DOES THE PREDATOR BECOME THE PREY? KNOWLEDGE SPILLOVER AND THE LEARNING OF KNOWLEDGE PROTECTION IN ALLIANCES

Jens-Christian Friedmann
Department of Management and Technology
Bocconi University
Via G. Roentgen 1
20136 Milano, Italy
E-mail: jenschristian.friedmann@unibocconi.it

Dovev Lavie
Department of Management and Technology
Bocconi University
Via G. Roentgen 1
20136 Milano, Italy
E-mail: dovev.lavie@unibocconi.it

Linda Rademaker
Department of Strategy and Entrepreneurship
BI Norwegian Business School
Nydalsveien 37
0484 Oslo, Norway
E-mail: linda.rademaker@bi.no

April 10, 2022

Please do not circulate or cite without authors' permission.

Acknowledgments: We would like to thank J.P. Eggers, Torben Pedersen, Uriel Stettner, and Pengfei Wang for their feedback. We are also grateful for the comments received from seminar participants at Bocconi University and BI Norway and from participants of the 2021 Annual Meeting of the Academy of Management. We appreciate the research assistance of Nathan Bucolo, Arianna Crutto, and Viviana Fortunato. Dovev Lavie acknowledges his fellowship with the Invernizzi Center for Innovation, Organization, Strategy and Entrepreneurship (ICRIOS) and the Bocconi University Senior Researcher grant. Linda Rademaker acknowledges the BI Norwegian Business School research grant.

DOES THE PREDATOR BECOME THE PREY? KNOWLEDGE SPILLOVER AND THE LEARNING OF KNOWLEDGE PROTECTION IN ALLIANCES

ABSTRACT

Does a firm that successfully absorbs knowledge from its partner learn to protect its own knowledge in a subsequent alliance? Our analysis of 529 alliances of East Asian firms during 1999–2015 suggests that as firms more skillfully overcome their partners' knowledge protection, they learn to better protect their own knowledge in subsequent alliances, but such vicarious learning increases at a diminishing rate. This learning is further reinforced when the appropriability regime in the previous partner's country is stronger than that in the firm's country and when the firm's business similarity with its previous partner is greater than with its subsequent partner. In turn, this learning is weakened by increased value chain scope and the firm's relative absorptive capacity in its previous alliance.

INTRODUCTION

Interfirm alliances enable firms to combine complementary assets and realize synergies (Dyer & Singh, 1998) while accessing each other's knowledge (Gomes-Casseres, Hagedoorn, & Jaffe, 2006; Hamel, 1991; Mowery, Oxley, & Silverman, 1996). The spillover of content knowledge to partners in alliances is a primary concern to managers who seek to protect their firms' knowledge from imitation that can diminish the firm's appropriated value in alliances (Lavie, 2006; Shih & Wang, 2013). Therefore, some alliances feature a competitive learning dynamic whereby each party seeks to gain private benefits by absorbing the other's knowledge, while shielding its own knowledge from spilling over to the partner (Khanna, Nohria, & Gulati, 1998; Larsson, Bengtsson, Henriksson, & Sparks, 1998; Yang, Zheng, & Zaheer, 2015). Early work has alluded to firms' predatory learning practices that enable them to "out-learn" their partners (e.g., Hamel, 1991; Hamel, Doz, & Prahalad, 1989), with more recent work acknowledging protective practices that shield proprietary knowledge from spilling over to partners (Diestre & Rajagopalan, 2012; Hallen, Katila, & Rosenberger, 2014; Katila, Rosenberger, & Eisenhardt, 2008). By devising suitable governance structures (Devarakonda & Reuer, 2018; Oxley & Sampson, 2004) and nurturing embedded relationships with their partners (Dyer & Nobeoka, 2000; Kale, Singh, & Perlmutter, 2000), firms attempt to protect their own knowledge while absorbing their partners' knowledge (Contractor, 2019; Monteiro, Mol, & Birkinshaw, 2017; Wadhwa, Bodas Freitas, & Sarkar, 2017). Despite research on the interplay between knowledge absorption and protection in a given alliance, we know little about the extent to which a firm learns practices for absorbing or protecting knowledge in one alliance and subsequently applies the learned practices in other alliances.

We ask: can a firm that has learned to overcome its partners' knowledge protection and absorb their knowledge reverse roles[1] and effectively protect its own proprietary knowledge, thus limiting knowledge spillover to partners in subsequent alliances? Answering this question can shed light on the prospects of managing competitive learning dynamics in knowledge-driven industries (Duysters & de Man, 2003). Prior research has examined how experience in one governance mode can foster or inhibit learning in another mode, such as across alliances and acquisitions (Castellaneta, Valentini, & Zollo, 2018; Haleblian & Finkelstein, 1999; Heimeriks, 2010; Meschi & Métais, 2013; Porrini, 2004; Zollo, 2009).[2] In turn, we draw upon research on vicarious learning, which explains how firms observe and imitate others (Haunschild, 1993; Haveman, 1993; Huber, 1991). Whereas this research has centered on learning and applying the same activity, we study how engaging in one activity, i.e., knowledge absorption, affects the ability to vicariously learn and apply another activity, i.e., knowledge protection.

