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Technological dissimilarity in R&D alliances: The moderating effects of exploratory strategy and knowledge stock

研發聯盟夥伴之技術差異性：探索策略與知識存量之調節效果

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Abstract: This study aims to examine how technological diversity between R&D partners affects firm performance. Drawing on the knowledge-based view, we posit that partner technological dissimilarity between R&D alliance partners has a curvilinear relationship with firm performance. Furthermore, two factors: a firm's exploration strategy and knowledge stock, are identified as moderating this relationship. We conducted analyses on 747 R&D alliances announced during the period of 2001–2014 in the U.S. biopharmaceutical industry. The results reveal an inverted-U shaped relationship between partner technological dissimilarity and firm performance, which is positively moderated by a firm's knowledge stock and exploration strategy. Possible explanations for our findings as well as their theoretical and practical implications are subsequently discussed herein.

Keywords: R&D alliance, technological dissimilarity, knowledge stock,

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exploration strategy.

摘要：本研究旨在於探索研發聯盟夥伴之間的技術差異性是否影響營運績效。根據知識基礎理論，本研究認為技術差異性對於聯盟參與公司的績效會產生曲線型的影響。除了探討技術差異性對參與公司績效的影響外，亦進一步分析參與公司的探索策略與知識存量之調節效果。依據 2001-2014 年間的 747 筆公司年樣本，本研究發現技術差異性與聯盟參與公司的績效之間呈現倒 U 型的關係，而探索策略與知識存量則會對此關係產生正向調節效果。針對本研究發現的解釋以及所衍生之理論與實務意涵，也於文中詳述。

關鍵詞：研發聯盟、技術差異性、知識存量、探索策略

1. Introduction

Although research and development (R&D) alliances have been widely used as a viable approach to accelerating innovation and reaping economic benefits, scholars have observed that such alliances do not always entail positive implications for firm performance. The mainstream research elucidates this observation by the rationale of the knowledge-based view (KBV) that heterogeneous knowledge resources among firms are the primary sources of value (Youndt *et al*., 2004). Accordingly, KBV theorists ascribe this view to the differences between the knowledge bases of allied firms (Sammarra & Biggiero, 2008). Such differences can not only be based on resource complementarity that facilitates novel innovation, but can also be due to technical complexity that engenders additional costs which erode profit margins (Cheng, 2017; Jiang *et al*., 2010).

Scholars generally use the terms “partner dissimilarity (similarity)” or “partner diversity” to connote the differences between alliance partners. Jiang *et al*. (2010) define alliance partner diversity as the level of variance between partners’ knowledge-based resources. In studying R&D alliances, scholars further focus on a technological aspect of partner diversity/dissimilarity, that is, partner technological dissimilarity (PTD). PTD refers to the heterogeneity between the technological knowledge bases of a focal firm and its alliance partners (Sampson, 2007). Recognizing the importance of PTD, previous literature has looked into the effect of partner diversity on firm outcomes. However, the empirical evidence about the role of PTD in explaining the variance in performance is inconsistent. The findings range from support for a linear relationship between PTD and firm performance to suggesting a curvilinear effect of PTD on performance (e.g., Sampson, 2007). Furthermore, the linear effect has been found positive (Colombo and Rabbiosi, 2014) or negative (Ahuja, 2000). Clearly, the debate on this issue remains inconclusive albeit recent research continues to support the positive aspect of partner technological similarity (e.g., Frankort, 2016).

Academics posit that the way variables were measured could have contributed to the mixed results in the extant literature (Baer and Oldham, 2006; Deng and Zhang, 2018). Therefore, we re-examine whether prior studies have effectively captured the economic value generated by R&D alliances. While most these studies measured outcomes in terms of innovations, innovation is not always beneficial for economic performance because, in practice, not all innovations are eventually converted into viable commercial products (Rosenbusch *et al*., 2011). The true economic value of R&D alliances may be overestimated if only innovations are assessed. Furthermore, Saxton (1997) emphasized that the influence of alliances on firm performance can result not only through innovations, but also via intangible assets. Mouri *et al*. (2012) called for studies to capture intangible assets for evaluating the performance effect of alliances. In this respect, a long-term financial performance measurement may be more accurate in determining how firms exploit and benefit from forming R&D alliances (Roberts and Dowling, 2002). Furthering the understanding of the relationship between PTD and financial performance is crucial because firms' competitiveness is eventually a function of whether they are able to transform acquired technological knowledge into saleable products (Frankort, 2016). Our research addresses this issue by examining the nature of the relationship between PTD and financial performance.

When investigating this focal relationship, scholars (Choi, 2020; Lee *et al*. 2015; Subramanian *et al*., 2018; Zhang al., 2019) have suggested that rigorous theorizing must consider contingent factors; owing to alliance partner dissimilarity, logically, not all firms benefit to the same extent (Oerlemans *et al*., 2013). Given that acquiring partners' technological knowledge entails a learning process, learning strategies occupy a prominent position. Learning strategies have been classified as exploration and exploitation strategies. Lechner *et al*. (2010) argue that an exploration strategy allows an organization to create more value from diverse knowledge compared to an exploitation strategy because an exploration strategy requires knowledge diversity to trigger novel solutions, whereas an exploitation strategy that focuses on limited learning appears to conflict with such diversity. Firms executing exploratory strategy are able to maximize the benefits of relevant knowledge from different technological fields (Yang *et al*., 2011). Collectively, it is plausible to extrapolate that exploration strategy positively moderates the performance effect of PTD.

Moreover, a social exchange perspective proposes another explanation for why some firms benefit more from technological dissimilarity in alliances than others do (Choi, 2020). Undoubtedly, interfirm learning determines whether firms can capitalize on PTD. According to the social exchange perspective, reciprocal knowledge exchange is a precondition for effective interpartner learning. A greater knowledge stock enables a firm to exert stronger bargaining power (Reitzig, 2003), thereby increasing the possibility of exchanging requisite knowledge with its partner. Additionally, a technologically strong firm is characterized by its substantial knowledge stock (Srivastava *et al*., 2015), which is conducive to the establishment of ability-based trust between partners. This type of trust has been substantiated to be the most potent force in facilitating interfirm learning (Muthusamy and White, 2005). Hence, it is imperative to clarify whether a firm's knowledge stock can alter its effect on firm performance.

The above discussion leads us to the following questions: What is the nature of the relationship between PTD and firm performance? Do exploratory strategy and knowledge stock moderate this relationship? In particular, we take the firm's perspective rather than the alliance perspective because not all alliances make a definite contribution to the allying firms. Overall, this study contributes novel insights that lead to a more complete understanding of why some firms benefit more from using R&D alliances than others do; furthermore, it also offers a solution to the challenge of managing technological diversity.

