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The role of knowledge base homogeneity in learning from strategic alliances

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ABSTRACT

Strategic alliances are important channels for interfirm learning, especially for small firms that are resource constrained. Of the several alliance attributes, technological distance between partners (measured as the distance between partners' innovative outcomes) is shown to have a significant influence on the learning benefits from strategic alliances. Drawing upon the theory of recombination, our study argues that the influence of technological distance on learning is best understood by not only measuring the distance between innovative outcomes, but by also taking into consideration the knowledge elements underlying the innovative outcomes. We develop a concept of knowledge base homogeneity that captures the extent to which the innovative outcomes of partnering firms draw upon similar sets of knowledge elements. Using patent and alliance data from 201 small biotechnology firms during the period 1996–2010, we confirm that the technological distance has an inverted u-shaped relationship on interfirm learning. We further demonstrate that this u-shaped relationship is moderated by the knowledge base homogeneity between partners, such that benefits of technological distance are enhanced and the costs of technological distance are mitigated when the knowledge base homogeneity between alliance partners is high. The results have important implications for interfirm learning, especially in the context of small firms that are limited in their knowledge stocks.

1. Introduction

In a highly dynamic technological environment, few firms possess all the internal capabilities required for successful and continuous innovation (Powell et al., 1996). As a result, firms frequently turn to external sources to fulfill their knowledge requirements (Rosenkopf and Nerkar, 2001). While prior research has demonstrated the importance of strategic alliances as a mechanism for learning and accessing external knowledge, empirical evidence suggests that actual learning varies across different alliances (Hamel, 1991; Hagedoorn, 1993; Inkpen and Dinur, 1998; Inkpen, 2000; Yang et al., 2015). Several factors have been shown to affect inter-organizational learning in strategic alliances, including number of partners (Ahuja, 2000), alliance structure (Dyner et al., 2008; Koka and Prescott, 2008; Owen-Smith and Powell, 2004; Phelps, 2010), relational attributes (Kale et al., 2000; Rowley et al., 2000), alliance capability (Heimeriks and Duysters, 2007), and alliance management (Davis and Eisenhardt, 2011; Gulati, 1995a,b; Kale et al., 2002; Parise and Casher, 2003). Among these factors, the technological distance between alliance partners has received the most attention from scholars as it directly affects the interfirm learning process (Mowery et al., 1996; Lane and Lubatkin, 1998; Sampson, 2007; Phelps, 2010).

The measure of technological distance was pioneered by Jaffe, who proposed that firms can be located at different positions in a multidimensional space based on their technological capabilities (Jaffe, 1986; Jaffe, 1989). The technological space is constructed such that firms with similar technological portfolios are placed closer to each other (Stuart and Podolny, 1996). Thus, the technological distance between two firms refers to the differences in their technological focus or profile (Nooteboom et al., 2007). Earlier research on the relationship between technological distance and interfirm learning viewed technological distance as an obstacle to learning, because any increase in technological distance was perceived to result in loss of absorptive capacity (Mowery et al., 1996; Stuart, 1998). In contrast, a few scholars had optimistic views of technological distance and proposed that heterogeneity in partners' technological capabilities could create more opportunities for learning and recombination (Nooteboom et al., 2007). More recent research has combined both perspectives, suggesting that there are two opposing mechanisms at work in the relationship between technological distance and interfirm learning. Although increased technological distance between alliance partners provides access to novel knowledge (Granovetter, 1973; Burt, 1992), when the technological distance becomes too high, firms may not have the necessary absorptive capacity for learning to take place (Cohen and Levinthal, 1990). Thus, an inverted u-shaped relationship between technological distance and interfirm learning through strategic alliances is expected, and has been corroborated by many empirical studies (Mowery et al.,

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1998; Nooteboom et al., 2007; Gilsing et al., 2008; Petruzzelli, 2011). Despite the advancement of research related to the relationship between technological distance and inter-organizational learning, we believe that existing literature is limited in at least two aspects.

First, most studies capture technological distance as the distance in firms' innovative outcomes (such as patents created, products introduced, industries that firms are operating in), while neglecting the knowledge bases or individual knowledge elements that have laid the foundation for these knowledge outcomes. Our representation of knowledge base and knowledge elements is very similar to the recombinant search literature. According to this literature, firms have a repository of knowledge elements and they recombine these existing knowledge elements into new combinations to generate valuable innovation (Fleming, 2001; Yayavaram and Ahuja, 2008). A firm's knowledge base and the knowledge elements in the knowledge base evolve in response to the firm's knowledge search, growth, and strategies. Therefore, not all firms have similar knowledge bases. Even if knowledge elements in knowledge bases are similar, there is *N* number of potential combinations of elements, which can lead to a combinatorial explosion of the number of possible inventions (Fleming, 2001). In solving technological problems, firms may decide to always use two knowledge elements together, or they might consider using them independently. This is clearly explained by Yayavaram and Ahuja (2008) using an example from the semiconductor industry: "whenever we use silicon as the chip material, we use CMOS as the chip architecture, or alternatively what kind of chip we design, logic versus memory has no bearing on what chip stamping technology we use".

Therefore, the creation of innovative outcomes is a search process across a set of alternative knowledge elements (which differ across firms) that can be recombined with one another (the recombination choices differ across firms). Thus, firms with similar technological outcomes need not have similar knowledge elements. Similarly, firms with similar knowledge elements in their knowledge base need not generate similar outcomes. This was corroborated by Krafft et al. (2014) who studied the dynamics of technological alliances and the structure of knowledge bases in the pharmaceutical industry by explicitly considering (a) variety of knowledge elements in the knowledge bases, (b) similarity/dissimilarity in the pieces of knowledge used, and (c) differences in the way that knowledge elements are combined. We therefore believe that viewing innovative outcomes as a black box, and thus ignoring the knowledge elements of partnering firms and the extent of overlap among them, has limited our understanding of how technological distance influences inter-organizational learning.

In addition, the literature had paid less attention to the significance of technological distance to learning through strategic alliances in the context of small firms. Unlike large established firms, which are relatively more self-sufficient and inward-looking, small firms are limited in their knowledge stocks and are therefore more reliant on external sources of knowledge (Almeida and Kogut, 1997; Almeida et al., 2003). For small firms, both the benefits and costs of technological distance are more prominent. On the one hand, small firms are limited in their ability to assimilate external knowledge (Cohen and Levinthal, 1990). As a result, they are likely to be more sensitive to the decrease in absorptive capacity caused by higher technological distance. On the other hand, the key to the competitive advantage of a small firm lies in the distinctiveness of its technological capabilities (Baum et al., 2000). Therefore, small firms minimally benefit from alliances with partners of similar technological profiles. Faced with increased tensions, the selection of alliance partners presents a bigger challenge for small firms.

