1. Technological diversity and firm performance

Technological diversity captures the difference in technological capabilities between a focal firm and its alliance partners. Alliance activities represent an alternative form of inter-firm collaborations in which participating firms can gain access to complementary or necessary knowledge (Goerzen and Beamish, 2005; Jiang et al., 2010; Kale and Singh, 2007; Kale et al., 2000; Park and Zhou, 2005). In knowledge- or technology-based industries where resources and capabilities are often organizationally embedded (e.g., Ahuja, 2000; Baum et al., 2000), alliance activities can be critical mechanisms enabling firms to acquire new capabilities from their partners (Haas and Hansen, 2007; Kogut and Zander, 1992; Ozman, 2010; Sampson, 2007). For example, Zheng et al. (2010) showed that biotechnology start-ups have superior firm valuation, measured as the total market value of a firm’s equity, because they conduct many alliance activities with external organizations. This suggests that a firm’s alliance activities are beneficial to its valuation and future direction. Thus, collaboration between different but complementary alliance partners may be more likely to tap a potential of synergy (Luo and Deng, 2009). Such collaboration can be instrumental to developing and enhancing competitive capabilities and improving firm performance.

Gaining access to diverse technologies can influence firm performance (Park and Zhou, 2005). A wide knowledge base reinforces the capacity of firms to assimilate new knowledge (Katila, 2002), and it leads to an expanded approach to problem-solving with new or refined methods (Ahuja and Katila, 2001). Using diverse resources to augment knowledge capabilities, firms can develop new products faster than their rivals who possess relatively insufficient new resources (Wadhwa and Kotha, 2006). Firms can utilize these complementary resources to strengthen product functionality and add new features to existing products (Katila, 2002). As March (1991) indicated, technological diversity between alliance partners may provide new opportunities to solve existing and potential problems regarding technologies, products, and market competition. Pooling the technological diversity or distinct capabilities of alliance firms provides advantages in terms of knowledge creation, contributing to the future value of firms.

Sampson (2007) cautioned that a high level of technological diversity may decrease firm performance. The over-absorption of diverse knowledge is likely to raise collaborative costs, reduce original reliability, and pose barriers to the contributions of alliance activities. As Whetten (1981) suggested, coordinative costs increase as a function of the differences between collaborating firms. In general, firms can only manipulate and assimilate resources that are sufficiently similar to their own (Luo and Deng, 2009; Sampson, 2007). When knowledge possessed by partners is so tacit and firm-specific that it is difficult to transfer and integrate (Nelson and Winter, 1982; Simonin, 1999), firms need certain capabilities for assimilating and utilizing such heterogeneous knowledge from partners. Firms lacking these capabilities experience difficulties in absorbing and acquiring their partners' knowledge, incurring higher costs. For example, overcoming these difficulties may necessitate investment in new capabilities. In this case, performance will eventually decrease as coordination costs exceed the benefits of the newly acquired knowledge.

Alliance partners that are dominant in different technological fields present a serious concern. They tend to have dissimilar cultures and routines, and this dissimilarity is referred to as organizational distance (Simonin, 1999). The barrier of organizational distance hinders the sharing and exchange of diverse technologies between alliance firms, and reduces the speed of knowledge absorption and utilization necessary for firms to innovate (Kraatz, 1998). This means that the costs in managing and acquiring diverse knowledge, stemming from organizational distance, can eventually erode profit margins at a high level of technological diversity.

Given the positive and negative aspects of technological diversity, firms often experience trade-off between technological complementarity and collaborative costs.

Technological complementarity in alliances allows firms to improve and enhance the capabilities that are critical to successful product/technology development and innovation, which in turn translates into high firm performance. However, this improvement is constrained by the collaborative costs associated with the assimilation of diverse technologies because dissimilar knowledge may require additional investment in knowledge absorption and utilization capabilities. Hence, we argue that firm performance initially increases with technological diversity because of the advantages of technological complementarity. By contrast, the increasing collaborative costs along with technological diversity can reach a point at which they outweigh any potential benefits of collaboration, which decreasing firm performance. Thus, it is postulated:

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. Learning capability and network capability

Researchers assert that a firm's ability to cope with technological diversity hinges on its capacity to absorb and harness external knowledge (Conner and Prahalad, 1996; Grant, 1996; Lane and Lubatkin, 1998). To derive the complementary and valuable knowledge from diverse alliance partners, firms require mechanisms pertaining to knowledge absorption and utilization, and the organizational capability to assimilate external resources and inbound knowledge (Daghfous, 2004; Kim and Song, 2007; Liu and White, 1997). Therefore, firms must build sufficient capabilities to acquire and absorb resources before engaging in extensive collaborative efforts.

Hitt et al. (2000) argued that learning allows companies to build up their resource endowments. Perez-Nordtvedt et al. (2010) further suggested that organizational resources can only be accumulated if the learning process is effective. In other words, effective learning enables a firm to internalize acquired knowledge and subsequently apply them to its operations to improve its productivity (Kale and Singh, 2007; Perez-Nordtvedt et al., 2010; Szulanski et al., 2004; Yang et al., 2010). In addition, network capability plays an essential role in managing multiplex inter-firm networks. Defined as a firm's ability to develop and utilize relationships with various external partners (Walter et al., 2006), a firm’s network capability is manifested in its network position (Gulati, 1999). An advantageous position in an alliance network can provide a rich exchange of resources (Dyer and Hatch, 2006; Gulati, 1999; Kale and Singh, 2007; Rampersad et al., 2010). If a firm occupies the central position in the network, it can access more knowledge from a wider variety of connections (Freeman, 1979; Zaheer and bell, 2005). Another benefit conferred by advantageous positions is quick access to resource exchange partners (Uzzi, 1997). In brief, a superior network position may exert a positive influence on the process of utilizing resources to improve organizational performance by gaining better access to resources (including information or knowledge). Accordingly, this study treats learning and network attributes, which are viewed as the manifestations of learning and network capabilities, respectively, as key moderators when examining the effect of technological diversity on firm performance.