2. Theoretical background and hypotheses development

An R&D alliance is an innovation-driven, inter-firm collaboration initiated for specific problem solving or significant technological advances. There are several motivations for forming R&D alliances. Firms may decide to seek allies in order to spread the costs and risks of innovation, especially in industries characterized by increasing development investments, such as the aerospace, biopharmaceutical, and information technology industries (Caner and Tyler, 2015). Collaboration between buyers and suppliers of new products and technologies may aim at establishing technical standards and dominant designs (Liu, 2010; Sammarra and Biggiero, 2008). However, one of the most widely cited motivations for R&D alliances is the acquisition of knowledge and capabilities from partner firms (Mowery *et al*., 1996). This reason for engaging in R&D alliances has been justified by considering that firms are characterized by heterogeneous knowledge bases (Dosi *et al*., 2000). Therefore, the KBV offers an apposite theoretical angle to explicate collaborative learning activities that occur in R&D alliances.

The KBV initially focused on knowledge internal to the firm, but has subsequently been extended to firms needing to exchange complementary knowledge with each other (Caner and Tyler, 2015). The fundamental assumption of the KBV is that organizations are the repositories of different idiosyncratic knowledge, which explains the significant performance variance among firms (Grant, 2002). The KBV regards knowledge as an inimitable resource that is intimately related to a firm's core competence (Grant, 1996). Firms outperform market challengers because of their capability to organize a distinctive set of knowledge (Kogut and Zander, 1992). The most efficient and effective approach whereby a firm develops a unique knowledge portfolio is differential access to externally created knowledge (Lamont *et al*., 2019). Firms generally acquire requisite knowledge through joint ventures, mergers and acquisitions, alliances, and other inter-firm cooperation agreements. The alliances serve as platforms where firms can tap into complementary knowledge: market, industrial, and technical, that they currently lack (Luo and Deng, 2009; Zhang, 2016). Such knowledge, derived from alliances, is valuable because it provides firms with the opportunity to achieve synergistic performance. For instance, while developing new products, biopharmaceutical companies often do not house all the requisite technological knowledge internally and tend to engage in R&D alliances to access external knowledge (Caner and Tyler, 2015).

In particular, complementary knowledge, which connotes a low degree of redundancy between two firms' knowledge bases, is also referred to as knowledge dissimilarity (Fang, 2011). A strand of alliance research focuses on technological dissimilarity between alliance partners and its subsequent influence on firm performance. As discussed, however, there are positive and negative views of PTD. The positive view highlights the benefits; thus, technological dissimilarity is seen as providing an opportunity for integrating the knowledge of allying firms and utilizing potential complementarities and synergies (de Leeuw *et al*., 2014; Frankort, 2016). The negative view elucidates the disadvantages related to the risks and costs that accompany greater technological dissimilarity (Oerlemans *et al*., 2013). Although these studies have produced mixed findings, a widely accepted result is the curvilinear relation between PTD and performance (e.g., Lee *et al*, 2015; Sampson, 2007); this result is based on combining the positive and negative views of PTD. Notably, the performance considered herein is at the firm level. Sampson (2007) holds that alliances affect their members directly and indirectly so that knowledge derived from partners may benefit not only alliance projects, but also non-alliance projects; to capture both, it is prudent to examine performance at the firm level instead of at the alliance level. Given that we follow Sampson (2007) in exploring how a firm's performance varies with technological dissimilarity between the two alliance partners, the relation between them is assumed to be curvilinear.

Knowledge acquisition from alliance partners entails not only a knowledge management process, but also a social exchange process (Frankort, 2016; Muthusamy and White, 2005; Zhang, 2016). As discussed above, firms' learning strategies steer the manner by which their personnel manipulate and process newly external knowledge; meaningful knowledge exchanges between partners play a pivotal role in inter-partner learning. Accordingly, we extrapolate that the PTD-performance is contingent on exploration strategy and knowledge stock by synthesizing the KBV and the social exchange view. This will be elaborated in detail below.

2.1 Alliance technological dissimilarity

In the extant research, the positive relationship of PTD to firm performance has been explained by the KBV. This perspective asserts that technological dissimilarity enables firms to tap into distinct and non-redundant knowledge bases that complement their innovation efforts. Partners with dissimilar knowledge obviously have more to learn from each other than partners with similar knowledge (Frankort, 2016). Alliances characterized by large technological overlaps may experience reduced benefits from R&D collaborations. Wuyts and Dutta (2014) elaborated the benefits brought by PTD, namely the facilitation of new knowledge assimilation as well as the enhancement of the breadth of perspective and creative thinking. A dissimilar knowledge base can trigger the generation and recombination of knowledge (Ahuja, 2000), which leads to an expanded approach to problem-solving with novel or refined methods (Ahuja and Katila, 2001; Katila, 2002). For example, firms prefer developing new products with modular architectures. The novel recombination of knowledge elements can lead to innovative products by reconfiguring the modular structures (Subramanian *et al*., 2018). Indeed, technological dissimilarity provides new opportunities for solving existing and potential problems regarding technologies, products, and market competition (March, 1991). Accordingly, superior performance can be achieved by fusing the knowledge bases of partners and exploiting possible complementarities.

Although different knowledge elements resemble puzzle pieces that connect to each other to form a picture of competitive capability, a significant technological distance between partners hinders the integration and exchange of knowledge (de Leeuw *et al*., 2014). A significant technological distance leads to communication and coordination difficulties (Sakakibara, 1997), which substantially raise the costs of collaboration and monitoring (Combs and Ketchen, 1999). Indeed, Sampson (2007) ascribes the decline of firm performance to additional costs that accompany high levels of PTD. When allying with partners in disparate technological domains, firms need to invest more efforts and capabilities in transferring the external knowledge (Lamont *et al*. 2019). Specifically, assimilating technologically distant knowledge requires additional time to develop connections among knowledge elements, optimize knowledge combination and, in turn, derive a solution (Song *et al*., 2003). The time invested to process knowledge increases with the degree of its diversity. If firms cannot fully digest acquired knowledge in a given time period, they are likely to reach compromise solutions due to the time pressure, rather than optimal ones by constructively integrating diverse knowledge (Swink and Song, 2007). In this case, technologically distant knowledge cannot function effectively or ensure it is synergistic with current knowledge in aiming to create expected value. The costs associated with PTD would outweigh the benefits when coping with overly dissimilar knowledge, a process that is both laborious and time consuming.

At moderate levels of technological dissimilarity, firms maximize the benefits stemming from the dissimilarity of inflowing knowledge, and simultaneously handle the difficulties effectively via knowledge absorption. Existing empirical evidence lends support to the curvilinear argument, although in slightly different contexts. Sampson (2007) demonstrated that in R&D alliances, PTD was related to firm patenting in an inverted U-shaped manner. In the context of acquisitions, Ahuja and Katila (2001) reported that technological similarity between targets and acquirers bore a nonlinear relationship with acquirer patenting. Applied to the R&D alliance context, we thus posit the following hypothesis:

Hypothesis 1: There is an inverted U-shaped relationship between PTD and firm performance.