Extending this research, we consider how a firm's experience in absorbing its partners' knowledge exposes it to these partners' knowledge protection practices (e.g., tools, procedures, contracts), and how this, in turn, enables the firm to learn vicariously how to develop its own protection practices and restrict knowledge spillover to a partner in a subsequent alliance. We then explain how, beyond a certain threshold of absorbed knowledge, further absorption does not contribute to the firm's efforts to develop knowledge protection practices in subsequent alliances. Accordingly, we conjecture that a firm's ability to protect its knowledge in a subsequent alliance

---

[1] "Role reversal" is defined here as the case of a firm that had focused on absorbing its partners' knowledge in previous alliances and then, once it has developed its proprietary knowledge, shifts its attention to protecting that knowledge from spilling over to its partners in subsequent alliances. This does not mean that the firm did not protect its knowledge in the previous alliances or ceased to absorb knowledge from partners in subsequent alliances.

[2] For example, Agarwal, Anand, Bercovitz, and Croson (2012) studied how collaborative routines learned in an alliance facilitate collaboration when the firm acquires its partner, while Zollo and Reuer (2010) revealed that alliance experience is beneficial only for acquisitions which echo characteristics of the alliance context. Still, this research concerns the same parties applying a practice across distinct governance modes rather than applying the practice with different parties in the same mode. Although some studies have examined experience transfer across modes with similar aims (Bingham, Heimeriks, Schijven, & Gates, 2015; Villalonga & McGahan, 2005; Zollo & Reuer, 2010), these studies do not shed light on whether gaining experience with one activity provides insights into its counter activity (e.g., knowledge protection versus knowledge absorption) in subsequent instances of the same mode.

increases at a diminishing rate with its absorption of its previous partners' knowledge. The rationale is that stronger expertise in knowledge absorption enables the firm to develop refined and complex practices for knowledge protection, yet the development of protection practices becomes limited as the firm encounters more intricate protection practices and exhausts learning opportunities, while its specialization in knowledge absorption limits attention to knowledge protection.

Finally, we examine boundary conditions common to the literature on learning in alliances (e.g., Inkpen & Tsang, 2007) that collectively influence the *motivation*, *ability*, and *opportunities* of the firm to absorb its partners' knowledge (Argote, McEvily, & Reagans, 2003) and thus affect its development of protection practices. Specifically, we suggest that the extent to which expertise in knowledge absorption restricts knowledge spillover is constrained by the value chain scope and the firm's relative absorptive capacity in its previous alliances. We further expect the effect of knowledge absorption to be reinforced by the strength of the appropriability regime in the previous partners' countries relative to that in the firm's country, and by the business similarity between the firm and its previous partners compared to that with its current partner.

We test our hypotheses with a sample of 529 alliances formed during 1999–2015 by 87 East Asian firms that operate in knowledge-intensive industries. These firms have traditionally absorbed knowledge from Western multinational enterprises (Liu & Buck, 2007; Zhang, Li, Li, & Zhou, 2010) but have since developed proprietary knowledge (Huang & Li, 2019; Mathews, 2006). Our focus on this context ensures that firms seek to safeguard their knowledge assets from spilling over to their partners and rely on effective protection practices. We use patent citation data to proxy for knowledge flows in pairs of previous and subsequent alliances, finding support for our hypotheses.

Our study contributes to research on learning in alliances. By studying how absorbing knowledge from a partner affects a firm's ability to protect its proprietary knowledge from spilling over to a partner in a subsequent alliance, we go beyond research on the interplay of knowledge absorption and protection within a given alliance (e.g., Devarakonda & Reuer, 2018; Kale et al., 2000; Oxley & Sampson, 2004; Oxley & Wada, 2009). We also shift focus from firms' absorption of their partners' content knowledge (e.g., Gomes-Casseres et al., 2006; Mowery et al., 1996; Rosenkopf & Almeida, 2003) to studying the implications of learning partners' practices. We contend that learning a protection practice improves a firm's ability to develop and apply that practice when the "student" reverses its role to a "teacher" in subsequent alliances. Our study further suggests, perhaps counter intuitively, that the more effort a firm invests to overcome its partners' knowledge protection, the more likely that firm is to vicariously learn and successfully apply protection practices in subsequent alliances. Hence, we contribute to the learning literature by showing how firms effectively learn to protect knowledge when reversing roles in alliances. These valuable insights can help managers leverage the experience gained in previous alliances to excel in protecting their knowledge in subsequent alliances.

THEORY AND HYPOTHESES

Alliances enable firms to absorb knowledge from partners (Hamel, 1991; Inkpen & Tsang, 2007) and subsequently apply it independently for private gains (e.g., Mowery et al., 1996; Vasudeva & Anand, 2011; Yang et al., 2015). Knowledge absorption refers to the process by which a firm identifies its partner's valuable knowledge and internalizes it for commercial use in its own inventions (Lane & Lubatkin, 1998). Besides absorbing content knowledge (know-what), a firm can learn the partner's procedural behavior and practices (know-how) during their alliance. Research on vicarious learning explains how a firm observes its partner and subsequently imitates practices that it perceives as desirable or effective (Duysters, Lavie, Sabidussi, & Stettner, 2020; Howard, Steensma, Lyles, & Dhanaraj, 2016; Huber, 1991; Tsang, 2002). However, knowledge protection and knowledge absorption counter each other because the extent to which a partner's knowledge is accessible is inversely related to the strength of the partner's knowledge protection (Larsson et al., 1998; Simonin, 2004). In turn, knowledge protection can restrict knowledge exchange with partners (Arslan, 2018; Kale et al., 2000; Wadhwa et al., 2017) and limit its absorption (Liebeskind, 1996; Oxley & Sampson, 2004). Nevertheless, we claim that by managing to absorb its partner's knowledge, the firm vicariously learns about the partner's knowledge protection practices, which enhances the firm's ability to protect its own knowledge and restrict spillover to partners in subsequent alliances.[3] Knowledge absorption and protection are distinct yet interdependent, so engaging in one activity affects the ability to learn and apply the other.