2.2.1. The moderating role of learning speed

Learning speed refers to the rate at which a firm learns new technological knowledge and applies it to technology or product development (Gopalakrishnan and Bierly, 2006). It reflects a firm's ability to integrate new knowledge with its existing knowledge base (Bierly and Chakrabarti, 1996). High learning speed represents an efficient value-creating process in that new and existing knowledge can be effectively integrated into a superior collective knowledge base (Gopalakrishnan and Bierly, 2006; Perez-Nordtvedt et al., 2010). As Gopalakrishnan and Bierly (2006) argue, therefore, learning speed can mirror the learning capability that equips firms to assimilate and utilize new technologies.

Alliance activities provide interactive platforms in which firms can gain access to their desired resources to expedite their innovation processes (Gopalakrishnan and Bierly, 2006; Kale and Singh, 2007; Kale et al., 2000; Kraatz, 1998). However, how to realize these benefits is a primary concern. Sampson (2007) showed that the heterogeneous capabilities of alliance members strongly affect the extent to which firms can learn from each other in collaborative relationships. Firms must cope with the diversity of these external resources before extracting economic value from them. Simonin (2004) indicated the major reason why some firms are able to outperform other firms in alliances is that they have superior learning capabilities. He argues that these capabilities accelerate learning process, which enhances knowledge transfer. This learning capability enables firms to assimilate and integrate external resources quickly, and plays a pivotal role in the collaboration period (Murovec and Prodan, 2009; Perez-Nordtvedt et al., 2010; Xia and Roper, 2008). Firms with greater learning capability can build a wide knowledge base to absorb and harness new knowledge. They are more likely to acquire diverse technologies with complementary resources to fill what they currently lack in a timely manner, and in turn to optimize their resource combinations for operations. As such, the diversity of partner capabilities is a lucrative economic opportunity rather than a time- and cost-consuming problem. With great learning capability, firms are adept at dealing with the diversity of technologies. This may augment the positive effect and depress the negative effect of technological diversity on firm performance. Consequently, we propose the following hypothesis:

Hypothesis 2. *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 than when learning speed is lower.*

2.2.2. The moderating role of network centrality

Network centrality captures an important characteristic of a network structure, namely, the central location that a firm occupies in the indusial network (Shipilov, 2009; Stam and Elfring, 2008; Wasserman and Faust, 1994). Freeman (1979) defined network centrality as the number of direct ties that increase the acquisition of diverse resources from different connections. Thus, as discussed above, network centrality can represent a firm's network capability to obtain resources outside the firm. Shipilov et al. (2010) showed that a firm has the power to acquire knowledge and controls the flow of knowledge in a competitive environment if it occupies a central location in the industrial network. In addition, Perez-Nordtvedt et al. (2010) considerd that centrality allows a firm to explore multiple types of knowledge because it allows the firm to receive plentiful resources from numerous connectors in the network. High network centrality increases the capacity of firms to acquire and utilize various resources from alliance partners. These resources extend their current knowledge, which is a primary source of competitive advantage. In summary, a high level of network centrality increases the amount of knowledge available because of an advantageous position.

This study views network centrality as a critical moderator based on the contention of firms' network-enabled capabilities (Bell, 2005; Zaheer and Bell, 2005). In this perspective, if a firm is unable to comprehend novel knowledge from a given source adequately, it may need another partner to complement its absorptive capacity (Bell, 2005; Gilsing et al., 2008). In other words, the extent to which one's partners are linked may help in dealing with technological diversity to any of them (Gilsing et al., 2008; Zaheer and Bell, 2005). Along this vein, network centrality helps firms reinforce their absorptive capacity in two ways. A firm's absorptive capacity is its ability to (1) recognize the value of new external knowledge, (2) assimilate it, and (3) apply it to commercial ends (Cohen and Levinthal, 1990, p. 128). First, firms occupying a centralized position within an alliance network can capture whole pictures of industrial and technological tendency by pooling abundant information (Gulati, 1999; Ozman, 2010; Zaheer and Bell, 2005). These firms are less likely than others to miss vital information and are more likely to assess the potential value of knowledge (Bell, 2005). Hence, network centrality can improve the firms' absorptive capacity.