In this paper, we address these limitations by adopting a contingency perspective and introducing the concept of knowledge base homogeneity (KBH) between firms (Wang, 2016). We define KBH as the extent to which the innovation outcomes of two firms are built upon similar knowledge bases or knowledge elements. In line with prior studies, we first predict and test a baseline hypothesis that the technological distance between alliance partners has an inverted u-shaped effect on a small firm's learning. An initial increase in technological distance is argued to improve interfirm learning by increasing novelty value, but beyond a moderate level, the effect of technological distance will become negative due to the lack of relative absorptive capacity that is essential for successful learning. Furthermore, we posit that KBH between alliance partners will positively moderate the effect of technological distance on learning in small firms. More specifically, higher levels of KBH will enhance the benefits of technological distance by ensuring the relevance of novel knowledge held by alliance partners and facilitating the learning process. At the same time, a high KBH will mitigate the cost of increased technological distance and allow firms to maintain the absorptive capacity necessary for learning to occur.

To test our hypotheses, we compiled longitudinal data on the alliance activities of 201 small biotechnology firms during the period of 1996–2010. The biotechnology industry was chosen as the empirical setting for two reasons. First, strategic alliance is a prevalent means by which biotechnology firms pursue inter-organizational learning (Baum et al., 2000; Deeds and Hill, 1996; Powell et al., 1996). Secondly, prior research has demonstrated that, in the pursuit of developing significant innovations, biotechnology firms differ significantly in their knowledge recombination activities (Hsu and Lim, 2006; Soh and Subramanian, 2014). The results are consistent with our theoretical expectations. We find that small firms' learning effect is maximized when they ally with partners that are moderately distant in the technological space. Moreover, our results show that the relationship between technological distance and learning is positively moderated by the KBH between alliance partners.

This study contributes to the existing research on inter-organizational learning by showing how knowledge base homogeneity and technological distance between alliance partners interact to influence small firms' learning through alliances. Thus, learning through strategic collaborations warrants careful consideration to innovative outcomes, as well as knowledge elements that form the basis of innovative outcomes. Our results have practical implications for small firms when choosing their alliance partners and suggest that, rather than merely looking at the structural characteristics of alliances, equal attention should be paid to firms' internal knowledge bases.

The rest of this paper proceeds as follows. In the next section, we discuss the current literature and theories in technological distance and interfirm learning, which leads to the development of our hypotheses. Following that is a detailed description of the data, specification of the variables, and description of the estimation method used in this study. The next two sections present the empirical results and a concluding discussion of their implications.

2. Theory and hypothesis development

Though firms enter into alliances in the anticipation of learning from other organizations (Hamel et al., 1989), whether or not learning occurs is contingent on many factors. The factors affecting inter-organizational learning through strategic alliances comprise multiple dimensions including (a) size, (b) structure, (c) relations, (d) capability, and (e) management. First, the size dimension, as represented by the number of alliances, is known to influence the benefits derived from strategic alliances (Ahuja, 2000). Studies examining the impact of size on interfirm learning have shown that the learning opportunities available to a firm increase with an increase in the number of partnerships that the firm engages in (Shan et al., 1994). Nevertheless, increases in the number of partnerships beyond a threshold has been shown to impair a firm's ability to learn because of the information and knowledge overload. Thus, the size of partnerships is known to have an inverted u-shaped relationship with the learning benefits derived from alliances (Deeds and Hill, 1996).

Second, drawing upon the alliance portfolio and social network literature, research has shown the significance of several structural aspects of alliance configuration that impact interfirm learning. These factors include the functional, geographical, and technological diversity of portfolio partners, technological distance between partnering firms, structural holes, betweenness and closeness centrality of alliance network, and network connectivity (Ahuja, 2000; Baum et al., 2000; Dyner et al., 2008; Hoffmann, 2007; Koka and Prescott, 2008; Owen-Smith and Powell, 2004; Phelps, 2010; Wuyts and Dutta, 2014; Van Beers and Zand, 2014). An important contribution of this stream of work is demonstrating the synergetic effect enjoyed by the focal firm as an outcome of the interdependencies among partners in an alliance portfolio (Doz and Hamel, 1998; Powell et al., 1996). Several researchers have elucidated that a portfolio of partners not only results in synergetic super-additive interdependencies, but also create sub-additive interdependencies, owing to the conflicts arising among partners in the portfolio (Parise and Casher, 2003; Vassolo et al., 2004).

The third dimension is related to the relational aspects of alliances and their role in facilitating interfirm learning. This portfolio of research has demonstrated that trust and reciprocity developed through repeated partnerships, strong ties, and cohesive networks are key factors that influence collaborative learning (Collins and Riley, 2013; Gulati, 1995a,b; Gulati, 1999; Kale et al., 2000; Rowley et al., 2000; Subramanian and Soh, 2016). Such relational attributes are also known to moderate the benefits derived from the structural attributes of alliance configuration.

Fourth, research on the capability dimension has examined how the ability of both the focal firm and alliance partner influence the extent of learning through strategic alliances. Extensive research has adopted the absorptive capacity perspective to establish the importance of internal R & D and human capital in order to benefit from external collaborations (Cockburn and Henderson, 1998; Cohen and Levinthal, 1990; Subramanian et al., 2013). In a similar vein, the technological strength and status of partnering firms are shown to be significant predictors of learning opportunities available to the focal firm (Stuart et al., 1999; Stuart, 2000). The relative abilities of firms entering alliance agreements have also been shown to result in a learning race among partners, influencing the extent to which they benefit from partnerships (Khanna, 1998).

Fifth, alliance management is recognized as a critical factor determining whether or not a firm reaps benefits from collaborative agreements. Governance mechanisms, designated teams to oversee alliance functions, and rotational leadership styles are a few management practices known to influence the benefits attained through alliances (Davis and Eisenhardt, 2000,b; Gulati, 1995a,b; Kale et al., 2002; Parise and Casher, 2003). A few influential works in this stream of research have stressed the importance of firms developing alliance capability to successfully master alliance management (Heimeriks and Duysters, 2007). Alliance capability refers to a firm's ability to identify partners, initiate partnership, manage collaboration, and terminate such relationships when required. Such alliance management capabilities are attained by enhancing alliance experience, which is acquired by engaging in multiple alliances over an extended period of time (Hoang and Rothaermel, 2005; Kale et al., 2002; Simonin, 1997).

Among these various factors, the structural configuration of an alliance portfolio is considered to be the predominant determinant of interfirm learning. Specifically, the technological distance between alliance partners and its impact on interfirm learning has received the most research attention to date (Mowery et al., 1996; Nooteboom et al., 2007; Sampson, 2007; Phelps, 2010).