Knowledge absorption and protection across alliances

Knowledge absorption and protection involve different practices. For example, knowledge absorption involves practices such as reverse-engineering, hacking, and codifying information, whereas knowledge protection practices relate to secrecy, contractual safeguards, use of network firewalls, process fragmenting, and strategic staffing of employees (Contractor, 2019; Liebeskind, 1996; 1997; Palomeras & Wehrheim, 2020; Zhao, 2006). Because of these differences, engaging in knowledge absorption may not necessarily assist in developing protection practices. Furthermore, preexisting structures and schemata that favor allocating attention to familiar activities may restrict the learning of new activities (Ocasio, 1997), which can constrain the firm's ability to develop practices for knowledge protection.

Notwithstanding the above, the firm's absorption of its partner's knowledge suggests that it has managed to familiarize itself with that partner's knowledge protection practices and overcome them. Partners seek to conceal their valuable knowledge when interacting with the firm during their

[3] We do not contend that the alliance was formed with the intent to absorb the partner's knowledge or to learn its knowledge protection practices. Although we do not exclude this possibility, alliances are formed for various reasons other than learning. Still, learning and knowledge spillover often occur as a byproduct of alliances (Lavie, 2006).

alliances, but by protecting this knowledge they reveal to the firm their knowledge protection practices, e.g., use of non-disclosure agreements and firewalls. In this process, the firm can vicariously learn how to implement such practices and restrict spillover of its own knowledge in a subsequent alliance. The underlying logic is that as a firm makes an effort to successfully overcome its partner's knowledge protection and absorbs the partner's knowledge, it gains exposure to the partner's knowledge protection practices and develops insights into their inner workings. This enables the firm to vicariously learn how to protect its own knowledge. As the firm's understanding of the partner's protection practices becomes sufficiently profound to neutralize them, the firm learns to devise and implement similar practices in its subsequent alliances. In fact, when the firm manages to overcome its partner's knowledge protection, it must have identified the strengths and vulnerabilities of the partner's practices. Accordingly, it can avoid imitating vulnerable practices, remediate their vulnerabilities, or instead apply observed practices that are more effective and that can enhance the effectiveness of its own knowledge protection.[4] Moreover, it can further refine and perfect the practices that it has adopted. Hence, as the firm becomes competent at neutralizing protection practices and absorbs knowledge from its partners, it learns to apply similar or improved practices to protect its own knowledge from spilling over to a partner in a subsequent alliance. If the firm experiences substantial outbound spillover of its knowledge to a partner in such an alliance, this implies that it failed to successfully implement the learned knowledge protection practices. Accordingly, we expect a positive association between the ability to absorb a previous partner's knowledge and the prevention of knowledge spillover to a partner in a subsequent alliance. Yet, as we argue next, the ability to protect knowledge increases at a diminishing rate with the extent to which the firm absorbed the previous partner's knowledge.

[4] If a firm did not manage to overcome its partner's protection, this implies that it could only gain limited insights into the practice's inner workings, which makes it more difficult to successfully imitate and improve upon that practice.

First, a firm that is less proficient in knowledge absorption can overcome only basic protection practices of its partner, such as secrecy and contract design, that are relatively generic and thus easy to learn. To the extent that the firm is unfamiliar with these practices, exposure to them can greatly improve its ability to prevent knowledge spillover in a subsequent alliance. However, if the firm has already learned these easy-to-implement protection practices from its partner, it is likely to encounter its more intricate means of protection. Such practices may be organizationally embedded, complex, and causally ambiguous, which makes them difficult to comprehend and implement (Dierickx & Cool, 1989; Simonin, 1999; Szulanski, 1996). Examples include process fragmentation and the strategic allocation of personnel, which may entail modifying the firm's current routines. Thus, the more proficient the firm becomes at absorbing a partner's knowledge, the smaller the resulting improvement of its protection practices.

Second, the firm's capacity to overcome increasingly sophisticated means of knowledge protection provides it with further insights into such practices, and it becomes better at discerning effective means of protection. However, as the firm implements these practices and gains first-hand experience with them, further knowledge absorption and exposure to protection practices would provide only limited new insights. Similarly, as the firm continues to identify vulnerabilities in its partner's protection practices, it is less likely to encounter new critical vulnerabilities that it has not already identified, so it learns less about how to improve its own knowledge protection.

Finally, a firm that becomes proficient in overcoming and neutralizing its partner's knowledge protection practices may find it more difficult to adopt a protective mindset in a subsequent alliance. Its routine application of knowledge absorption routines prompts a myopic mindset (Leonard-Barton, 1992), so the more specialized the firm becomes in absorbing knowledge, the greater the perceived tension with its knowledge protection efforts. Resolving this tension requires the firm to acknowledge its transition to a protective role (Argyris & Schön, 1978), which becomes more challenging with the accumulated knowledge absorbed from its partner.