Second, the ability to assimilate novel knowledge relies on prior knowledge base (Cohen and Levinthal, 1990). A central position in the network exposes firms to a rich flow of knowledge, allowing them to accumulate substantial knowledge bases (Bell, 2005). When acquiring new knowledge in similar areas, these knowledge bases help firms expedite the process of assimilating and exploiting. This in turn makes their product and technology development more effective and efficient. In particular, firms encounter a dilemma if they derive new knowledge form their partners that is valuable to them but differs significantly from their current knowledge bases. In this case, central firms are better positioned to access the knowledge they require in a timely manner. This is because the central position in the network enables them to quickly develop the linkages among knowledge nodes (Choi et al., 2010; Gulati, 1999). Accordingly, central firms are able to comprehend and absorb the new external knowledge. That is, the difficulties attributable to technological diversity are partially offset by the advantage of a central position in the network. Taken collectively, by enhancing the absorptive capacity of firms, network centrality exerts an influence on the relationship between technological diversity and firm performance. These arguments lead to the following hypothesis:

> **Hypothesis 3.** *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 than when the degree of centrality is lower.*

3. Method

3.1. Sample and data collection

The hypotheses were tested using a data set on the alliance and patenting activities of U.S. firms in various industries (i.e., SIC classes 28, 35, 36, 38, 73, and 87). We focused on research-related alliances, including research on technology components and the co-development of new technology. We constructed the data set 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 is compiled from publicly available sources, such as the Securities and Exchange Commission (SEC) filings, industry and trade journals, and news reports. To increase the reliability of the SDC data, we adopted the two-step approach recommended by Sampson (2007). First, all deals for which an alliance announcement date was set had been verified against the Lexis-Nexis database. Second, because the SDC data became comprehensive after the year 1990, we gathered data on R&D alliances for the years 1990 to 2006. We collected comprehensive data on company portfolio, finances, and patenting activities from listed U.S. firms to ensure the availability of secondary data from the Compustat database and USPTO. Based on these criteria, we collected data for 242 firms involved in 808 R&D alliances; altogether, our sample included 817 firm-year observations.

3.2. Dependent variable

Firm performance: We adopted Tobin's Q, a market-based performance measure, as performance measure herein. Tobin's Q is superior to other accounting based measures such as return on assets (ROA) because it is forward looking and thus can avoid the potential concern of a time lag between firm strategic behavior and accounting-based performance (Wang and Choi, 2010). Thus, Tobin's Q is an appropriate measure of a firm's strategic performance (Chakravarthy, 1986). Although some studies criticized Tobin's Q by asserting that it centers on the issue of measurement error and consequently results in a biased estimation of the coefficient (Whited, 2001), this potential measurement error is less of a concern in studies where Tobin's Q is a dependent variable (Lu and Beamish, 2004). Tobin's Q is defined as 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 and 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 and Pruitt, 1994). The data for Tobin's Q was obtained from the Compustat database.

3.3. Independent variables

Technological diversity: Based on Jaffe (1986), Sampson (2007) measures the diversity of partner technological capabilities by examining the extent to which partners' patents are in the same technology classes. We employed Sampson's (2007) formula that can capture the technological position of the 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, $F_i = [F_i^1 \cdots F_i^s]$, where F_i^s represents the number of patents assigned to partner firm *i* in patent class *s*. Diversity of partner capabilities is as follows:

$$Technological\ diversity\ = 1 - \frac{F_i F_j'}{\sqrt{(F_i F_i')(F_j F_j')}}, \text{where } i \neq j$$

The range of technological diversity varies from 0 to 1. A value of 1 indicates the greatest possible technological diversity between alliance partners. In general, patents are categorized according to the US Patent Classification (UPC). In this study, a firm's patents in year (t) include all the patents that it successfully applied for in the past 5 years, i.e., from year (*t*–5) to year (*t*–1), because new technological knowledge loses its significant value within approximately five years (Argote, 1999). However, most patents belong to more than one class. We thus classified patents based on the first number of the UPC code of each patent, denoting the patent's primary domain of technological applications.

Learning speed: This variable is to capture a firm's capability of acquiring and utilizing new technologies. According to Gopalakrishnan and Bierly (2006) and Katila (2002), learning speed is measured as technology cycle time, the average age of the patents cited by a firm's patents. High technology cycle time means that a firm takes long time to incorporate new technologies into its new products or processes. Thus, low technology cycle time is indicative of high learning speed (Gopalakrishnan and Bierly, 2006).

Network centrality: To measure the centrality of firms in an network, we created a network of alliances and calculated the positions of the firms in this structure. This 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. Although information about the dissolution of these ties is not disclosed in most circumstances, we can assume that these alliances continue to stay for only a specific duration, because it is impossible that ties once formed continue to stay and are never dissolved (Ahuja, 2000). Previous studies have indicated that alliances last an average of 3 years (Harrigan, 1985; Pangarkar, 2003). Based on the analysis of a three-year window (Paruchuri, 2010), we considered alliance ties older than three years as being 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 each year. Using the moving three-year window analysis, we considered alliance ties that are formed by firms in the three-year duration ending in year *t*. For example, we constructed the alliance network by calculating the ties among firms during 2002-2004, ending in year *t*. Subsequently, we measured the network variable in 2005, year ($t+1$). Ties before 2002 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 and Duysters, 2002). We calculated eigenvector centrality by using UCINET VI software based on the formula described below (Borgatti et al. 2002; Bonacich, 1987; 2007):

$$C_{\mathrm{i}} = \alpha \sum_{j=1}^{\mathrm{n}} A_{ij} C_j \,, i = 1, \ldots, \mathrm{n}$$

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

3.4. Control variables

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

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 since the number of employees can be highly correlated with market-based performance (He and Wong, 2004) and firm age would predict performance due to Stinchcombe's (1965) argument of "liability of newness".

Industry: Different industrial segments represent systematic differences between innovation and financial factors of firms (Molina-Morales and Martinez-Fernandez, 2009). We classified our sample firms into six industrial segments according to SIC codes (i.e., SIC codes: 28, 35, 36, 38, 73, and 87).