2.2 The contingent role of exploration strategy

March (1991) classified learning strategies as exploitation and exploration strategies. Exploitation strategy centers on refining and extending current knowledge bases. In contrast, exploration strategy refers to a conscious attempt to shift away from existing organizational routines, processes, and knowledge to cope with relevant problems (March, 1991). Learning strategies shape the manner in which individuals search for and utilize new knowledge, and affect the way in which organizational resources are allocated to these activities (Argote, 1999).

R&D alliances aim to translate technological diversity into valuable outcomes, which fundamentally depend on how proficiently partners deal with a great diversity of knowledge (Ardila *et al*., 2020). In this respect, firms must not only understand acquired knowledge, but also develop meaningful and innovative methods of coordinating and integrating external knowledge with internal capabilities (Sampson, 2007), involving a trial-and-error process that requires experimentation, risk-taking, and a continuous search for viable solutions. These procedures are shared by an exploratory learning strategy, which implies that high PTD is consistent with such learning. As argued by Lechner *et al*. (2010), exploratory initiatives profit more from increasing the diversity of knowledge than exploitive initiatives, although exploration learning has a relatively high risk of loss. Especially in non-routine tasks involving technological uncertainties, such as the technological development discussed herein, the benefits of exploratory learning can offset its potential risks (Edmondson and Nembhard, 2009). Researchers have observed that exploration strategy promotes the capability to flexibly reconfigure knowledge and cognitive skills (Sidhu *et al*., 2004; Tsai and Huang, 2008), in turn, enabling firms to extend their knowledge to unfamiliar domains and renew their existing knowledge base by fusing different knowledge elements (Kostopoulos and Bozionelos, 2011). Thus, firms are more likely to obtain new insights and promising ideas from knowledge fusion. Meanwhile, exploration strategy prompts people to engage in creative thinking and experiment with new solution alternatives, thereby fostering their potential to yield novel problem-solving solutions (Escribá-Carda *et al*., 2017). Such potential is conducive to generating optimal solutions that overcome bottlenecks in managing diverse knowledge bases. To summarize, firms are better able to transform PTD into concrete commercialized outcomes while implementing exploration strategy. Therefore, we expect the positive slope of the relationship between PTD and firm performance to be steeper for exploratory strategy and the negative slope to be flatter. We offer the following hypothesis:

Hypothesis 2: Exploration strategy positively moderates the relationship between PTD and firm performance. Specifically, the inverted U-shaped relationship between PTD and firm performance will shift upward when the level of exploration strategy is higher.

2.3 The contingent role of knowledge stock

Knowledge stock refers to the amount of knowledge elements that a firm has developed at a certain point in time (Dierickx and Cool, 1989). Although PTD offers some benefits, a firm can only realize concrete outcomes when inter-partner learning is effective. In R&D alliances, interpartner learning entails knowledge exchanges and combination. Social exchange theorists stress that knowledge exchange is a reciprocal behavior (Muthusamy and White, 2006), and that a partnership is built on mutually rewarding activities, namely, “mutual give and take” (Ring and Van de Ven, 1994). Generally, allying with a technologically dissimilar partner connotes a firm’s intention to develop new products in a new, unfamiliar domain (Lin, 2011). To generate desired products, the focal firm relies on the requisite knowledge of new products that its partner can supply (De Clercq and Dimov, 2008). A partner’s willingness to offer knowledge is determined by their expectation of receiving reciprocal value in resources (Liu, 2010). In this respect, the greater the amount of knowledge a firm possesses, the more likely it is that the firm will derive the requisite knowledge from its partners via the dyadic exchange of knowledge. For example, technological knowledge is typically in the form of patents, which are often used as “bargaining chips” for trading technologies or cross-licensing (Reitzig, 2003).

Furthermore, given that a firm’s knowledge stock reflects its technological capabilities (Srivastava *et al.*, 2015), a firm’s accumulated knowledge base increases the likelihood that it can offer that knowledge when its partner requests. If a firm can provide its partner with the specialized knowledge and capabilities essential to alliance outcomes, its partner will continue to be confident regarding the firm’s abilities (Hamel, 1991). When a firm can inspire its partner’s confidence with its expertise, the partner will hold the firm in high esteem (Lui and Ngo, 2004). This confidence is instrumental in the establishment of ability-based trust, which is rooted in the recognition that alliance partners possess valuable knowledge and capabilities (Muthusamy and White, 2005). Trust between partners facilitates the exchange and combination of resources (Tsai and Ghoshal, 1998). Scholars have confirmed that ability-based trust is more potent in enhancing interfirm learning in alliances compared to other types of trust, such as integrity-based and benevolence-based trust (Lui and Ngo, 2004; Muthusamy and White, 2005).

In summary, a vast amount of knowledge accumulated in firms promotes knowledge exchange between partners; this will serve as the basis for interfirm learning and the successful utilization of PTD. Consequently, the benefits of allying with technologically dissimilar partners are best achieved when the focal firm has a high level of knowledge stock. We thereby posit:

Hypothesis 3: Knowledge stock positively moderates the relationship between PTD and firm performance. Specifically, the inverted U-shaped relationship between PTD and firm performance will shift upward when firms have a higher level of knowledge stock.

3. Methods

3.1 Sample and data

Our purpose was to collect detailed information about the technological dissimilarity between alliance partners and the allying firms' financial outcomes, exploratory strategy, and knowledge stock. Hence, we chose announced R&D alliances in the biopharmaceutical industry as the empirical setting for the following reasons. First, this industry is the most R&D-intensive industry in the United States, with the highest alliance frequency among high-technology industries (Pereira *et al*., 2021). Second, characterized by frequent within- and cross-industry collaboration (Yang *et al*., 2015), the biopharmaceutical industry is an ideal research subject for observing the merits/demerits of PTD. Third, the observation of single industries might provide an inherent control of extraneous factors, such as environmental uncertainty, which would impact alliance formation patterns. In addition, patenting is crucial to the survival of biopharmaceutical firms (Kim and Valentine, 2021) because patents as innovation outcomes can directly enhance profits by forestalling competition. Patent data offer an opportunity to examine the innovative behavior of firms (Katila and Ahuja, 2002; Kehoe and Tzabbar, 2015). Therefore, it is reasonable to believe that the biopharmaceutical industry provides a proper context herein for scrutiny.