2.1. Technological distance and learning through strategic alliances

As one of the earliest studies on technological distance and interfirm learning, the paper by Mowery et al. (1996) found that a firm's absorption of technological capabilities through strategic alliance is positively related to the pre-alliance level of technological overlap with its partner. An organization needs to possess prior related knowledge in order to assimilate external knowledge (Cohen and Levinthal, 1990). The ability to "recognize the value of new information, assimilate it, and apply it to commercial ends" was further defined as the absorptive capacity of a firm. Increased technological distance would lower a firm's absorptive capacity and hinder inter-organizational learning. A later study by Lane and Lubatkin (1998) transformed the concept of absorptive capacity into a dyad-level construct, namely the relative absorptive capacity, which refers to a firm's ability to learn from a specific firm (Lane and Lubatkin, 1998). They tested their theories using a sample of alliance activities in the biotechnology industry, and the empirical results showed that technological proximity between firms contributes to inter-organizational learning. Similarly, using alliance data from U.S. semiconductor firms, a study by Stuart (1998) also revealed that firms are better able to evaluate and assimilate the knowledge of technologically similar firms. In sum, prior research suggests that increased technological distance between alliance partners will lead to decreased relative absorptive capacity, thereby reducing inter-organizational learning through alliances. The costs associated with increased technological distance will be even more severe for small firms because of their limited knowledge stocks. Small firms, with their younger vintage of knowledge, are constrained in their ability to assimilate distant knowledge (Cohen and Levinthal, 1990) and are therefore more sensitive to the decrease in absorptive capacity caused by higher technological distance.

While earlier studies tend to view technological distance as an obstacle that must be overcome for learning to occur, later research has challenged this notion by proposing that technological distance can also lead to opportunities for interfirm learning. The resource-based view of the firm suggests that heterogeneity in firms' resources provides potential for learning and innovation (Hagedoorn, 1993; Powell et al., 1996; Ahuja, 2000; Rowley et al., 2000). According to Rosenkopf and Almeida (2003), alliances between technologically distant firms provide access to novel knowledge. They further supported their arguments with empirical results demonstrating that interfirm learning through alliances increases with technological distance between alliance partners. By allying with firms that are technologically distant from themselves, firms are able to gain access to distinct capabilities, which encourages learning and innovation (Sampson, 2007; Phelps, 2010). In contrast, allying with firms of similar technological capabilities can lead to information redundancy and reduce the potential for learning. According to Baum et al. (2000), alliances are redundant to the extent that they provide access to the same information or capabilities (Burt, 1992; Gomes-Casseres, 1994; Ahuja, 2000). In an extreme situation where two firms have identical technological capabilities, no learning would occur as neither firm has anything to learn from the other (Mowery et al., 1998). The disadvantages of increased technological similarities between alliance partners are especially prominent for small firms. Since the key to small companies' competitive advantage lies in the distinctiveness of their technological capabilities, allying with firms with similar technological profiles provides little added value. Furthermore, as a firm increases the number of alliance activities in which it is involved, it imposes a greater burden on management (Deeds and Hill, 1996). Due to resource constraints and limitations in management's ability to monitor alliance activities, a small firm can only engage in a limited number of alliances simultaneously. Therefore, the opportunities to learn novel knowledge provided by technologically distant partners are more important for small firms.

More recent research has combined the two opposing views and proposed a curvilinear model of technological distance and learning. This stream of literature argues that, in the relationship between technological distance and inter-organizational learning, there are two opposing mechanisms at work: the ability to learn and the opportunity to learn (Nooteboom, 1999). On the one hand, a firm's ability to learn from its alliance partners decreases with technological distance due to loss of absorptive capacity (Cohen and Levinthal, 1990; Lane and Lubatkin, 1998). On the other hand, the opportunity to learn novel knowledge increases with larger technological distance between alliance partners (Rosenkopf and Almeida, 2003). Therefore, a moderate level of technological distance is desirable to optimize inter-organizational learning. Although a certain level of technological overlap is necessary to facilitate learning across firm boundaries, a high degree of technological similarity between alliance partners will lead to information redundancy and offer little added value (Wuyts et al., 2005; Nooteboom et al., 2007; Gilsing et al., 2008; Petruzzelli, 2011). Moderate levels of technological distance are more conducive for small firms as they exert only a moderate burden on the firms' absorptive capacity, yet enable them to leverage the learning opportunities provided by the partnering firms. In line with previous studies, we test the following baseline hypothesis concerning the relationship between technological distance and learning from strategic alliances in the context of small firms:

Hypothesis 1. Technological distance between a small firm and its alliance partners has an inverted u-shaped relationship on the small firm's learning.

2.2. Knowledge base homogeneity between alliance partners

According to Schumpeter (1939), technological novelty arises from recombination of existing technologies. The innovation process can therefore be viewed as a search process where new inventions are generated by recombining existing knowledge elements in novel ways (Kogut and Zander, 1992; Fleming, 2001). Due to cognitive limits, a firm is able to consider only a small subset of the knowledge universe in their search process. This subset of knowledge is defined as the knowledge base of the firm (Yayavaram and Chen, 2015). The knowledge base is not a static concept as an organization constantly learns and adds new elements to its knowledge base. A firm's knowledge base evolves in response to the firm's knowledge search, growth, and strategies. The expansion of a knowledge base can be achieved through multiple means, including internal research and development (R & D) activities (Cohen and Levinthal, 1990), formal or informal interactions with other organizations in the scientific community (Baum et al., 2000), and the hiring of new research personnel (Rosenkopf and Almeida, 2003). Thus, firms learn and evolve along different trajectories, ultimately leading to the heterogeneity in the knowledge bases of different firms (Dosi, 1982; Cohen and Levinthal, 1994; Rosenkopf and Nerkar, 2001). Viewed from the perspective of recombinatory search, although the knowledge elements that can potentially be recombined (the knowledge universe) are the same for all firms, the elements that are actually considered for recombination (the knowledge base of the firm) differ across firms (Yayavaram and Ahuja, 2008).

In addition to differences in their knowledge bases, firms also differ in their understanding of the relationships between different knowledge elements. According to Yayavaram and Ahuja (2008), the pattern of underlying interdependence between knowledge elements is part of the natural world, which is the same for all firms. However, a firm's understanding of these interdependencies at a given time is shaped by its past experience (Ahuja and Katila, 2001). Given that firms have developed along different paths, each firm has formed a unique cognitive map of the natural world. This cognitive map will then drive the firm's decision-making in the process of recombinatory search. To the extent that the perceived interdependencies between knowledge elements vary across firms, this will lead to different knowledge recombination behaviors in the process of technological search. In sum, organizations differ in their knowledge bases, as well as their understanding of the interdependencies between knowledge elements.