Consequently, despite the need to protect its proprietary knowledge in a subsequent alliance, beyond a certain threshold of knowledge absorbed from a partner in a previous alliance, the firm's ability to vicariously learn that partner's knowledge protection practices and to implement them in the subsequent alliance improves only marginally. Hence, knowledge spillover to a partner in a subsequent alliance is expected to decrease at a diminishing rate with the knowledge that the firm absorbed from its previous partner (exhibiting an L-shaped association as shown in Figure 1).

Hypothesis 1: *Knowledge spillover from a firm to a partner in a subsequent alliance will decrease at a diminishing rate with the firm's absorption of knowledge from a partner in a previous alliance.*

************* Insert Figure 1 here *************

Boundary conditions for the association between knowledge absorption and protection

The firm's absorption of a previous partner's content knowledge enhances its practices for protecting its own knowledge, thus reducing knowledge spillover in a subsequent alliance. This assumes, however, that the firm indeed managed to overcome the knowledge protection practices of its partner. In this process, the more challenging these practices were to overcome, the more the firm has learned about knowledge protection. Yet this depends on the firm's *motivation*, *ability*, and *opportunities* to absorb its partner's content knowledge (Argote et al., 2003). We next examine some commonly studied conditions in the literature on learning in alliances (e.g., Inkpen & Tsang, 2007): (a) the value chain scope of the firm's alliances, (b) the relative strength of the appropriability regimes in the parties' home countries, (c) the business similarity between the firm and its previous and subsequent partners, and (d) the firm's relative absorptive capacity. We argue that these conditions influence the motivation, ability, and opportunities to absorb the previous partner's content knowledge (i.e., the partner's inventions), and hence the firm's effort to overcome this partner's knowledge protection, which in turn affects its vicarious learning of protection practices. Thus, each condition moderates the negative effect of absorbed knowledge in the previous alliance on knowledge spillover in the subsequent alliance. Our underlying logic is that the more effort a firm needs to invest in successfully managing to overcome its previous partner's protection practices and hence access its content knowledge, the more likely the firm to vicariously learn these practices and successfully incorporate and improve upon them in a subsequent alliance.

Consider how the value chain scope of the alliance affects the firm's *opportunities* to absorb its previous partner's content knowledge: the more activities the firm and its partner engage in, the more channels are available for transferring knowledge between them (Lioukas & Reuer, 2020; Oxley & Sampson, 2004). Greater alliance scope increases the number of employees that engage with the partner and their interactions in joint activities. Hence, the alliance's scope increases the potential volume and variety of knowledge flows from the partner, and thus the opportunities to absorb the partner's content knowledge (Oxley & Sampson, 2004; Palomeras & Wehrheim, 2020). As the scope of value chain activities in an alliance increases, the partner's gatekeepers face challenges in regulating knowledge flows in the exchange with the firm (Baughn, Denekamp, Stevens, & Osborn, 1997). For example, when the firm fails to access the partner's knowledge in their joint R&D activities, it has alternative opportunities to absorb that knowledge through other channels, such as their joint marketing activities in which technical documents, training material, and sensitive product information may be shared. This increases the likelihood of overcoming the partner's knowledge protection incidentally. The firm may rely on trial-and-error to overcome the partner's protection practices using the multiple opportunities to access the partner's knowledge, and there is a greater chance that the partner will inadvertently reveal some proprietary knowledge to the firm in their alliance (Oxley & Sampson, 2004). By contrast, when the value chain scope of the alliance is narrow, the alliance offers limited opportunities to interact with the partner, which strengthens the partner's knowledge protection (Baughn et al., 1997). Given the challenge of overcoming this protection, the firm must invest greater effort to neutralize it.

Consequently, as the value chain scope of the alliance increases, less effort is needed to overcome the partner's knowledge protection practices, which limits opportunities for the firm to learn these practices. This undermines the firm's ability to adopt and deploy these practices when seeking to protect its own knowledge in a subsequent alliance. Thus, the firm's improved ability to restrict knowledge spillover in a subsequent alliance is constrained by the value chain scope of the previous alliance. This, in turn, attenuates the negative association between the absorption of knowledge from a previous partner and knowledge spillover to a partner in a subsequent alliance.

Hypothesis 2: *The negative association between a firm's knowledge absorption from a previous alliance partner and knowledge spillover from the firm to a partner in a subsequent alliance will become weaker with an increasing scope of value chain activities in the previous alliance.*

Next, the appropriability regimes in the parties' home countries affect both the *opportunities* and *motivation* of the firm to absorb its partner's content knowledge. The appropriability regime defines the extent to which legal protection for the proprietary knowledge is furnished by the institutional system in a country (Cohen, Goto, Nagata, Nelson, & Walsh, 2002). The strength of this regime indicates the degree to which a knowledge owner can appropriate the value of inventions using its knowledge (Levin, Klevorick, Nelson, & Winter, 1987; Teece, 1986).

A firm that operates under a weaker appropriability regime relative to that of its alliance partner has a greater incentive to absorb its partner's knowledge. This is because such a firm can benefit more from the partner's knowledge given that a violation of the partner's intellectual property rights is less likely to be penalized under the weaker appropriability regime in the firm's home country (Liebeskind, 1997). Anticipating the greater hazard of knowledge misappropriation by the firm, the partner is likely to deploy more advanced practices for knowledge protection to fend off the firm's attempts to absorb its knowledge (Dickson, Weaver, & Hoy, 2006; Oxley, 1999; Zahra & George, 2002). As a result, there will be fewer opportunities for the firm to absorb the partner's knowledge in the course of their alliance, and the firm would need to exert greater effort to overcome its partner's knowledge protection. In making such an effort, the firm is likely to gain a more profound understanding of its partner's protection practices. This, in turn, would enable the firm to use the learned insights to improve its own knowledge protection in a subsequent alliance, which can further restrict knowledge spillover to the partner in such an alliance.