To collect the R&D alliance sample, we first obtained the initial sample from the Securities Data Company (SDC) database because the SDC alliance database is the most commonly used in alliance-related studies (Schilling, 2009). Some prior studies report possible errors in the SDC announcement date data (Oxley *et al*., 2009), but the announcement dates in our sample R&D alliances have been verified using US newspapers and wires from the LexisNexis database. The announcement date is defined as the date on which the company's initial announcement appeared and was published. Next, because most alliances are dyadic (Colpan and Hikino, 2018) and multilateral partnerships are complex in nature (Li *et al*., 2012), the non-dyadic sample was removed to generate results that can be applied directly to most practical situations. The observations were then included only if the financial data information was available in COMPUSTAT, and the patent data were available from the United States Patent and Trademark Office (USPTO). Owing to the availability of the database of the researchers' institutions, we could obtain the alliance data only before 2014. However, the data for the period of 2001 to 2014 can produce more valid and generalizable estimates because they capture a broad sense of business cycles and economic conditions (Baecke and Bocca, 2017; Lin and Chang, 2015). Finally, after excluding the R&D alliance participants with missing data, the final sample consisted of 747 observations.

3.2 Variables

Firm performance: Several objective financial indicators are used for analyzing the financial benefits of allying, such as ROA, ROI, Tobin's Q, and other performance measures. However, there is no consistent way to measure the performance effect of forming an R&D alliance. Among other accounting-based measures of performance, ROA is the most ubiquitous measure of firm performance for strategy studies (Bergh and Gibbons, 2011; Karniouchina *et al.*, 2013) and the most commonly used measure in the literature on inter-firm relationships (Cho and Arthurs, 2018; Papadakis and Thanos, 2010). Therefore, following prior alliance studies (e.g., Caner and Tyler, 2015; Lin and Wu, 2010; Yamakawa *et al.*, 2011), this study uses ROA to proxy for firm performance. In addition to the ROA, Tobin's Q is often used to proxy for firm performance in the biopharmaceutical industry-related studies (e.g., Chen and Shih, 2011; Darroch and Miles, 2011); thus, it will be used to check the robustness of this study. Considering that the benefits or costs of joining R&D alliances may lag by a few years, the average of a firm's ROA in three succeeding years (i.e., *t*, *t+1*, and *t+2*) is used to approximate firm performance.

PTD: As mentioned above, patenting is crucial to the success and survival of biopharmaceutical firms (Kim and Valentine, 2021) because patents can directly enhance profits by forestalling competition. As innovation outcomes, patents provide descriptions of technical problems and their solutions (Funk and Owen-Smith, 2017). As many studies suggest, patent data offer an opportunity to examine the innovative behavior of firms (Katila and Ahuja, 2002; Kay *et al*., 2014; Kelly and Kim, 2018). Therefore, patent data enable us to observe a biopharmaceutical firm's technological and knowledge processing capabilities.

This study measured PTD at the dyadic level by examining the extent to which partner firms' patents are in the same technological classes (Jaffe, 1986). Specifically, the underlying knowledge or technology of a patent is classified based on the USPTO patent classification system, that is, the US Patent Classification (USPC). According to most patent-based studies (e.g., Kaplan and Vakili, 2015; Phelps, 2010), the primary three-digit patent class is commonly used because the USPTO provides a formal definition of each three-digit patent class. Following Sampson (2007), this study generated each firm's knowledge portfolio by measuring the distribution of its patents across patent classifications. However, considering the sharp depreciation of knowledge capital within five years (Ahuja and Katila, 2001), we adopted a five-year (t-5~t-1) window for the technological portfolio. This distribution is captured by a multidimensional vector: $F_i = [F_i^1 \ldots\ldots F_i^s]$, where F_i^s represents the number of patents assigned to partner firm i in patent class s. The technological dissimilarity of partner firms is ($1 - F_iF_j' / \sqrt{(F_iF_i')(F_jF_j')}$), where $i \neq j$. The range of the PTD is from 0 to 1; a value of 1 indicates that the focal firm has the greatest possible PTD to its alliance partners. In Table 1, we use one of our samples, the R&D alliance formed by King Pharmaceuticals and Palatin Technologies in 2004, to demonstrate how to calculate PTD. King Pharmaceuticals and Palatin Technologies respectively had five and two granted patents distributed among three fields in 1999-2003.

Knowledge stock: We measured a firm's knowledge stock by using current technology indicators. By referring to relevant studies, in a patent-intensive industry, a firm's patent counts can be a good proxy for its knowledge accumulation (e.g., Lin *et al*., 2006; Ma and Takeuchi, 2017; Roper and Hewitt-Dundas, 2015). Argote (1999) suggests that current information about the

Table 1
Calculating partner technological dissimilarity (PTD) using a sample

Step 1. Construct a table showing the technological distribution of both King Pharmaceuticals and Palatin Technologies.

Primary three-digit US Patent Classification	King Pharmaceuticals	Palatin Technologies
424	1	1
514	4	0
530	0	1

Step 2. Calculate the numerator and denominator of the PTD.

Numerator for technological dissimilarity

$$(1 \quad 4 \quad 0)\begin{pmatrix}1\\0\\1\end{pmatrix}=1$$

Denominator for technological dissimilarity

$$\sqrt{(1 \quad 4 \quad 0)\begin{pmatrix}1\\4\\0\end{pmatrix}\times(1 \quad 0 \quad 1)\begin{pmatrix}1\\0\\1\end{pmatrix}} = 5.83095$$

Step 3. Obtain the value of PTD between King Pharmaceuticals and Palatin Technologies.

The PTD between "King Pharmaceuticals" and "Palatin Technologies" is 1-(1/5.83095) =0.82850.

contents of a firm's learning and innovation are contained solely in recent patents. Thus, knowledge stock was gauged by the number of patents granted during the latest five years. To account for skewness in the data, *ln* (patent count) was used to measure a firm's knowledge stock.

Control variables: We first considered five firm-level controls: *firm age*, *firm size*, *R&D intensity*, *prior performance,* and *debt ratio. Firm age* refers to the number of years that have elapsed since the date of founding. *Firm size* was measured as the natural logarithm of the total number of full-time employees. *R&D intensity* has been identified as an antecedent of firm performance and was measured by a natural logarithm of R&D spending per employee. *Prior performance* was measured as ROA_{t-1} to control for its potential effect on firm activities; this is based on the arguments on firm capital structure (Chang *et al*., 2008). The effect of capital structure can be assessed by debt ratio, which is the proportion of the debt to total assets. These data were obtained from COMPUSTAT.