Therefore, the assumption made in prior research that a firm's knowledge structure mirrors the structure of products or technological outcomes is questionable. Although organizational researchers have speculated about the relationship between modular products and modular organizational structures (Sanchez, 1999), the relationship is not straightforward in the case of technological/innovation outcomes and knowledge bases. As elucidated by Yayavaram and Ahuja (2008), there are important differences between how interdependencies affect products as compared to knowledge structures. In products or technological outputs, decomposability or modular architecture is preferred because it enables the use of one module to buffer another to overcome ripple effects. However, such ripple effects may be desirable in the case of knowledge structures as they lead to novel recombination of knowledge elements across different modules. Thus, firms with very similar technological outputs could have built their innovations based on very different knowledge bases. Furthermore, even if two firms have similar knowledge bases, the dynamics of recombining the knowledge elements could be very different, thereby resulting in a combinatorial explosion of the number of possible innovative outcomes. The differences across technological outcomes and knowledge structures underlying the outcomes require due consideration (Krafft et al., 2014).

To capture differences in firms' knowledge bases, we developed the concept of knowledge base homogeneity (KBH). The KBH between two organizations is defined as the extent to which the innovative outcomes of the two firms draw upon similar sets of knowledge elements. While technological distance reflects the differences in firms' innovative outputs, KBH considers the knowledge elements that formed the basis of firms' innovative outcomes.

In the following section, we will elaborate on how KBH interacts with technological distance to influence inter-organizational learning through strategic alliances.

2.3. The moderating role of knowledge base homogeneity

Successful learning requires the small firm to recognize the value of knowledge that resides in its alliance partner, assimilate it, and apply it in future recombinant searches. As technological distance increases, the relative absorptive capacity of the small firm is reduced, which hinders knowledge transfer across firm boundaries. However, at increased levels of KBH, the small firm would be able to maintain a higher level of relative absorptive capacity even if it is technologically distant in terms of its innovative outputs (Lane and Lubatkin, 1998). When the KBH between alliance partners is high, the small firm will possess a certain amount of prior knowledge that provides the basis to understand the new knowledge held by its partner. The common basic knowledge will then allow the small firm to better comprehend the new knowledge and facilitate inter-organizational communication, thereby enhancing the learning effect (Doz, 1996). In contrast, firms with low levels of KBH need to nurture and develop common knowledge before effective learning can occur. Hence, high levels of KBH will mitigate the cost associated with increased technological distance.

Higher technological distance between alliance partners contributes to the learning effect by providing access to novel knowledge. KBH enhances the benefits of increased technological distance in two ways. First, greater KBH between alliance partners will increase the likelihood that the novel knowledge held by the partner firm is relevant to the small firm (Fleming, 2001; Schildt et al., 2012). According to Fleming (2001), inventions that combine knowledge elements with which the firm is already familiar tend to have higher values, on average. Thus, homogeneity in the knowledge bases of alliance partners provides a greater chance for the small firm to acquire novel knowledge that could be incorporated into future recombinant searches. Secondly, as higher technological distance creates more opportunities for learning, mutual understanding between alliance partners enables the small firm to better utilize these opportunities by reducing the risks involved in the alliance activity. Greater KBH leads to more familiarity with the knowledge bases of the partner firm, which in turn breeds trust and lowers the risk of opportunism (Gulati, 1995a,b). This will serve as the basis for successful collaboration and facilitate knowledge transfer across firm boundaries. Therefore, the benefits of allying with technologically distant partners are best achieved when the two parties have a higher level of KBH.

Hypothesis 2. The knowledge base homogeneity (KBH) between a small firm and its alliance partners moderates the inverted u-shaped relationship between technological distance and learning. This association is such that when the knowledge base homogeneity among partners is high, the positive effect of high technological distance on learning is enhanced. Conversely, the negative effect of low technological distance on learning is reduced

3. Data and methods

3.1. Data

We drew our sample from BioScan, an independent industry directory founded in 1988 that covers over 2000 biotechnology and pharmaceutical firms. The directory provides comprehensive coverage of financial information, new products in development, mergers, strategic alliances, licensing, and R & D agreements of companies and has been extensively used in prior studies (Rothaermel and Deeds, 2004; Sytch and Tatarynowicz, 2014; Whittington et al., 2009; Yang et al., 2015). Since the focus of this study is small companies, we limited our sample to publicly listed firms established after 1994. Focusing on firms established after 1994 also allowed enough duration since the firms' establishment to capture their patenting, alliancing, and learning activities. This criteria yielded a total of 266 small firms as the initial sample. These firms were observed over a 15-year period from 1996 to 2010. The panel is unbalanced as firms might have zero or more than one alliance activities in a given year. We combined three types of data in constructing the dataset for statistical analysis. First, we collected information on alliance activities of the 266 firms from Recombinant Capital (Recap), a database that provides a comprehensive summary of all alliance agreements in the biotechnology industry. The database has also been frequently used by other researchers in the field (Bunker et al., 2009; Gopalakrishnan et al., 2008; Soh and Subramanian, 2014). There are 26 types of alliances listed in ReCap (see Table 1). As we aimed to observe interfirm learning, we looked at R & D alliances only, which corresponded to alliance types 4, 6, 9, and 20 (Subramanian et al., 2013). During the period from 1996 to 2010, a total of 1689 R & D alliances were formed by these firms.

Table 1
Type of Alliances in ReCap.

1	Acquisition
2	Asset purchase
3	Assignment
4	Co-development
5	Co-market
6	Collaboration
7	Co-promotion
8	Cross-license
9	Development
10	Distribution
11	Equity
12	Joint Venture
13	Letter of intent
14	License
15	Loan
16	Manufacturing
17	Marketing
18	Merger
19	Option
20	Research
21	Security
22	Settlement
23	Sublicense
24	Supply
25	Termination
26	Warrant

Table 2
U.S Patent Classes Relevant to Biotechnology.

Class	Description
424	Drug, bio-affecting and body treating compositions
435	Chemistry: molecular biology and microbiology
436	Chemistry: analytical and immunological testing
514	Drug, bio-affecting and body treating compositions
530	Chemistry: natural resins or derivatives; peptides or proteins; lignins or reaction products thereof
536	Organic compounds
800	Multicellular living organisms and unmodified parts thereof and related processes

Next, patent data was retrieved from Thomson Innovation for all small firms in the initial sample and for each of their alliance partners. We searched for U.S patents issued prior to December 31, 2014, that were assigned to one of the seven US patent classes (UPC) relevant to biotechnology (see Table 2). The patent classes were chosen according to the USPTO Technology Profile Reports used in Lim (2004) and the descriptions were drawn from the USPTO website (USPTO). Following the above search, small firms with no identified patent data were removed from the initial sample. Furthermore, we removed alliance observations where either the small firm or its alliance partner had no patent records until the year the alliance was formed.