R&D expense, past R&D expense $_{(t-1)}$, annual sales, and past annual sales $_{(t-1)}$: These variables represents the firms' current- and prior-period endowments of intellectual property or financial assets (Baum et al., 2000). In particular, prior-period performance on sales and investment on innovations may impact current-period sales and innovations (He and Wong, 2004; Bonner and Jr. Walker, 2004). Therefore, we controlled for variation in current- and prior-period endowments of each firm before and at the time of alliance formation by including these four variables.

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; Ebben and Johnson, 2005). Successful past performance provides firms with relatively rich resources to explore new technologies and market opportunities (Baum et al., 2000; Zahra et al., 2000). We thus controlled for these profitability indicators to lessen the influence of past profitability on current-period firm performance.

Joint venture: The ownership difference at the founding of a strategic alliance influences organizational performance (Baum et al., 2000). If firms found the joint venture, more opportunities may accrue from polling complementary assets from other network firms (Shenkar and Li, 1999). We thus accounted for such possibilities by including dummy variables, using code 1 if firms founded the joint venture and 0 otherwise.

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×(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).

4. Results

Table 1 presents the descriptive statistics and correlations. We conducted a hierarchical regression analysis to test the hypotheses. The results are presented in Table 2 and Table 3.

Insert Table 1 about here

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 (β=0.34, t=3.13, $p<0.01$) while the coefficient for the squared term of technological diversity is negative and significant (β=–0.33, t=–2.99, $p<0.01$), indicating the inverted U-shaped relationship between technological diversity and firm performance (Aiken and West, 1991). 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.

Insert Fig. 2 about here

Hypotheses 2 and 3 explore whether learning speed and network centrality will moderate the relationship between technological diversity and firm performance. In Table 3, Model 3 shows that the coefficient for the interaction between learning speed and technological diversity squared is positively significant(β=0.67, t=2.94, $p<0.01$). Therefore, Hypothesis 2 is supported. Moreover, the coefficient for the interaction between network centrality and technological diversity squared is also positively significant (β=0.34, t=2.50, $p<0.05$). Hence, Hypothesis 3 receives support.

Insert Table 2 and Table 3 about here

To increase the robustness of our results, we constructed Fig. 3 and Fig. 4, which illustrate the influence of technological diversity on firm performance over the range of learning speed and network centrality, respectively. Fig. 3 shows that, at low levels of learning speed, the relationship between technological diversity and firm performance is an inverted U-shaped curve. At high levels of learning speed, the negative slope of this curve flattens, but the positive slope of this curve does not steepen. Therefore, Hypothesis 2 is partially supported.

As shown in Fig. 4, at low levels of network centrality, the relationship between technological diversity and firm performance is a definite inverted U-shaped curve. However, at high levels of network centrality, this curvilinear relationship becomes a U-shaped curve.

Specifically, at extremely low and high levels of technological diversity, firm performance rises sharply, and at moderate levels of technological diversity, firm performance remains unchanged. This pattern partially contradicts Hypothesis 3, which will be discussed below.

Insert Fig. 3 and Fig. 4 about here

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5. Discussion and conclusions

This work contributes to the literature in several aspects. First, our study deepens our understanding of similarity or diversity between partners (Ahuja and Katila, 2001; Sampson, 2007; Miller, 2006; Park and Zhou, 2005; Wadhwa and Kotha, 2006) by weighing the pros and cons of technological diversity. Previous studies have proposed a curvilinear relationship to reconcile two compelling but contrary arguments (e.g., Jiang et al., 2010). We adopted this approach and our results confirmed that an inverted U-shaped relationship existed between technological diversity and firm performance. This finding echoes the assertion that the relationship between technological diversity and performance is complex and may even be nonmonotonic (Beckman and Haunschild, 2002; Kraatz, 1998; Rodan and Galunic, 2004; Wadhwa and Kotha, 2006; Zheng et al., 2010). Furthermore, this study extends the empirical evidence for such a relationship across a broader range of industries than was previously documented. Drawn from the wide range of industries, the results of this study are not subject to an industry-specific bias. Thus, our findings provide important insight into the overall relationship between technological diversity and performance.

Second, this study constitutes an initial attempt to identify the moderators of the inverted U-shaped relationship between technological diversity and performance. We found that learning speed and network centrality moderated the curvilinear relationship between technological diversity and firm performance. However, these findings did not entirely support our hypotheses. Specifically, the positive effect of technological diversity on firm performance was significantly nullified by learning speed, at high levels of learning speed (see Fig. 3). This finding can be explained by McEvily and Marcus's (2005) argument of "vicarious learning". That is, those firms with great learning capability might actively learn from other network contacts that are not their R&D alliance partners. Thus, R&D alliances may merely reflect some of the effects of firms' learning from their overall networks.

The results also showed a surprising U-shaped pattern for high network centrality (see Fig. 4), suggesting another implication worthy of further discussion. When network centrality is high, it reverses the inverted U-shaped relationship between technological diversity and performance, which becomes a U-shaped relationship. Wadhwa and Kotha (2006) ascribed this type of reversion to the strong moderation effect of a moderator. In fact, this finding bolsters some extant arguments on both similarity and diversity between partners and the associated alliance outcomes. As Lechner et al. (2010) stated, high levels of centrality provide benefits but incur the cost of maintaining a large number of ties. Hence, the effect of network centrality on firm performance depends on whether the benefits exceed the cost of maintaining alliance relationships.