Therefore, the firm's ability to restrict knowledge spillover in a subsequent alliance improves with the effectiveness of absorbing a previous partner's knowledge, with this ability becoming stronger when the appropriability regime in the firm's home country is weaker than the regime in the previous partner's home country.

Hypothesis 3: *The negative association between a firm's knowledge absorption from a previous alliance partner and knowledge spillover from the firm to a partner in a subsequent alliance will become stronger when the appropriability regime in the firm's home country is weaker than the appropriability regime in the previous partner's home country.*

The firm's *motivation* to absorb its partner's content knowledge is also influenced by the similarity between their businesses (Hamel, 1991; Yang et al., 2015). Such similarity increases the competitive tension between them, which facilitates conflict, opportunistic behavior, and misappropriation of knowledge (Baum, Calabrese, & Silverman, 2000; Cui, Yang, & Vertinsky, 2018). Business similarity makes it likely that the alliance generates competitive learning dynamics in which the parties strive to absorb each other's knowledge (Hamel, 1991; Khanna et al., 1998).

The competitive tension arising from business similarity with the partner incentivizes the firm to absorb its partner's knowledge. This knowledge helps the firm anticipate the partner's innovations and respond by developing substitute products that compete with those of the partner (Cui et al., 2018). To prevent this scenario, the partner is likely to invest more in protecting its proprietary knowledge (Oxley & Sampson, 2004). The competitive tension also motivates the firm to be more tenacious in its attempts to overcome the partner's knowledge protection, and thus learn its protection practices. This increases the firm's exposure to its partner's protection practices, so that it can vicariously learn how to protect its own knowledge in a subsequent alliance. Finally, the greater the firm's business similarity to—and hence competitive tension with—the partner, the greater the firm's incentive to protect its own knowledge from the partner, which directs the firm's attention to knowledge protection (Ocasio, 1997). Hence, the firm is expected to increase its receptivity when learning the partner's knowledge protection practices and gain more insights into these practices, which it can then codify and apply in its subsequent alliance.

In the same vein, when a firm's business similarity with a subsequent partner is weaker than with the previous partner, the lessened competitive tension in the subsequent alliance may prompt the new partner to be less aggressive in absorbing the firm's knowledge compared with the previous partner's efforts. Accordingly, in the subsequent alliance, the firm and its partner are likely to adopt a more cooperative approach rather than attempt to "out-learn" one another (Khanna et al., 1998; Yang et al., 2015). This enables the firm to more effectively protect its knowledge by leveraging the protection practices it has learned in its previous alliance. Such protection practices should be sufficient to defend against knowledge spillover to the subsequent partner given the partner's weaker motivation to absorb the firm's knowledge. Therefore, when the business similarity in a previous alliance is greater than in the subsequent alliance, the firm's protection practices learned in the previous alliance become more effective. This enhances the firm's ability to prevent knowledge spillover to a partner in a subsequent alliance. Overall, this reinforces the negative association between the effectiveness with which the firm absorbs knowledge from a previous partner and knowledge spillover to a partner in a subsequent alliance.

Hypothesis 4: *The negative association between a firm's knowledge absorption from a previous alliance partner and knowledge spillover from the firm to a partner in a subsequent alliance will become stronger when the business similarity between the firm and its partner in the previous alliance is greater than that between the firm and its partner in the subsequent alliance.*

Finally, the firm's *ability* to absorb a partner's content knowledge also depends on its accumulated experience in the partner's knowledge domain, i.e., its relative absorptive capacity (Lane & Lubatkin, 1998). The greater the similarity between the firm's and its partner's knowledge bases, the better the firm's ability to absorb its partner's knowledge (Mowery et al., 1996; Vasudeva & Anand, 2011). A strong relative absorptive capacity enables the firm to assess, internalize, and use the knowledge absorbed from the partner in its own inventions (Lane & Lubatkin, 1998). Hence, as this capacity improves, it becomes easier for the firm to comprehend the partner's knowledge and overcome its knowledge protection practices because of its enhanced familiarity with the content, utility, and value of the partner's knowledge (Devarakonda & Reuer, 2018). Consequently, the firm can more easily bypass the partner's knowledge protection and absorb its knowledge. An example is the case of co-located employees that interface with the partner, and thus can informally exchange information with the partner's personnel (Oxley & Wada, 2009; Palomeras & Wehrheim, 2020; Sampson, 2007). Such brief exposure can suffice to absorb the partner's knowledge when the firm enjoys a strong relative absorptive capacity that enables it to effectively interpret limited information. Thus, relative absorptive capacity reduces the effort that the firm needs to invest in overcoming its partner's knowledge protection.