Finally, financial data for the small firms was obtained from Compustat, a prevalently used database that provides financial, statistical and, market information of active and inactive companies from around the world. Alliance observations were excluded for those years when financial data for the small firms were unavailable. The entire data collection process yielded a final sample of 201 small firms. During the observation period (1996–2010), a total of 1042 alliances formed by these firms met the criteria described above and were included for further statistical analysis.

3.2. Dependent variable: learning through alliances (Post citation)

Following methodology used in prior research, we measured each small firm's learning effect based on the extent to which the firm cited its partner's patents post-alliance (Mowery et al., 1996; Almeida et al., 2003; Schildt et al., 2012). This was done in a two-step procedure. For each alliance observation, we first identified the patents issued to the focal small firm prior to December 31, 2014, that were applied after the year the alliance was formed. Next, we calculated the post citation frequency by capturing the number of citations made by patents of focal firm to the alliance partner's patents. For example, if focal firm i formed an alliance with partner j in year t, we first collected all patents of firm i that were applied after year t and issued before December 31, 2014. Next, we calculated the extent to which firm i's patents cited firm j's patents and called that the post citation frequency. We chose the year that the alliance was formed as the cutoff to ensure that the measurement reflected the learning effect through alliance. We also controlled for pre-alliance citation frequency and patent stock, which is explained in subsequent sections.

3.3. Explanatory variables

3.3.1. Technological distance between alliance partners (Tech distance)

For the purposes of this study, we chose cosine distance to measure the technological distance between alliance partners, which is the most widely adopted method in previous studies (Sampson, 2007; Phelps, 2010). Specifically, we looked at patents issued to both the small firm and its partner, where the application year is no later than the year the alliance was formed. We then calculated the distribution of their patents across the seven UPCs relevant to biotechnology. This procedure yielded two multidimensional vectors representing the technological positions of the small firm and its alliance partner. The technological distance between firm i and j was then calculated as:

$$CSD_{i,j} = 1 - \frac{\sum_{k=1}^{N} p_{ik}p_{jk}}{\sqrt{\sum_{k=1}^{N} {p_{ik}}^2 \sum_{k=1}^{N} {p_{jk}}^2}}$$

In the above formula, p_{ik}denotes the percentage of firm i's patents that were assigned to UPC class k. As we identified seven UPCs relevant to biotechnology inventions, N equals seven. The measurement of technological distance was bounded between zero and one. If two firms have exactly the same distribution of technological capabilities, the technological distance between them is zero. On the contrary, when two firms have entirely different technological capabilities, the two vectors are orthogonal to each other, resulting in a technological distance value of one. This method was first developed by Jaffe (1986, 1989) and has been used by scholars in economic and strategy research ever since.

3.3.2. Knowledge base homogeneity between alliance partners (KBH)

Similar to citations in academic publications, patent citations are made to technological antecedents of the current invention (i.e. prior art). Therefore, patent citations convey information on previously existing knowledge upon which the patent builds (Trajtenberg, 1990). Moreover, patent citations carry legal aspects. Upon application for a patent, applicants are obliged to submit any 'prior art' that they are aware of. The patent examiners will then conduct a thorough prior art search and decide on the ultimate citations to be included (Cotropia et al., 2013). These citations will determine the scope of property rights awarded to the focal patent (Hall et al., 2005). Therefore, while patents reflect a firm's innovative outputs, citations made by the patent represent the knowledge bases upon which the innovation builds.

The KBH between alliance partners measures the extent to which the innovative outcomes of the two firms draw upon similar sets of knowledge elements. In bibliographic coupling, the percentage of shared references can be seen as a proxy for the knowledge base similarity of two papers (Kessler, 1963; Boyack et al., 2005). We used a similar approach and measured KBH in the following manner[1]:

1) For each observation in the sample, the patents of both the small firm and its alliance partner were grouped according to their main UPCs (3-digit). The number of groups within a typical firm ranged from one to seven.

2) Citations to prior patents made by each group of patents were compiled and duplicates were removed. Assuming there are n patent groups in the small firm's portfolio and m groups in that of its partner, this procedure would generate $n + m$ groups of citations made by patents in each group.

3) There would be $n \times m$ group pairs between the patent groups of the small firm and its alliance partner. For each group pair, we calculated the Jaccard coefficient[2] between their citations using the following formula:

$$C(i, j) = \frac{S_{ij}}{S_i + S_j - S_{ij}}$$

In this formula, S_i and S_j represent the total number of distinct citations made by patents in group i of the small firm and in group j of the partner firm, respectively. S_{ij} is the number of common citations between group i and group j. Thus, $C(i, j)$ measures the degree of overlap between citations made by patents in group i and group j. After calculating $C(i, j)$ for each group pair, we constructed a $n \times m$ matrix comprised of Jaccard coefficients for all group pairs (see Fig. 1).

4) We then calculated KBH between the small firm and its alliance partner by taking an average of all the values in the matrix.

$$\text{KBH} = \frac{\sum_i \sum_j C_{ij}}{n \times m}$$

The value of KBH between two firms ranges from zero to one. A value of zero indicates that the two firms have entirely different knowledge bases and that there is no overlap between them. In contrast, KBH equals one when two firms have identical knowledge bases in every technological field.

3.4. Control variables

Several variables that might affect inter-organizational learning through alliances were included as controls. Some of the control variables are specific to the alliance dyad, while others are controls at the firm-year level. A brief description of the variables included in this study is provided in Table 3.