In addition, partner similarity is known to contribute to alliance learning (Lane and Lubatkin, 1998). A low level of technological diversity between the partners suggests that the costs of managing alliances would be relatively low (Jiang et al., 2010; Luo and Deng, 2009). Initially, at extremely low levels of technological diversity, firms tend to perform well because the partners are able to benefit from each other without incurring high coordinative costs. However, as the diversity between partners increases, the costs of maintaining the relationship increase and start to erode the profit margin; thus, performance begins to decline. This decline continues until technological diversity is beyond a certain moderate level (here, 0.58). Afterward, the benefits from the synergy of network centrality and technological diversity exceed the costs, thereby improving firm performance. Such finding corroborates Gilsing et al.'s (2008) proposition that technological distance between partners is conducive to exploration performance when the number of direct and indirect ties possessed by the partners, akin to the measure of eigenvector centrality used here, is great enough. Our results also support the argument on the network-enabled capabilities of a firm (Bell, 2005; Zaheer and Bell, 2005). In brief, network centrality can enhance a firm's absorptive capacity, which enables the firms to fully capitalize on its diverse, externally-acquired capabilities to gain a competitive advantage. From the results, we infer that network centrality and technological diversity act synergistically only when both variables occur at high levels.

5.1. Managerial implications

While firms desire to acquire some capabilities from their partners, they should not only see the learning and resource access benefits accruing from collaboration with diverse partners, but they should also foresee the difficulty and complexity of managing them. Initially, greater technological diversity can be beneficial; however, greater diversity can be detrimental to firm performance beyond a certain level. The main reason is that high enough volume of different alliance partners produces undue complexity and deters knowledge accumulation from a lack of systematic learning. Managers should make a conscious choice to maintain an optimum level of technological diversity dependent on the extent to which their firms' current capabilities are sufficient; that is, firms should be aware of the vital roles played by both learning capability and network position in handling the diverse capabilities of their partners. Once firms have built an appropriate learning capability and occupy an advantageous network position to avail against the downside of technological diversity, they are able to assimilate external capabilities and use them to create value. Our findings imply that successful firms are those who know how to maneuver themselves into favorable positions by strategically designing and constructing their alliance networks. Firms should proactively consider the ramifications on future choice of each new tie they form and structure a network of alliance where they are situated in centrally.

Moreover, our findings highlight the importance of the learning capability in alliances. Learning capability refers to the firm's specific resources and assets that can be deployed to drive the learning process and improve its efficiency (Simonin, 2004). In fact, scholars have suggested several ways by which alliance firms can facilitate their inter-firm learning. For example, effective inter-firm learning requires firms to adapt their existing knowledge-based resources to fit (Dyer and Hatch, 2006), and depends on specific mechanisms such as joint problem solving (McEvily and Marcus, 2005). Thus, firms must continuously align their learning capability with the degree of technological diversity. When allying with a new partner, firms should have appropriate mechanisms in place while simultaneously evaluating and upgrading their resources to optimize their full resource portfolio. In this way, eventually, the intrinsic benefits associated with technological diversity will outweigh the costs and the net impact on firm performance will be positive.

5.2. Limitations and directions for future research

The implications of this study should be seen within the context of its limitations, which could also provide the basis for directing future research. First, the performance of alliance firms is affected by their alliance history. That is, 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 (Kale et al., 2000; Muthusamy and White, 2005). This study only investigated the effect of the former because of our restriction by secondary data from the SDC Database. Future research should consider the effect of the latter.

Second, although this study considered network centrality as critical moderator, future research should devote more attention to other network characteristics. For example, tie strength and structural holes are also related to the availability, diversity, and richness of external resources (Ahuja, 2000; Dyer and Hatch, 2006; Szulanski et al., 2004; Tomlinson, 2010; Burt, 1992; Lin et al., 2009; Paruchuri, 2010; Shipilov, 2009).

Finally, 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 (Ahuja and Katila, 2001; Katila, 2002). However, technological portfolios do not exclusively contain patents (Ahuja, 2000; Sampson, 2007). Patenting is a strategic choice. To prevent technology diffusion, firms may not patent all of their technological innovations (Ahuja, 2000). In addition, patents do not always include tacit knowledge (Almeida and Phene, 2004). Thus, the degree of technological diversity between allying partners may be underestimated by using patent data alone. Future research could assess technological diversity in different ways, such as by using a multiple-item measure. In this manner, future studies can replicate this study to examine the robustness of our findings. Notwithstanding these limitations, this study yields several important theoretical and managerial implications, and we hope it will trigger future research.