By contrast, if the firm's relative absorptive capacity is weak, occasional exposure to the partner's knowledge may be insufficient for overcoming the partner's protection and absorbing its knowledge. The firm would need to study the protection practices more thoroughly, and as a result of this effort it is likely to gain in-depth understanding of the partner's protection practices. This increases the likelihood that the firm vicariously learns these practices and successfully implements them in a subsequent alliance, which further restricts knowledge spillover to a partner in a subsequent alliance. It follows that a strong relative absorptive capacity constrains vicarious learning of the previous partner's knowledge protection practices, so that the firm gains limited insight into how to develop and implement these practices in a subsequent alliance. Hence, although the firm's ability to restrict knowledge spillover to a partner in a subsequent alliance improves with the absorption of knowledge from a partner in a previous alliance, the decline in knowledge spillover is attenuated by the firm's relative absorptive capacity in the previous alliance.

Hypothesis 5: *The negative association between a firm's knowledge absorption from a previous alliance partner and knowledge spillover from the firm to a partner in a subsequent alliance will become weaker with an increase in the firm's relative absorptive capacity in the previous alliance.*

METHODS

Sample and Data

We test our theory with a sample of alliances formed by publicly listed firms headquartered in China, Singapore, South Korea, or Taiwan, which reversed roles from absorption to protection of knowledge at the turn of the 21st century (e.g., Huang & Li, 2019; Mathews, 2006). We sampled dyadic alliances, which, unlike multiparty consortia, often feature competitive learning dynamics (Khanna et al., 1998; Larsson et al., 1998). We rely on SDC Platinum to trace such firms that formed at least two dyadic alliances between 1999 and 2015 with publicly listed partners originating mostly from North America, Europe, or Japan. During this period, Western and Japanese partners were at risk of involuntary knowledge spillover when allying with East Asian firms, and thus relied on advanced knowledge protection practices (Contractor, 2019). As an executive noted: "When I moved to China from the U.S.A., I never imagined that I would have to include IP protection management in almost all of our business processes. I think about the issue actively every day" (Schotter & Teagarden, 2014: 42). We obtained patent data via Orbis Intellectual Property, firm data from Compustat and Orbis, executive data from BoardEx, and country data from the CEPII, the Heritage Foundation, the Hofstede Institute, and the World Bank.

We focus on industries in which at least 20 percent of the publicly listed firms were issued patents, with a minimum of three firms per industry (SICs 36, 35, 28, 37, 48, 29, 33, and 73). In these industries, knowledge is considered the most valuable asset, so firms use patents as a means for knowledge appropriation (Cohen, Nelson, & Walsh, 2000). We require that the sampled firms and their partners applied for, on average, at least four patents per year during the study's timeframe (Duysters et al., 2020) with the USPTO, EPO, or JPO. The final sample included 435 firms: 87 focal firms from Taiwan (50.58%), South Korea (34.48%), China (11.50%), and Singapore (3.45%), and their 381 partners from various countries, of which 33 also serve as focal firms.

The East Asian focal firms and their partners had formed 529 dyadic alliances during 1999–2015.[5] These alliances encompass various value chain activities: R&D, licensing, manufacturing, marketing, OEM, and supply. Hence, besides upstream alliances, East Asian firms relied on downstream alliances to absorb their partners' knowledge. For instance, China's Haier Group relied on various manufacturing, OEM, and supply alliances with Western partners to catch up and build its proprietary knowledge base (Duysters, Jacob, Lemmens, & Jintian, 2009).

To analyze how knowledge absorption in a previous alliance affects knowledge spillover in a subsequent alliance, we structure our data in pairs of previous and subsequent alliances. In the previous alliance we examine how a firm absorbs knowledge from its partner, while in the subsequent alliance, we examine how the firm manages to protect its knowledge from spilling over to its partner.[6] We consider an alliance to be subsequent if it was announced between one to ten years after the launch of a previous alliance.[7] Because different alliances expose the firm to

[5] SDC lists 12,684 dyadic alliances during 1999–2015 in which at least one party originates from China, Singapore, South Korea, or Taiwan. In 2,102 of these alliances both parties were publicly listed, and out of these, 1,530 alliances were formed by 436 East Asian firms that had at least two successive alliances. 273 of those East Asian firms were active in our sampled industries and had formed 1,191 alliances with publicly listed partners. After dropping firms with fewer than four patents per year and those with missing data, 529 alliances formed by 87 East Asian firms remain.
[6] In most alliances learning is bi-directional. In ancillary analyses we account for the firm's knowledge spillover in the previous alliance and its knowledge absorption in the subsequent alliance, with no change to our reported findings.
[7] Because most firms do not announce alliance termination (Schilling, 2009), we assume a five-year alliance duration (e.g., Duysters et al., 2020; Gulati, 1995; Robinson & Stuart, 2007). If the subsequent alliance was formed less than a

different protection practices, and since the firm's learning varies from one previous partner to another, we study pairs of the firm's previous and subsequent alliances. Considering pairs of a previous alliance and a subsequent alliance enables us to distinguish the firm's vicarious learning of a particular partner's protection practices from the potentially confounding effect of the firm's accumulated alliance experience. Hence, if a firm had formed four successive alliances A, B, C, D, and these alliances were separated by at least one year and at most ten years, we generate six pairs of alliances: A–B, A–C, A–D, B–C, B–D, and C–D. Accordingly, we obtain 3,408 pairs of previous and subsequent alliances, with such pairs serving as our unit of analysis.