3.4.1. Alliance level control variables

First, as we used post-alliance citation frequency to capture learning effects in our dependent variable, it was essential to control for the pre-alliance citation frequency (Mowery et al., 1996; Mowery et al., 1998). Therefore, we calculated the number of times the small firm cited patents of its alliance partner before they entered the alliance. Secondly, since prior research has demonstrated that inter-organizational learning is affected by the governance structure of the alliance activity (Kogut, 1988; Mowery et al., 1996; Sampson, 2007), we included two dummy variables indicating whether the alliance was equity-based and whether it was exclusive. Moreover, we controlled for geographical proximity between the small firm and its alliance partner. Although international alliances provide access to diverse knowledge (Rosenkopf and Almeida, 2003), they also incur higher coordination and communication costs due to cultural differences. We included a dummy variable that takes a value of one for domestic alliances and zero for international alliances. Furthermore, research in organizational learning has shown that prior ties between firms can increase interfirm trust (Gulati, 1995a,b) and help develop relationship-specific knowledge transfer routines (Dyer and Singh, 1998; Lane and Lubatkin, 1998; Dyer and Nobeoka, 2000). This suggests that firms are better able to learn from repeated alliance partners. Therefore, we included a dummy variable to control for whether the two firms had prior alliance experience. The dummy variable takes a value of one if the two firms had at least one prior alliance, and zero otherwise. In addition, we calculated relative patent portfolio size by dividing the number of patents of the small firm by that of its alliance partner. This variable controls for the relative technological stock of the small firm compared to its alliance partner. A

C(1,1)	C(1,2)	C(1,3)	…	C(1,m)
C(2,1)	C(2,2)	C(2,3)	…	C(2,m)
C(3,1)	C(3,2)	C(3,3)	…	C(3,m)
…	…	…	…	…
C(n,1)	C(n,2)	C(n,3)	…	C(n,m)

Fig. 1. Matrix of Jaccard coefficients.

[1] Calculation is based on patents with an application year no later than the alliance year, for both the focal firm and partner firm. By citations, we refer to citations made to patent documents only. Non-patent citations (newspaper articles, technical documents, etc.) are excluded from the calculation.

[2] Jaccard coefficient is a statistic commonly used in bibliometric studies to compare the similarity of publications. It is defined as the size of intersection divided by the size of the union of the sample sets.

Table 3
Definition of variables.

Category	Variable Name	Definition
Dependent Variable	*PostCitation*	- Number of times focal firm (i) cites partner firm (j) after alliance - Based on patents with application year > alliance year, publication year ≤ 2015
Independent Variable	*TechDistance*	- 1 minus cosine similarity of focal firm (i) and its alliance partner (j) - Calculated based on patents with application year ≤ alliance year, publication year ≤ 2015
Moderator	*KBH*	- Average Jaccard coefficient calculated across UPC group pairs between focal firm (i) and alliance partner (j) - Calculated based on patents with application year ≤ alliance year, publication year ≤ 2015
Control Variables	*PreCitation*	- Number of times focal firm cites partner firm before alliance - Based on patents with application year ≤ alliance year, publication year ≤ 2015
	Equity	- Dummy variable, = 1 if the alliance is equity-based
	Exclusivity	- Dummy variable, = 1 if the alliance is exclusive
	Domestic	- Dummy variable, = 1 if the focal firm (i) and partner firm (j) are from the same country
	PriorTie	- Dummy variable, = 1 if the focal firm (i) has alliance activities with the partner firm (j) before
	RelativePPS	- Relative patent portfolio size (focal firm patent portfolio size/partner firm patent portfolio size) - Calculated based on patents with application year ≤ alliance year, publication year ≤ 2015
	FirmAge	- Logarithm of firm age at the year of alliance
	R & DIntensity	- R & D intensity of focal firm (R & D expenditure/total assets)
	UPC	- Logarithm of total numbers of UPCs focal firm's patent portfolio covers

smaller value for this variable indicates that the partner firm has a much larger technological stock than the small firm, thereby providing more opportunities for learning.

3.4.2. *Firm-year level control variables*

We also included several control variables that are specific to the small firm in a given year. Firm age was calculated as the number of years elapsed since the small firm was founded as of the alliance formation year. As existing literature has proved that a firm's R & D investment contributes to its ability to absorb external knowledge (Cohen and Levinthal, 1990; Gambardella, 1992), we controlled for the firm's R & D intensity, which was calculated by dividing its R & D expenditure by total assets in year *t*. We used the firm's total assets instead of sales as the denominator, because the commercialization of biotechnology innovation is extremely lengthy and many young firms do not have positive sales figures in their early stages (Nishimura and Okada, 2014). We also captured the firm's technological breadth through the number of biotech-related UPCs covered by its patent portfolio as of year *t*. We controlled for technological breadth as it increases the likelihood of the small firm possessing knowledge related to its partner's knowledge, which in turn increases the likelihood of learning (Granstrand, 1998; Suzuki and Kodama, 2004). In addition, SIC (standard industrial classification) dummies were used to control for industrial differences. Finally, we used fixed year effects for each alliance observation to capture unobserved heterogeneity across years. For firm age and technological breadth, logarithmic values were used to account for unequal variation.

3.5. *Descriptive statistics*

Table 4 presents the pairwise correlations between the variables included in this study (except for SIC dummies and year fixed effects). As shown in Table 4, KBH between alliance partners is positively correlated with the post cross-citation frequency, suggesting that a high level of KBH contributes to interfirm learning. Two dummy variables, Exclusivity and Domestic, are also positively correlated with the dependent variable. This indicates that exclusivity in alliances enhances inter-organizational learning. Moreover, domestic alliances tend to have stronger learning effects compared to international alliances.

4. Results

Since our dependent variable is the post-alliance patent citation frequency of the focal firm to the partner firm, a count data model was appropriate. We used zero inflated negative binomial regression as there were excessive zeros in our dependent variable. Although the unit of analysis was individual alliance, some of the control variables were measured at the firm-year level. In order to attain robust estimations, we included robust standard errors clustered by firm-year in the regression. The explanatory variables, technological distance, and KBH were normalized $[(X - \mu)/\sigma]$before running the regression.

Table 5 presents the results of zero inflated negative binomial regressions. All specifications include fixed effects for both SIC code and alliance formation year. Model 1 shows only the control variables, and the main effects are individually added to subsequent estimation models to show the added explanatory power. To test our hypotheses, we examined the estimation outcomes in the full model (i.e., Model 6).

Table 4
Descriptive statistics.

S/N	Variables	Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12
1	PostCitation	2.2457	12.3514	1											
2	TechDistance	0.4676	0.3147	−0.0543	1										
3	KBH	0.0010	0.0040	0.1237*	−0.1415*	1									
4	PreCitation	1.3330	11.3400	0.4011*	−0.0756*	0.2023*	1								
5	Equity	0.0940	0.2920	0.1145*	−0.0158	−0.0161	−0.0051	1							
6	Exclusivity	0.3167	0.4654	0.0660*	−0.1315*	0.0758*	0.0857*	0.2895*	1						
7	Domestic	0.4585	0.4983	0.0642*	0.0578	0.0743*	0.0479	0.0154	−0.0639*	1					
8	PriorTie	0.0739	0.2617	0.0981*	−0.0018	−0.0143	0.0542	0.1226*	0.1310*	−0.0302	1				
9	RelativePPS	3.6869	12.3682	−0.0467	0.0944*	0.0017	−0.0332	−0.0235	−0.0465	−0.0893*	0.0045	1			
10	FirmAge	0.7971	0.2756	−0.0442	−0.1120*	0.0706*	0.0430	−0.0530	0.1387*	−0.0450	−0.0109	0.0830*	1		
11	R & DIntensity	0.8587	4.2556	−0.0118	0.0253	0.0039	−0.0083	0.0025	−0.0316	−0.0100	−0.0207	−0.0303	−0.0139	1	
12	UPC	1.2691	0.4246	0.0525	−0.1254*	0.0573	0.1091*	−0.0063	0.0780*	0.0163	0.0532	0.3207*	0.2058*	−0.0992*	1

* $p < 0.05$.