Furthermore, four alliance-level variables were considered: *alliance scope*, *alliance governance structure*, *geographic distance,* and *institutional proximity*. *Alliance scope* was coded as a dummy variable (1 = multiple purposes, 0 = a pure R&D alliance). R&D alliances with multiple purposes may have different impacts (Christ and Nicolaou, 2016). *Alliance governance structure* was coded as 1 if the R&D alliance was an equity joint venture, or 0 otherwise. Compared with other alliance types, equity joint ventures led to better interaction and knowledge transfer between alliance partners (Sampson, 2007); that is, performance is better achieved when R&D alliances are structured as equity joint ventures. *Geographic distance* is operationalized as the geographic proximity between R&D partners (Campbell *et al*., 2009). Based on the driving distance between the two firms' corporate headquarters, it was measured by *ln*(miles). Greater geographic distance between partners may lower the levels of effective governance and trust (Campbell *et al*., 2009). *Institutional proximity* was set to 1 if the firm's partner belonged to the biopharmaceutical industry, or 0 otherwise, because firms belonging to the same sector share norms that can affect their cooperation (Gutiérrez *et al*., 2016).

4. Methodology

Table 2 presents the descriptive statistics and correlation matrix for all variables used herein. Basically, except for the correlation coefficients of "knowledge stock-firm age," "knowledge stock-firm size" and "knowledge stock-exploration strategy," other correlation coefficients between variables are considered to be modest. The positive correlation between knowledge stock and firm age/size should be reasonable. Older and larger firms often command more resources and have higher managerial experience to enrich their knowledge pool (Kotha *et al*., 2011). The high correlation between knowledge stock and firm age/size also can found in extant studies (e.g., Ramachandran *et al*., 2019). Regarding the negative relationship between knowledge stock and exploration strategy, it has also been found in previous studies, such as Gao *et al*. (2018). The plausible reason to explain this relationship is that firms with large knowledge

Table 2
Descriptive statistics and correlations matrix

	Mean	S.D.	Min.	Max.	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1 Firm age	35.24	43.73	2.00	172.00	1.00													
2 Firm size	5.67	3.17	0.68	9.56	0.60**	1.00												
3 R&D intensity	5.47	29.87	0.00	408.07	-0.08	-0.11*	1.00											
4 Debt ratio	0.35	2.02	0.00	42.86	-0.03	-0.16**	0.06	1.00										
5 Prior performance	-0.30	0.66	-9.41	1.11	0.25**	0.52**	-0.05	-0.18**	1.00									
6 Multi purposes	0.63	0.48	0.00	1.00	0.09	0.01	0.06	-0.05	-0.06	1.00								
7 Joint venture	0.04	0.19	0.00	1.00	0.05	-0.03	-0.01	-0.02	0.09	0.03	1.00							
8 Geographic distance	6.40	1.86	0.00	11.79	-0.09	-0.06	0.03	-0.00	-0.07	0.00	-0.08*	1.00						
9 Institutional proximity	0.61	0.49	0.00	1.00	-0.07	0.02	0.00	-0.06	0.11*	-0.02	0.04	0.01	1.00					
10 PTD	0.25	0.34	0.00	1.00	0.13*	0.29**	-0.02	0.02	0.25**	0.05	0.03	-0.04	-0.01	1.00				
11 Exploratory strategy	0.31	0.18	0.00	1.00	-0.18**	-0.17**	0.03	0.05	-0.19**	-0.08	-0.01	0.13*	0.05	-0.12*	1.00			
12 Knowledge stock	3.20	2.13	0.69	8.00	0.66**	0.72**	-0.12*	-0.05	0.53**	0.04	0.09*	-0.08	-0.03	0.25**	-0.42**	1.00		
13 Firm performance (ROA)	-0.37	0.94	-10.35	3.45	0.20**	0.42**	-0.11*	-0.33**	0.53**	0.04	0.08	-0.05	0.07	0.17**	-0.02	0.36**	1.00	
14 Firm performance (Tobin's Q)	2.06	0.84	0.20	3.93	0.38**	0.50**	-0.04	-0.10*	0.27**	0.00	-0.00	0.01	0.02	0.21**	-0.07	0.38**	0.33**	1.00

Sample size: 747 firm-year observations
*p<0.05, **p<0.01
Year dummies are not shown for space reasons.

stock may become more inward-looking (Cohen and Levinthal, 1990). Still, such a relationship should not be constant because some studies have a contrary finding (e.g., Muratova *et al*., 2019). To assess for the presence of multicollinearity, we performed the variance inflation factor (VIF) test and found the average VIF to be within tolerable range (less than 3), suggesting that the multicollinearity problem is not a concern (Hair *et al*., 1998).

Before performing the data analysis, the skewness and kurtosis of all the variables were assessed to verify the normal distribution. According to Kline's (2011) criteria, a variable can be assumed to be normally distributed when skewness is less than 3 and kurtosis is less than 10. The results show that some variables are not normally distributed, such as R&D intensity, debt ratio, and prior performance. Subsequently, we used the data transformation method proposed by Blom (1958) to convert the data. Hierarchical moderated regression analysis followed to test the proposed hypotheses. By comparing the results derived from the non-transformed and transformed data, the directions and significance of the main exploratory variables are similar. The results presented are thus based on the non-transformed data. Table 3 presents the results of the regression analyses.

In Model 1, control variables were added as a baseline model. To test Hypothesis 1, PTD was firstly entered in Model 2. The result shows that the coefficient of PTD was positive but not significant. In Model 3, the squared term of PTD was entered to test the inverted-U effect. Both the linear (*coef.=0.471, $p<0.01$*) and squared (*coef.=-0.410, $p<0.01$*) terms were statistically significant, indicating that an inverted-U PTD-firm performance relationship was supported. Hypothesis 1 was thus substantiated. Hypothesis 2 proposed that the focal firm's exploration strategy would positively moderate the PTD-firm performance relationship. Model 4 reveals that the interaction between PTD and exploration strategy was positively significant (*coef.=1.548, $p<0.01$*), and the interaction between the squared PTD and exploration strategy was negatively significant (*coef.=-1.438, $p<0.05$*). Thus, Hypothesis 2 was supported. Hypothesis 3