We use patent citation data to model flows of proprietary knowledge between firms and their partners (e.g., Gomes-Casseres et al., 2006; Mowery et al., 1996; Rosenkopf & Almeida, 2003). Despite their limitations, patent citations can proxy for knowledge flows among firms (Corsino, Mariani, & Torrisi, 2019; Duguet & MacGarvie, 2005; Jaffe, Trajtenberg, & Fogarty, 2000) even if these flows are unintended (Corsino et al., 2019). Because applying for a patent requires disclosing the essence of the invention even though the patent may not be granted, firms typically rely on complementary safeguards to protect their knowledge (Contractor, 2019). Moreover, although patent filings are widely accessible, incorporating the underlying knowledge embedded in a partner's patent and recombining it with other knowledge elements is nontrivial and entails profound understanding of that knowledge (de Rassenfosse, Palangkaraya, & Webster, 2016). Hence, the citing of a partner's patent indicates a broader flow of knowledge wherein the firm's inventors learned the content of that patent's underlying knowledge and figured out how to ingeniously apply that knowledge in the firm's invention (Yang, Phelps, & Steensma, 2010). Thus,

year following a previous alliance, the firm is unlikely to have learned to apply the protection practices. However, because knowledge is subject to memory decay (Darr, Argote, & Epple, 1995; Martin de Holan & Phillips, 2004), learned practices may become less relevant after a decade. In auxiliary analyses, we consider alternative time windows.

citations to an alliance partner's patents that aim to exploit its underlying knowledge for the firm's private gain indicates a spillover which the partner seeks to avoid (Devarakonda & Reuer, 2018), despite other, more favorable implications for the partner (Hall, Jaffe, & Trajtenberg, 2005).

We rely on patent applications, assuming that the first date of filing a patent application (priority date) represents the time of invention. We account for patent applications filed by subsidiaries, assuming that their parent firm can access their knowledge (Mowery et al., 1996).[8] To account for changes in ownership, we consider acquisitions of subsidiaries, assuming that their knowledge is accessible to the parent following the acquisition (Puranam & Srikanth, 2007).

We consolidate citing patents at the patent family level, accounting for all the patents that cover the same invention (OECD, 2009).[9] We then identify unique citations in patents applied for by each firm, aggregating them at the patent-family level to avoid double counting citations. Table 1 exhibits the number of patent applications since the earliest applications in 1899 and until 2020.

************* Insert Table 1 here *************

Variables

Knowledge Spillover in a Subsequent Alliance (dependent variable). The extent of knowledge spillover from a firm to its partner in a subsequent alliance is captured by a count of the subsequent partner's backward citations to the firm's patents within five years following the alliance announcement (Gomes-Casseres et al., 2006). Because citations to older patents are less likely to reflect knowledge spillover (Caballero & Jaffe, 1993; Jaffe & Trajtenberg, 1999), we apply an annual discount rate of r = 10%, weighting each citation by a discount factor of $(1-r)^t$ (Duysters

[8] We obtained data on subsidiaries from Orbis and LexisNexis Corporate Affiliations, with data on acquisitions obtained from Zephyr and SDC Platinum. We identified 4,779 acquisitions involving 395 acquirers and 198 divesting firms and their 4,663 target entities. The final dataset includes patents of the 435 firms and their 19,562 subsidiaries.
[9] The patent offices with which the citing patents were filed—the USPTO, JPO, and EPO—are all globally relevant and follow similar standards (OECD, 2009). Hence, their patent citations are considered equally valuable. The pool of citable patents includes all patent offices worldwide (Gomes-Casseres et al., 2006).

et al., 2020; Stettner & Lavie, 2014), where t is the difference in years between the priority date of the citing patent and that of the cited patent. To avoid the possibility that the citations reflect joint inventions that the firm and its partner jointly developed in the course of their alliance, we excluded the parties' patent co-applications from the pools of cited and citing patents.

Knowledge Absorbed in a Previous Alliance (independent variable). The knowledge absorbed from a partner in a previous alliance is measured as the number of backward citations by the firm's patent applications to the previous partner's patents during the five years following the alliance announcement. As with the dependent variable, we apply a 10% annual discount rate and exclude the parties patent co-applications.

Scope of a Previous Alliance (moderator). We measure the scope of a previous alliance with the number of value chain activities covered by that alliance, standardized by the total number of possible activity types—licensing, manufacturing, marketing, OEM, R&D, and supply agreements—as indicated in the SDC database (Lavie, 2007). Scores range between 1/6 and 1, with a higher value indicating a broader value chain scope of the previous alliance.

Difference in Appropriability Regimes in a Previous Alliance (moderator). We measure the strength of the appropriability regime in the home countries of the firm and its partner in the previous alliance using the Heritage Foundation's Property Rights Index (e.g., Claessens & Laeven, 2003; Johnson, Kaufman, & Zoido-Lobaton, 1998). This index indicates the quality of laws protecting intellectual property rights and the efficiency of the enforcing judicial institutions. To calculate the difference in strengths of the appropriability regimes, we subtract the value of this index in the firm's country from its value in the partner's country at the time their alliance was announced. A positive difference suggests a weaker regime in the firm's country.

Difference in Business Similarity between Previous and Subsequent Alliances (moderator). The similarity between the firm's and its partner's businesses is measured as the overlap in their four-digit primary SIC codes (Haleblian & Finkelstein, 1999; Oxley & Sampson, 2004; Villalonga & McGahan, 2005), coded as 0 if the parties' SICs have no common digits, 0.25 for a first-digit match, 0.5 for a two-digit match, 0.75 for a three-digit match, and 1 for a four-digit match. We calculate the difference in business similarities of the firm and its partner in the previous versus subsequent alliances by subtracting the value in the subsequent alliance from that in the previous alliance. A positive difference indicates greater business similarity in the previous alliance.