Table 5
Regression results: zero-inflated negative binomial regression of technological distance and knowledge base homogeneity on post citation rate.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Negative binomial model						
CONSTANT	−2.8800*** [0.9705]	−2.6001*** [0.9352]	−1.8565* [1.0082]	−1.6869 [1.0606]	−0.7647 [1.0477]	−0.5585 [1.0070]
TechDistance		0.4190** [0.1991]	0.3454* [0.1828]		0.3565** [0.1745]	0.3827** [0.1562]
TechDistance^2			−0.4664** [0.2312]		−0.4464** [0.2218]	−0.4035** [0.2049]
KBH				0.4883** [0.2075]	0.4646** [0.1905]	0.6200* [0.3724]
TechDistance*KBH						1.1250** [0.5296]
TechDistance^2*KBH						0.8143*** [0.3024]
Equity	0.1156 [0.3759]	−0.3093 [0.4011]	0.0748 [0.4054]	0.3207 [0.3833]	0.2330 [0.4307]	0.4187 [0.4533]
Exclusivity	0.7281** [0.2887]	0.8246*** [0.2886]	0.9198*** [0.3019]	0.7086** [0.2868]	0.8763*** [0.3012]	0.9372*** [0.3114]
Domestic	1.0270*** [0.2659]	0.9862*** [0.2587]	1.0260*** [0.2677]	0.7032** [0.2950]	0.7135** [0.2825]	0.4963* [0.2800]
PriorTie	−0.1796 [0.4209]	0.1717 [0.4416]	0.1372 [0.4539]	−0.1479 [0.4261]	0.2502 [0.4736]	0.3603 [0.4761]
RelativePPS	−0.0446 [0.0283]	−0.0452 [0.0320]	−0.0525 [0.0325]	−0.0303 [0.0248]	−0.0380 [0.0293]	−0.0284 [0.0256]
FirmAge	1.2483** [0.5506]	1.4206*** [0.5337]	1.2346** [0.6117]	1.0470* [0.5851]	1.0502 [0.6708]	1.3485** [0.6555]
R & DIntensity	0.0723 [0.1034]	0.1073 [0.1041]	0.0617 [0.1125]	−0.0309 [0.0530]	−0.0445 [0.0676]	−0.0150 [0.0471]
UPC	1.0080** [0.3953]	0.9944** [0.4026]	0.8127* [0.4167]	0.7645* [0.3931]	0.5675 [0.4226]	0.4669 [0.4669]
Zero-inflation model						
COSTANT	1.7559*** [0.1827]	1.8227*** [0.1844]	1.7823*** [0.1922]	1.7230*** [0.1956]	1.7580*** [0.2029]	1.7152*** [0.2087]
PreCitation	−3.9977** [1.5703]	−4.1742** [1.7306]	−4.3905** [2.1808]	−4.1669** [2.0150]	−4.7609 [3.4679]	−4.9197 [4.2871]
Log likelihood	−816.9282	−814.9358	−813.4334	−813.601	−810.0786	−807.3012
No. of obs.	1042	1042	1042	1042	1042	1042

Standard errors appear in parentheses. Year fixed effect and SIC dummies was included but not reported.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

4.1. Effects of control variables on learning

Model 1 in Table 5 shows the effects of alliance-level and firm-level control variables on the small firm's learning effect, as measured by post-alliance citations. The coefficient estimates of alliance-level control variables, Domestic and Exclusivity, are statistically significant. As expected, the learning effect tends to be stronger in domestic alliances than in international alliances due to lower coordination and communication costs. Moreover, when the alliance is formed on exclusive terms, firms are less likely to suffer from appropriability problems and hold-up conflicts (Anand and Khanna, 2000). Therefore, exclusivity had a positive effect on interfirm learning as the risk of knowledge sharing is lowered. The firm level controls on firm age and technological breadth were also statistically significant, suggesting that older firms and firms with a broader technological portfolio are better able to learn from their alliance partners.

4.2. Main effects of technological distance and KBH on inter-organizational learning

In line with previous studies, the baseline Hypothesis 1 predicted an inverted u-shaped relationship between technological distance and small firms' learning. When technological distance and its quadratic term were introduced in Model 3 and Models 5–6, the effect of technological distance was positive and significant, while its squared term was consistently negative and significant. Moreover, using parameter estimates from the full model (Model 6), the maximum value of interfirm learning occurs when technological distance between alliance partners is 0.4742, which is within the sample range. Thus, Hypothesis 1 is supported by the regression results, thereby providing empirical validation of the u-shaped relationship between technological distance and learning from strategic alliances in the context of small firms.

4.3. Interaction effects between technological distance and KBH on inter-organizational learning

In Hypothesis 2, we predicted that KBH between the small firm and its alliance partners would moderate the relationship between technological distance and learning. To test this hypothesis, we interacted KBH with technological distance and its squared term in Model 6. The result showed that the coefficients of both interactions are positively significant. For a more intuitive illustration, we present the interaction effects in Fig. 2. First, the amplitude of interfirm learning is greater for high KBH at all levels of technological distance, which suggests that high KBH enhances the positive effect of technological distance. Secondly, the optimal technological distance is greater when KBH is high,

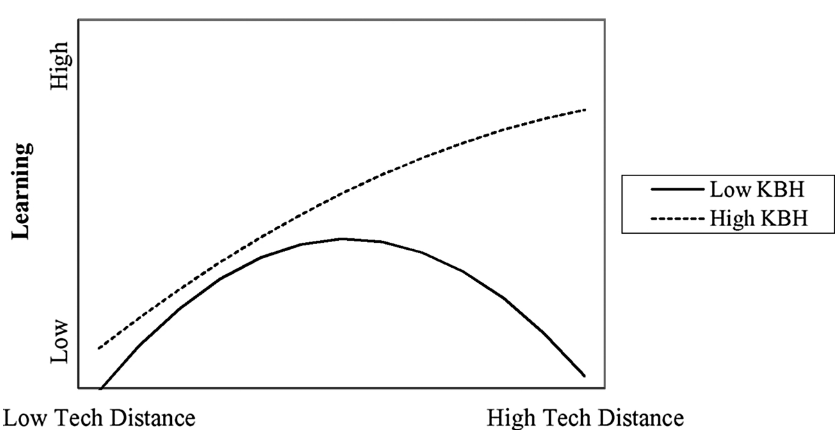

Fig. 2. Interaction between technological distance and knowledge base homogeneity.

indicating that high KBH can mitigate the costs associated with increased technological distance. Therefore, Hypothesis 2 is also supported.