Table 3
Regression results

	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Constant	-0.941***	(0.146)	-0.964***	(0.147)	-0.944***	(0.146)	-1.060***	(0.161)	-1.107***	(0.152)	-1.262***	(0.169)
Firm age	0.000	(0.001)	0.000	(0.001)	0.000	(0.001)	0.000	(0.001)	-0.001	(0.001)	-0.001	(0.001)
Firm size	0.087***	(0.013)	0.083***	(0.013)	0.081***	(0.013)	0.085***	(0.013)	0.075***	(0.014)	0.075***	(0.014)
R&D intensity	-0.001	(0.001)	-0.001	(0.001)	-0.001	(0.001)	-0.001	(0.001)	-0.001	(0.001)	-0.001	(0.001)
Debt ratio	-0.013	(0.016)	-0.014	(0.016)	-0.014	(0.016)	-0.012	(0.016)	-0.016	(0.016)	-0.015	(0.016)
Prior performance	0.354***	(0.056)	0.351***	(0.056)	0.336***	(0.056)	0.311***	(0.056)	0.305***	(0.056)	0.300***	(0.056)
Multi purposes	0.067	(0.052)	0.064	(0.052)	0.072	(0.052)	0.066	(0.052)	0.062	(0.052)	0.064	(0.052)
Joint venture	0.240*	(0.134)	0.237†	(0.134)	0.286*	(0.135)	0.194	(0.137)	0.178	(0.136)	0.144	(0.137)
Institutional proximity	-0.005	(0.014)	-0.005	(0.014)	-0.008	(0.014)	-0.004	(0.014)	0.001	(0.014)	0.000	(0.014)
Geographic distance	0.041	(0.052)	0.042	(0.052)	0.031	(0.052)	0.025	(0.052)	0.031	(0.052)	0.027	(0.052)
Year dummies	Included		Included		Included		Included		Included		Included	
PTD			0.134	(0.087)	0.471**	(0.156)	0.391*	(0.165)	0.575**	(0.182)	0.529**	(0.186)
PTD^2					-0.410**	(0.158)	-0.415**	(0.159)	-0.345*	(0.160)	-0.353*	(0.161)
Exploratory strategy (ES)							0.100	(0.219)			0.320	(0.231)
Knowledge stock (KS)									0.051*	(0.021)	0.063**	(0.021)
PTD × ES							1.548**	(0.468)			0.943†	(0.568)
PTD^2 × ES							-1.483*	(0.643)			-0.709	(0.751)
PTD × KS									0.079†	(0.047)	0.037	(0.056)
PTD^2 × KS									-0.168**	(0.052)	-0.125*	(0.063)
F	10.717***		10.374***		10.300***		9.702***		10.025***		9.310***	
adj R^2	0.223		0.224		0.230		0.240		0.246		0.250	

Sample size: 747 firm-year observations

†p<0.1, *p<0.05, **p<0.01, ***p<0.001

The regression coefficients shown were standardized.

postulates the moderating effect of knowledge stock. As shown in Model 5, the interaction between knowledge stock and PTD was significantly positive (*coef.=0.079,* $p<0.1$), whereas the interaction between knowledge stock and the squared PTD is negative and significant (*coef.=-0.168,* $p<0.01$). Hence, Hypothesis 3 was supported. In Model 6, all the explanatory variables were considered; the directions of variables and interaction terms remain consistent, suggesting that the stability of the results reported above is acceptable.

To clarify the moderating effect of exploration strategy, Figure 1 depicts the predicted values of Model 4, calculated at the sample mean (average values for control variables), for varying values of PTD and exploration strategy. PTD varies between "Low PTD (the lowest value: 0)" and "High PTD (the highest value: 1)" for two different values of exploration strategy: Low ES (average exploration strategy minus one standard deviation) and High ES (average exploration strategy plus one standard deviation). As observed from Figure 1, those firms that have pursued high exploration strategy positively intensified the relationship between PTD and firm performance compared to those with low exploration strategy; namely, the PTD-firm performance relationship is elevated when firms adopt exploration strategy. Figure 2 illustrates the moderating effect of knowledge stock by using the same plotting technique. The inverted U-shaped PTD-firm performance relationship is also raised when firms have a higher knowledge stock. Both Hypotheses 2 and 3 were further bolstered.

In addition to the above results, we conducted two robustness tests to confirm our findings. First, to reduce the possible influence of multicollinearity on model stability, we removed firm age and size from the regression models. As shown in Table 4, we found that the relationships of interest remain significant in the expected direction. Furthermore, some literature suggests that Tobin's Q could be used to evaluate the performance effect of participating alliances in the biopharmaceutical sector (e.g., Lee *et al*., 2015; Sivakumar *et al*., 2011). Since Tobin's Q can reflect both short- and long-term performance (Uotila *et al*., 2009), we follow the practice used by Lee *et al*. (2015) and Sivakumar *et al*. (2011) to use *ln*(Tobin's Q) at year *t* as the alternative indicator of firm performance. As

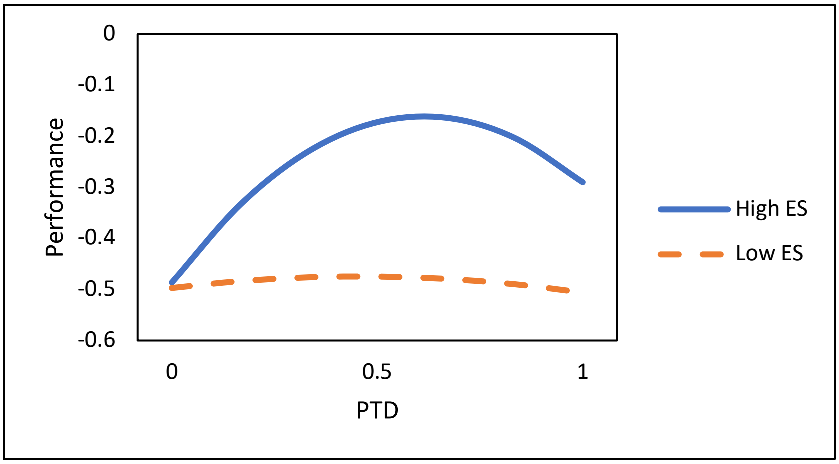

Figure 1

The moderating effect of ES on PTD-firm performance relationship

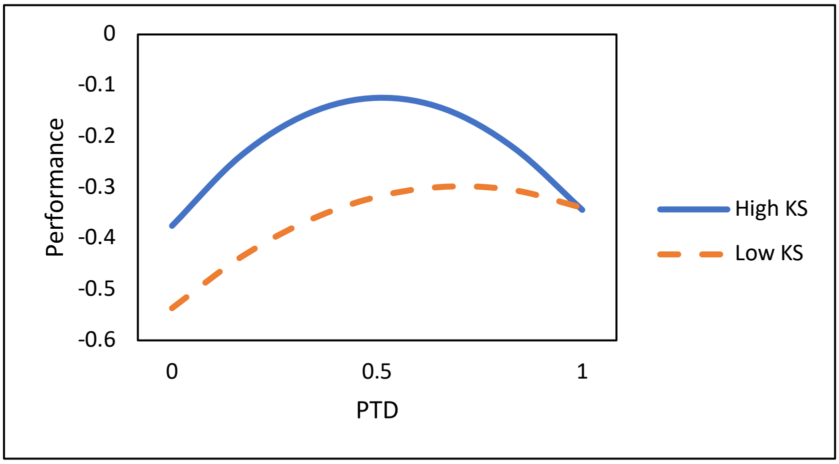

Figure 2

The moderating effect of KS on PTD-firm performance relationship

reported in Table 5, the results show that the directions of the main effects remain the same, although some significant levels have declined slightly. These additional tests confirm that the robustness of our findings.