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Appendix

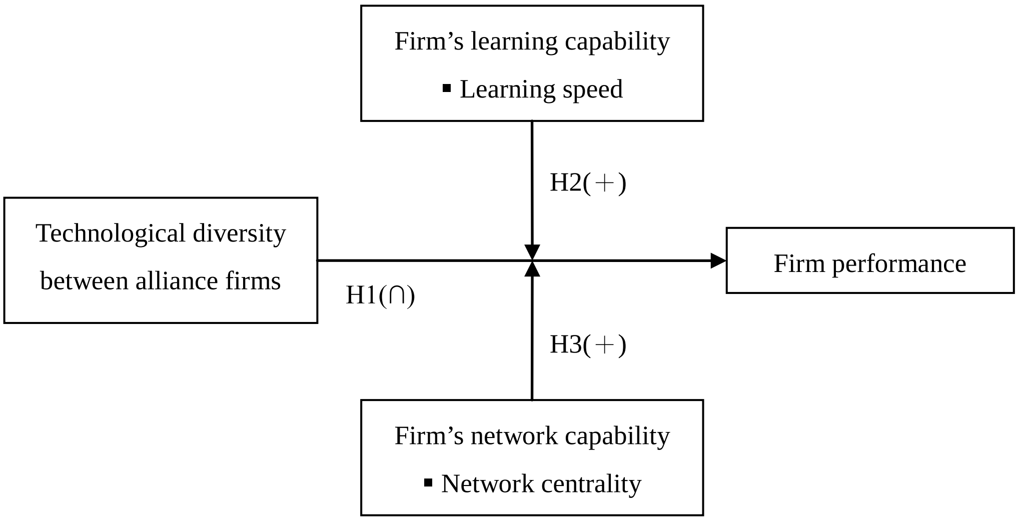

Fig. 1. Theoretical model of technological diversity and firm performance

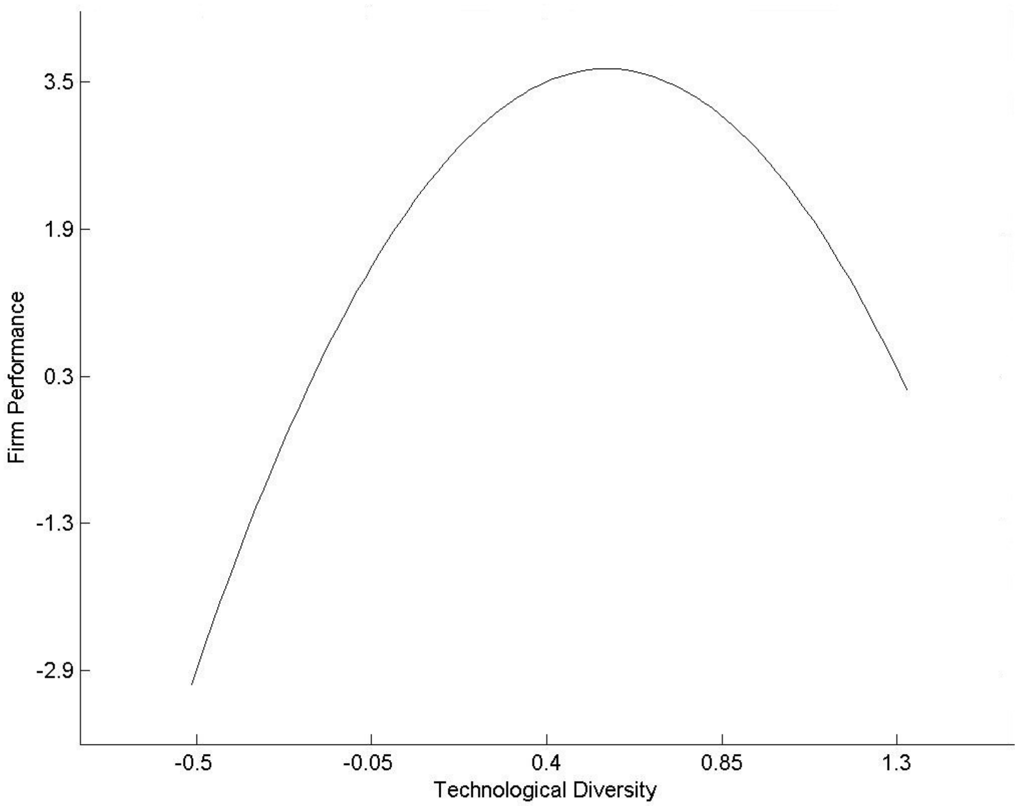

Fig. 2. Inverted U-shaped relationship between technological diversity and firm performance