5. Discussion and conclusion

In this paper, we have studied the relationship between technological distance and small firms' learning through strategic alliances. Furthermore, we have examined how the knowledge base homogeneity between alliance partners affects the impact of technological distance on interfirm learning. In line with previous research, we have found that there is an inverted u-shaped relationship between technological distance and interfirm learning. In seeking alliance partners, there is a trade-off to be made between novelty value and absorptive capacity. Going beyond the baseline results, this research has examined the role of knowledge base homogeneity in the relationship between technological distance and small firms' learning through alliances. As expected, we found that the benefits of technological distance are enhanced and the cost of technological distance mitigated when the knowledge base homogeneity between alliance partners is high. It was also found that small firms' learning effects are stronger in domestic and exclusive alliances.

This research contributes to the existing literature in several ways. First, we provide additional empirical validation of the existing notion that a moderate level of technological distance is optimal for learning in strategic alliances. We also demonstrated that the optimal distance is not fixed, but depends on many firm-level and relational factors. Current studies have explored a few contingencies in examining the effect of technological distance on learning. For example, Nooteboom et al. (2007) found that the impact of technological distance is affected by the focal firm's technological capital. However, the empirical analysis led to mixed findings. The authors explained the mixed effect by arguing that the technological capital of the focal firm might increase its absorptive capacity, but at the same time reduce the novelty value brought by increased technological distance. A more recent study by Schildt et al. (2012) examined the effect of technological distance on learning at different stages of alliances. Using a sample of collaborations in the ICT (information and communications technology) industry, they found that the benefits of technological similarities between alliance partners are stronger in later stages of the relationship.

Our research adds to this stream of work by developing the concept of knowledge base homogeneity, defined as the extent to which innovative outcomes of the two firms draw upon similar sets of knowledge bases. As successful learning requires the firm to recognize the value of external knowledge, assimilate it, and apply it to future recombinatory search, the differences in the firms' knowledge bases play an important role in the relationship between technological distance and interfirm learning. The regression results indicate that knowledge base homogeneity positively moderates the relationship between technological distance and learning. More specifically, when the knowledge bases of alliance partners are highly homogeneous, the benefits of technological distance are enhanced and the costs are mitigated. This implies that, all else being equal, the optimal technological distance would be greater between partners with higher homogeneity in their knowledge bases. Our findings also have practical implications for small firms in choosing their alliance partners. Apart from deciding on partnership solely based on structural configuration of alliances, one must pay equal attention to the internal knowledge bases. To assess the level of knowledge base homogeneity, firms could 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, small firms could make better decisions and achieve more effective learning through alliances.

Our study also contributes to the literature on absorptive capacity in the context of interfirm learning. These studies have typically measured absorptive capacity using patent stock, relative patent stock, R & D intensity, etc. (Ahuja and Katila, 2001; Cohen and Levinthal, 1990; Kim, 1998; Yang et al., 2015). Our results indicate that relative patent stock or R & D intensity do not have any impact on interfirm learning, measured in terms of cross citations. Instead, it is the extent of overlap of knowledge bases between partners that significantly influences interfirm learning. Thus, we advance this stream of work by introducing the concept of knowledge base homogeneity, which is a much closer representation of the extent to which a firm can learn from its collaborative partners.

Finally, this study makes methodological contributions by showing how bibliometric techniques can be applied to patent data to develop more advanced measurements. Bibliometric methods were originally developed for analyzing academic publications, based on the fundamental rationale that authors cite papers that they consider to be important to the development of their research (Pritchard, 1969). The same logic can be extended to patent citations where more advanced measurements can be developed using bibliometric techniques. Although patent data has been widely adopted, the use of bibliometric techniques in strategy research is rather limited (exceptions are Huang et al., 2011; Han, 2015; Park et al., 2015). Applying bibliographic coupling to patent data, the percentage of common backward citations can be seen as a proxy for the knowledge relatedness of two patents. Aggregated onto the firm level, as shown in this paper, this method can be used to reflect the similarities in knowledge bases. Our study provides an example of extending bibliometric techniques to patent data, and future research can build on this methodology and apply it to different research contexts. However, one must exercise caution in generalizing our findings by taking into consideration the following limitations of our research methodology.

First, we measured inter-organizational learning through citations made by the focal firm to patents owned by its alliance partner. Similarly, technological distance and knowledge base homogeneity are measured based on the patent stocks of focal firm and alliance partners. We recognize that not all inventions meet the legal requirements for a patent to be granted. Firms may also choose not to file patents for certain inventions due to strategic considerations. In addition, it is established that not all citations are included by the firm applying for patents. Alcacer and Gittelman (2006) have noted that 40% of the patent citations are included by the patent examiners. Our study has also neglected the non-patent references to scientific publications, which is an important element of interfirm learning, technological distance, and knowledge base homogeneity (Cockburn and Henderson, 1998). Further, interfirm learning could have occurred through sharing of tacit knowledge among employees, which is not captured in our measure. Therefore, the measures in our study reflect only a portion of the actual learning effect, technological distance, and knowledge base homogeneity. The generalization of our findings warrants careful consideration to the nuances of knowledge stock and interfirm learning, which are best captured through qualitative research or primary data on the perceptions of employees, who play the bridging role in the inflow of external knowledge.

Second, as the use of patents and alliances differs across industries, we limited our study to a single high-tech industry. In the biotechnology industry, patents are relatively effective in protecting proprietary knowledge, and most firms seek patent protection for their innovations. Moreover, strategic alliances are prevalent among biotechnology firms as a means to access external knowledge. Although our findings may apply to other high-tech settings, the generalizability of the results should be assessed with caution.

Finally, while our study focuses on alliances, there are other prevalent modes of external venturing activities, such as CVC investments, mergers, acquisitions, etc., which are prevalent in high technology industries. Future studies can assess the generalizability of our findings to other modes of external venturing activities and examine whether they substitute or complement the findings of our research.

Despite the above constraints, we believe our research offers valuable insights into the relationship between technological distance and inter-organizational learning. In particular, we examined how knowledge base homogeneity between alliance partners influences the benefits and costs of technological distance on interfirm learning.

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