Table 4
Robustness check (removing control variables that may cause multicollinearity concern)

	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Constant	-0.353**	(0.127)	-0.433***	(0.129)	-0.429**	(0.129)	-0.493**	(0.144)	-0.759***	(0.141)	-0.948***	(0.162)
R&D intensity	-0.002	(0.001)	-0.002	(0.001)	-0.001	(0.001)	-0.001	(0.001)	-0.001	(0.001)	-0.001	(0.001)
Debt ratio	-0.032*	(0.016)	-0.033*	(0.016)	-0.033*	(0.016)	-0.031*	(0.016)	-0.033*	(0.016)	-0.032*	(0.016)
Prior performance	0.561***	(0.050)	0.541***	(0.051)	0.517***	(0.051)	0.503***	(0.051)	0.440***	(0.052)	0.433***	(0.052)
Multi purposes	0.080	(0.054)	0.073	(0.054)	0.082	(0.054)	0.077	(0.054)	0.065	(0.053)	0.068	(0.053)
Joint venture	0.162	(0.138)	0.162	(0.137)	0.224	(0.138)	0.144	(0.141)	0.131	(0.139)	0.093	(0.014)
Institutional proximity	0.028	(0.054)	0.031	(0.054)	0.018	(0.053)	0.016	(0.054)	0.031	(0.053)	0.030	(0.186)
Geographic distance	-0.008	(0.014)	-0.007	(0.014)	-0.010	(0.014)	-0.007	(0.014)	-0.002	(0.014)	-0.003	(0.164)
Year dummies	Included		Included		Included		Included		Included		Included	
PTD			0.241**	(0.088)	0.643***	(0.159)	0.617***	(0.167)	0.708***	(0.183)	0.690***	(0.186)
PTD^2					-0.493**	(0.162)	-0.486**	(0.164)	-0.416*	(0.163)	-0.407*	(0.164)
Exploratory strategy (ES)							0.069	(0.225)			0.449†	(0.234)
Knowledge stock (KS)									0.092***	(0.019)	0.104***	(0.019)
PTD × ES							1.235*	(0.481)			0.872	(0.579)
PTD^2 × ES							-1.488*	(0.662)			-1.009	(0.763)
PTD × KS									0.038	(0.047)	0.000	(0.056)
PTD^2 × KS									-0.125*	(0.052)	-0.080	(0.063)
F		8.487***		8.509***		8.634***		7.930***		9.209***		8.542***
adj R^2		0.167		0.174		0.184		0.188		0.216		0.221

Sample size: 747 firm-year observations

$^{\dagger}p<0.1$, $*p<0.05$, $**p<0.01$, $***p<0.001$

The regression coefficients shown were standardized.

Table 5
Robustness check (using Tobin's Q as the alternative performance indicator)

	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Constant	1.176***	(0.141)	1.191***	(0.136)	1.203***	(0.136)	1.153***	(0.149)	1.176***	(0.141)	1.129	(0.158)
Firm age	0.002*	(0.001)	0.002**	(0.001)	0.002**	(0.001)	0.002**	(0.001)	0.002*	(0.001)	0.002	(0.001)
Firm size	0.109***	(0.013)	0.109***	(0.012)	0.108***	(0.012)	0.107***	(0.012)	0.109***	(0.013)	0.105	(0.013)
R&D intensity	0.000	(0.001)	0.000	(0.001)	0.000	(0.001)	0.000	(0.001)	0.000	(0.001)	0.000	(0.001)
Debt ratio	0.017	(0.015)	0.016	(0.015)	0.016	(0.015)	0.017	(0.015)	0.015	(0.015)	0.015	(0.015)
Prior performance	0.039	(0.052)	0.034	(0.052)	0.024	(0.052)	0.009	(0.052)	-0.001	(0.053)	-0.001	(0.053)
Multi purposes	-0.011	(0.049)	-0.017	(0.048)	-0.012	(0.048)	-0.018	(0.048)	-0.017	(0.048)	-0.017	(0.048)
Joint venture	0.048	(0.124)	0.044	(0.124)	0.074	(0.125)	0.004	(0.127)	-0.002	(0.127)	-0.023	(0.128)
Institutional proximity	0.007	(0.048)	0.009	(0.048)	0.002	(0.048)	0.006	(0.048)	-0.005	(0.048)	0.001	(0.048)
Geographic distance	0.015	(0.013)	0.016	(0.013)	0.014	(0.013)	0.018	(0.013)	0.020	(0.013)	0.019	(0.013)
Year dummies	Included		Included		Included		Included		Included		Included	
PTD			0.202*	(0.080)	0.411**	(0.145)	0.453**	(0.153)	0.280†	(0.169)	0.335*	(0.173)
PTD^2					-0.255†	(0.146)	-0.220	(0.147)	-0.278†	(0.149)	-0.250†	(0.150)
Exploratory strategy (ES)							0.070	(0.203)			0.207	(0.215)
Knowledge stock (KS)									0.001	(0.019)	0.004	(0.020)
PTD × ES							0.913*	(0.434)			0.339	(0.530)
PTD^2 × ES							-1.699**	(0.005)			-1.130	(0.701)
PTD × KS									0.125**	(0.044)	0.104*	(0.052)
PTD^2 × KS									-0.107*	(0.048)	-0.072	(0.058)
F	10.449***		10.341***		10.065***		9.312***		9.401***		8.601***	
adj R^2	0.218		0.224		0.226		0.231		0.233		0.234	

Sample size: 747 firm-year observations

$^{\dagger}p<0.1$, $^{*}p<0.05$, $^{**}p<0.01$, $^{***}p<0.001$

The regression coefficients shown were standardized.

5. Discussion

5.1 Theoretical implications

The mainstream literature on alliances has reached a consensus that PTD exerts a curvilinear influence on its consequences. For example, Choi (2020), Sampson (2007), Subramanian *et al*. (2018), and Zhang *et al*. (2019) suggest a curvilinear effect of partner technological distance/diversity on interfirm learning and innovation; unlike earlier studies that were biased toward either advantages or disadvantages of PTD, their arguments consolidate the two opposite views of PTD for allied firms. Nevertheless, the above findings may not be directly applied to firm performance because interfirm learning and innovation precede actual performance. This research complements recent empirical work on PTD by further theorizing that PTD retains a curvilinear influence on firm performance. As expected, our evidence reveals an inverted U-shaped relationship between PTD and firm performance. Furthermore, the curvilinear effect of PTD on interfirm learning or innovation can be extended to overall firm performance. In other words, the effect of PTD is much more profound than previously thought because PTD can directly, rather than indirectly, impact firm performance. The evidence reported here not only resonates with the KBV that heterogeneous knowledge bases among firms are the determinants of performance differences, but also bolsters the notion that the technology diversity in alliances is not always a panacea for alliance outcomes (Choi, 2020). Clearly, a moderate level of PTD is desirable to optimize inter-organizational learning. When PTD moves beyond the optimal point, costs resulting from the increased levels of complexity are likely to outweigh the overall benefits of the alliance.