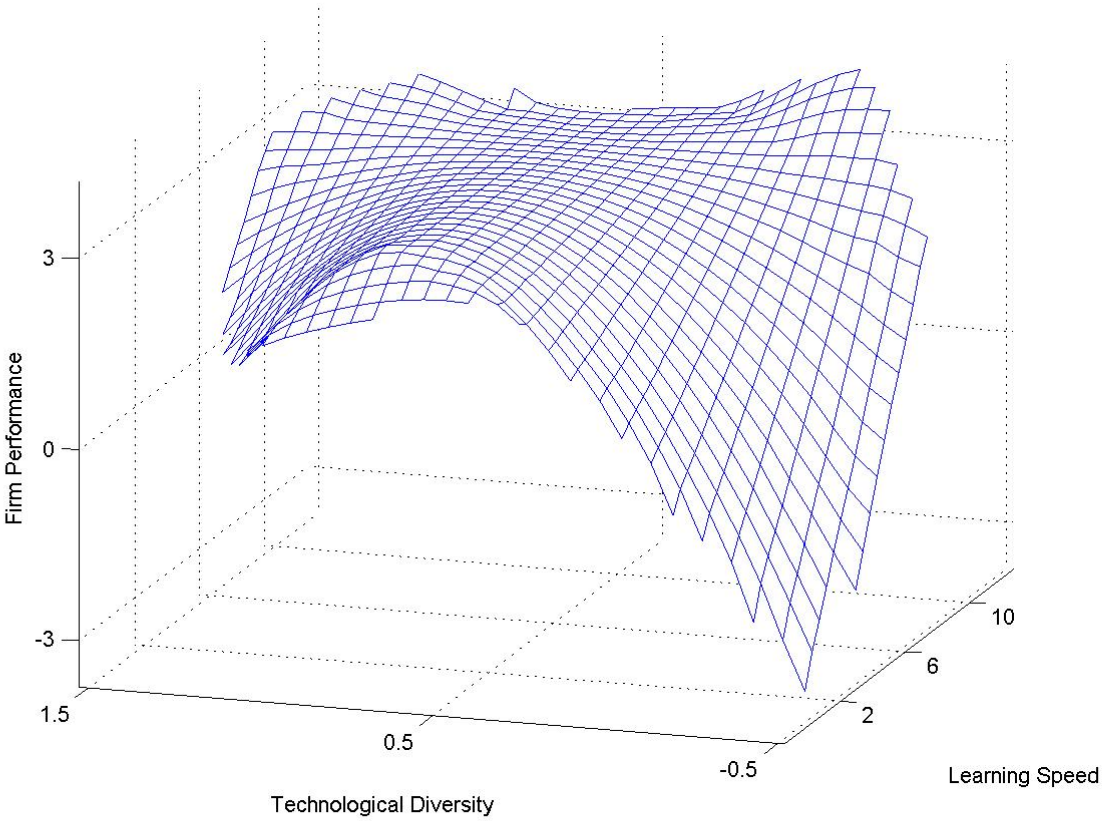

Fig. 3. Moderating effect of learning speed

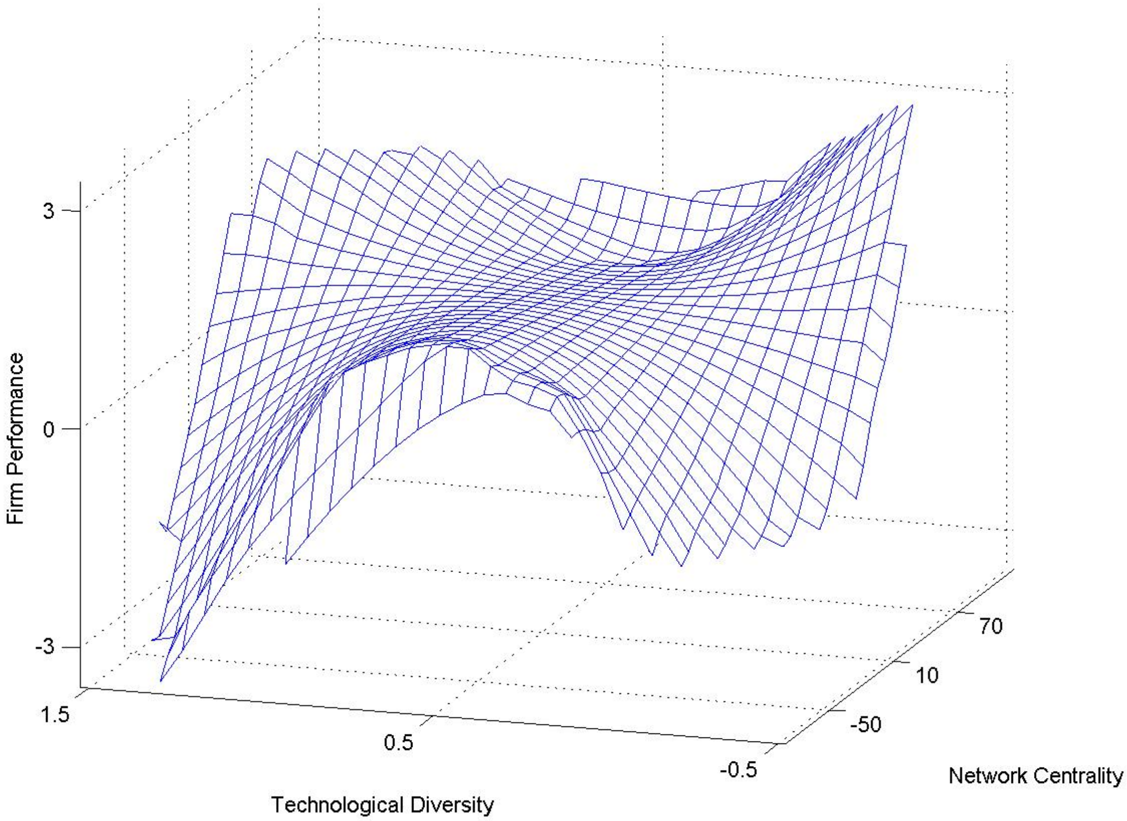

Fig. 4. Moderating effect of network centrality

Table 1

Descriptive statistics and correlations (N = 817 firm-year observations)