Moreover, scholars have stressed that the optimal level of PTD and the strength of the effects of PTD are not fixed, but rather are conditioned on specific factors. Responding to repeated calls for research to identify the moderators (Gilsing *et al*., 2008; Lai and Weng, 2013; Subramanian *et al*., 2018;

Zhang al., 2019), we identified and validated knowledge stock and exploration strategy as moderating factors. We found a positive moderating effect of knowledge stock. This finding lends empirical support to Chung *et al.*'s (2019) speculation that, in alliances, increasing knowledge diversity is more likely to provide a positive synergy for firms with abundant technological knowledge. However, firms with superior technological capabilities aggressively deplete resources to develop novel knowledge (Wales *et al.*, 2013). In this case, Chung *et al.* (2019) caution that, when the diversity reaches extremely high levels, resources required for leveraging the diverse knowledge would be overcharged. Indeed, our result, as shown in Figure 2, confirms this rationale. Meanwhile, the finding also echoes the social exchange view that capable firms can render their partner confident regarding their abilities (ability-based trust), which fosters interfirm learning. Furthermore, in this perspective, firms with a richer knowledge stock will be considered by their partners as better able to reciprocate benefits; these firms can therefore foster a meaningful and continuous exchange of knowledge with their alliance partners. When biopharmaceutical firms adopt an exploration strategy, the effect that PTD exerts on firm performance becomes more curved. This finding supports the view of Wu and Shanley (2009) that an exploratory orientation enables firms to maximize the utilization of distant knowledge. This is also consistent with Yang *et al.* (2011), who suggest that firms adopting exploratory learning strategies in alliances are more likely to benefit from less connected partners. In brief, our study complements existing alliance research by highlighting the pivotal role of a firm's aggressive learning posture in managing externally unfamiliar knowledge (Lavie and Rosenkopf, 2006).

5.2 Managerial implications

Our findings provide practical implications. First, allying with R&D partners with low overlapping technological knowledge cannot guarantee future profitability. Decision-makers must recognize the detrimental potential of technological distance, which makes inter-firm learning costly. Instead of deciding on partnership solely based on structural configuration of alliances, managers must pay equal attention to partners' knowledge bases. To assess the level of technological distance, firms can inspect the citation patterns in the patent portfolios of potential alliance partners. By conducting a more comprehensive evaluation of the knowledge bases of potential partners, firms can make better decisions and achieve more effective learning through alliances. Second, firms should sense that the performance effect of PTD can be intensified in specific contexts. Our findings suggest that extracting value from PTD necessitates absorptive capacity underpinned by substantial knowledge stock and exploratory orientation. In other words, biopharmaceutical firms cannot completely capitalize on PTD unless they emphasize exploratory orientation and build a rich knowledge stock to avail against dissimilarity downsides. Exploratory orientation guides the right ways in which firms identify, probe, and embed new technological competences. However, most firms are inclined to behave in exploitative ways (Lee *et al*., 2014). Therefore, they should set specific guidelines and provisional benchmarks, and realign their organizational culture, to become well-equipped for exploratory learning. Furthermore, before allying with dissimilar partners, biopharmaceutical firms must deliberate thoroughly whether they have constructed abundant knowledge bases. They should endeavor to enhance their bargaining power by expanding and upgrading their knowledge bases. With powerful bargaining chips, firms are better positioned to negotiate with their partners and persuade them to transfer proprietary know-how and technologies. However, internal R&D investments that catalyze knowledge creation cannot be disputed (Berchicci, 2013). Operating in a dynamic environment characterized by constant change and time pressure, biopharmaceutical firms are compelled to innovate rapidly (Caner and Tyler, 2015). They must generate a virtuous circle of knowledge accumulation by effectively allocating limited resources to their development of knowledge through internal R&D activities and acquiring knowledge from R&D alliances. In particular, alliance managers will need to carefully coordinate their activities with the internal R&D department responsible for integrating internal technical knowledge with external knowledge to create new combinations of knowledge stock. Collectively, it is imperative for biopharmaceutical firms to proactively develop a sound knowledge stock and exploratory orientation, whereby they profit most from PTD.

In addition to the aforementioned theoretical implications, our findings can be applied to other relevant fields such as mergers and acquisitions (M&A) and joint ventures (JV). Similar to R&D alliances, numerous M&As and JVs aim to effectively coordinate technological knowledge-based resources to improve their performance (Anand *et al*., 2010). The lessons gained from the knowledge integration process in R&D alliances can serve as a guideline for firms engaging in M&As and JVs to manage PTD. The findings on the moderating effects may help executives decide on strategic alternatives before entering an M&A or JV. Meanwhile, our findings may provide a new direction for researchers to consider learning strategies and knowledge-based capabilities as situational factors when examining the issue of technological dissimilarity in M&As and JVs.

5.3 Limitations

This study is subject to several limitations. First, firms' knowledge stock and exploration strategy are patent-based measures that are objective and widely adopted. However, using patent data alone may not accurately assess the degree of these two variables. Some industries are not patent-intensive and patenting becomes a strategic choice. To reduce the risk of technology diffusion, firms may strategically choose not to patent all of their technological innovations. In practice, firms often intentionally replace patenting with trade secrets to protect their innovation outcomes. Future research could validate and extend our findings in other industries by adopting other measurement instruments. Second, as R&D alliances are dyadic, this study focused on this form of partnership to meet the expectations of most real situations, suggesting that the implications generalized by this study might not be sufficiently applied to multi-partner alliances. However, multi-partner R&D cooperation is still an important cross-company strategy (Mishra *et al*., 2015). Researchers could explore the effects of technological diversity among multi-R&D partners on firm performance in the future. Third, the related research on the impact of R&D alliance has not achieved the same results when using different performance indicators, which suggests that no comprehensive indicator can be used to measure the performance effect of allying. Future research could develop a comprehensive indicator to capture the performance effect of an R&D alliance. Finally, because not all alliance participants are listed publicly, some information could not be controlled herein. The findings obtained using publicly listed firms cannot be fully utilized by small companies because small companies' reasons for participating in the R&D alliance may differ from those of publicly listed firms. This imperfection may be remedied by adopting a questionnaire survey or a case study. Despite these limitations, it is hoped that this study will open avenues for further research.

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