Variables	Mean	S.D.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1. Firm size [a]	44.76	68.09	--																		
2. Firm age	50.23	42.21	.449**	--																	
3. Annual sales [b]	11.47	18.72	.938**	.439**	--																
4. R&D expense [b]	.97	1.44	.772**	.500**	.843**	--															
5. Annual sales (t-1) [b]	10.48	17.84	.937**	.455**	.991**	.828**	--														
6. R&D expense (t-1) [b]	.88	1.43	.764**	.499**	.822**	.942**	.820**	--													
7. Return on assets (t-1)	.19	23.43	.114**	.039	.132**	.194**	.122**	.140**	--												
8. Return on equity (t-1)	.66	64.49	.088*	.096*	.100**	.141**	.094*	.101**	.663**	--											
9. Return on investment (t-1)	.42	39.99	.115**	.089*	.130**	.180**	.119**	.129**	.948**	.748**	--										
10. Joint venture	.07	.26	.004	-.002	.004	-.055	.003	-.050	.022	.010	.026	--									
11. Network density	2.36	7.23	-.111*	-.186**	-.120**	-.123**	-.119**	-.119**	.092*	.062	.074	.001	--								
12. Industry_Dum1	.28	.45	-.194**	.392**	-.138**	.002	-.119**	.003	-.258**	-.115**	-.188**	-.014	-.179**	--							
13. Industry_Dum2	.42	.49	.008	-.110**	-.040	-.110**	-.060	-.112**	.108**	.036	.086*	-.011	.131**	-.526**	--						
14. Industry_Dum3	.03	.16	.242**	-.048	.168**	.044	.163**	.044	.035	.045	.039	.046	-.054	-.104**	-.142**	--					
15. Industry_Dum4	.24	.43	.137**	-.241**	.171**	.165**	.176**	.162**	.188**	.093*	.131**	.000	.068	-.345**	-.472**	-.093**	--				
16. Industry_Dum5	.03	.18	-.083*	.004	-.097**	-.111**	-.093*	-.098**	-.138**	-.076*	-.118**	-.024	-.053	-.116**	-.159**	-.031	-.104**	--			
17. Technological diversity	.37	.31	.001	-.171*	-.003	.014	-.012	.016	.086	.062	.041	-.047	-.038	-.059	-.046	-.075	.158**	-.052	--		
18. Learning speed	6.40	1.54	.024	.250**	.057	.137**	.063	.136**	-.063	-.028	-.031	-.028	-.159**	.352**	-.133**	-.059	-.253**	.063	-.100	--	
19. Network centrality	12.20	22.20	.444**	.051	.486**	.490**	.477**	.524**	.164**	.075*	.123**	-.040	.039	-.270**	-.048	-.069	.412**	-.087*	.199**	-.173**	--
20. Firm performance	.32	.83	-.071	.117**	-.009	.157**	.009	.142**	-.291**	-.131**	-.307**	-.026	-.099*	.362**	-.207**	-.060	-.149**	.069	.014	.263**	-.148**

[a] Unit: Thousand

[b] Unit: Million

* p<0.05, ** p<0.01

Table 2

Results of regression analyses (N=817)

Variables	Model 1		Model 2	
Control variables				
Firm size	–0.28**	(0.01)	–0.29**	(0.01)
Firm age	–0.13**	(0.01)	–0.12**	(0.01)
Annual sales	–1.04***	(0.01)	–1.05***	(0.01)
R&D expense	0.68***	(0.06)	0.69***	(0.06)
Annual sales $_{(t-1)}$	0.97***	(0.01)	0.97***	(0.01)
R&D expense $_{(t-1)}$	–0.13	(0.06)	–0.13	(0.01)
Return on assets $_{(t-1)}$	0.11	(0.01)	0.08	(0.01)
Return on equity $_{(t-1)}$	0.09*	(0.01)	0.09*	(0.01)
Return on investment $_{(t-1)}$	–0.45***	(0.01)	–0.42***	(0.01)
Joint venture	0.01	(0.10)	0.01	(0.10)
Network density	–0.01	(0.01)	–0.01	(0.01)
Industry	YES		YES	
Independent variables				
Technological diversity(TD)			0.34**	(0.15)
Technological diversity squared			–0.33**	(0.53)
Learning speed				
Network centrality				
Interactions				
Learning speed × TD				
Network centrality × TD				
Learning speed × TD squared				
Network centrality × TD squared				
R^2	0.32		0.33	
Adj. R^2	0.30		0.31	
Model *F*	21.91***		20.22***	
$\triangle R^2$			0.01	
$\triangle F$			4.89**	

Note: Numbers in parentheses are standard errors.

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

Table 3

Results of regression analyses (continued)

Variables	Model 3		Model 4	
Control variables				
Firm size	–0.28**	(0.01)	–0.28**	(0.01)
Firm age	–0.13***	(0.01)	–0.12**	(0.01)
Annual sales	–0.97***	(0.01)	–0.97***	(0.01)
R&D expense	0.66***	(0.06)	0.67***	(0.06)
Annual sales $_{(t-1)}$	0.91***	(0.01)	0.90***	(0.01)
R&D expense $_{(t-1)}$	–0.05	(0.06)	–0.05	(0.06)
Return on assets $_{(t-1)}$	0.09	(0.01)	0.08	(0.01)
Return on equity $_{(t-1)}$	0.09*	(0.01)	0.08*	(0.01)
Return on investment $_{(t-1)}$	–0.44***	(0.01)	–0.43***	(0.01)
Joint venture	0.01	(0.10)	0.01	(0.10)
Network density	0.01	(0.01)	0.01	(0.01)
Industry	YES		YES	
Independent variables				
Technological diversity(TD)	0.36***	(0.47)	1.04***	(1.15)
Technological diversity squared	–0.33**	(0.52)	–1.14***	(1.24)
Learning speed	0.11***	(0.02)	0.13***	(0.02)
Network centrality	–0.16***	(0.01)	–0.14***	(0.01)
Interactions				
Learning speed × TD			–0.59*	(0.18)
Network centrality × TD			–0.29*	(0.02)
Learning speed × TD squared			0.67**	(0.19)
Network centrality × TD squared			0.34*	(0.02)
R^2	0.35		0.37	
Adj. R^2	0.34		0.35	
Model F	20.38***		17.95***	
$\triangle R^2$	0.03		0.01	
$\triangle F$	15.00**		4.10	

Note: Numbers in parentheses are standard errors.

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