Relative Absorptive Capacity in a Previous Alliance (moderator). Following prior research (e.g., Oxley & Sampson, 2004; Sampson, 2007; Vasudeva & Anand, 2011), we measure a firm's relative absorptive capacity as the technological overlap between the firm and its partner in the previous alliance. We compute this overlap using the cosine index of the vectorized frequency distributions of the firm's and its partner's patent applications across patent classes (Jaffe, 1986). We define the patent class at the subclass level of the International Patent Classification (IPC) (e.g., Palomeras & Wehrheim, 2020; Rosenkopf & Nerkar, 2001) and consider all patents applied for starting ten years prior to the formation of the alliance and ending five years after that (Devarakonda & Reuer, 2018). The distribution of patent applications across patent subclasses is captured by $F_i = (f_i^1 \dots f_i^k)$ for firm i and partner j in subclasses 1 to k. The extent of technological overlap is $S_{ij} = (F_i F_j')/[(F_i F_i')(F_j F_j')]^{1/2}$, where F_i' is the transpose of vector F_i. Scores range from 0 to 1, with higher values of this measure indicating greater relative absorptive capacity.

Control Variables

Our moderators served also as control variables in addition to their equivalents in the subsequent alliance. In addition, we control for characteristics of the firm, its partners, the previous and subsequent alliances, and pairs of previous and subsequent alliances. Firm and partner controls include their age, size, R&D intensity,[10] and partnering experience at the time of announcing the previous and subsequent alliances. Mature firms (*Age*) typically accumulate broader knowledge (Cohen & Levinthal, 1990; Zahra & George, 2002). *Siz*e, measured as total assets, indicates the resources available to support innovation (Hagedoorn & Schakenraad, 1994). *R&D intensity*, calculated as R&D expenses divided by revenue, indicates the investment in internal knowledge development. The measures of firm age, size, and R&D intensity rely on a moving average over the five years following the alliance announcement. In addition, we control for the firm's general partnering experience (*GPE*) at the time of the previous alliance, which relates to nurturing alliance management and knowledge protection practices (Gulati et al., 2009). GPE is measured using a decay function over a decade prior to the alliance announcement: $E_i = \sum_{t=0}^{S} x_t(1-r)^t$, where x_t is the number of alliances announced at year t, t = 0 the year preceding the alliance announcement, and r a decay rate of 10% (Duysters et al., 2020; Stettner & Lavie, 2014). Using similar measures, we control for the previous and subsequent partners' GPE, and for *Intermediate firm GPE* between the previous and subsequent alliances.

In addition, we control for the characteristics of the firm and its partners in the previous and subsequent alliances. We account for the patenting experience and backward citations of the absorbing party and for the scientific impact captured by forward citations of the protecting party in the previous and subsequent alliances. We also control for how frequently the absorbing party cited the protecting party prior to their alliance, and for the number of patents purchased by the absorbing party from the protecting party during their alliance. A firm's *patenting experience* indicates its overall absorptive capacity (Corredoira & Rosenkopf, 2010) and relates to the ability of the absorbing party to appropriate the knowledge of its partners (Cohen et al., 2000; Levin et al.,

[10] We exclude the partners' R&D intensity because we encountered 15.82% missing values for their R&D expenses.

1987). Patenting experience is measured by the number of patent applications in the decade prior to the alliance announcement, assuming a 10% annual decay rate (Duysters et al., 2020). The *total backward citations* of the absorbing party counts the number of citations in its patent applications during the five years following the alliance announcement. It controls for the likelihood that the absorbing party cites the patents of the protecting party irrespective of their alliance (Gomes-Casseres et al., 2006). The *scientific impact* measures the average forward citations per patent in the patent applications of the protecting party during the five years following the alliance announcement. It controls for how commonly the patents of the protecting party are cited because of their quality, value, or foundational influence on subsequent inventions, irrespective of the alliance (e.g., Hall et al., 2005; Harhoff, Narin, Scherer, & Vopel, 1999). In addition, we control for *pre-alliance citations* during the five years prior to the alliance, which sets a baseline for the knowledge absorbed from the protecting party (Devarakonda & Reuer, 2018; Oxley & Wada, 2009). Next, we control for *patent purchasing* by counting the patents that the absorbing party purchased from the protecting party during the five years after the alliance announcement. This captures the extent to which the protecting party concedes to the absorbing party's appropriation of its knowledge spillovers. We also control for the protecting party's dedicated alliance function (*DAF*) at the time of the alliance announcement, by flagging positions with corporate responsibility for alliances in the firm's top management.[11] Having a DAF implies reliance on more sophisticated means of knowledge protection during the alliance (Findikoglu & Lavie, 2019).

We also control for characteristics of the previous and subsequent alliances between the firm and its partner. We control for the *joint partnering experience* between the firm and its partner by counting their previous joint alliances. This experience may facilitate knowledge exchange in the

[11] We used BoardEx to identify holders of positions such as "Director-Strategic Alliances", "VP-Alliances", "VP-Alliance Management", "VP-Strategic Partnerships", "VP-Global Strategic Partnerships", or "Chief Alliance Officer".

alliance (Gulati, 1995; Gulati et al., 2009). We control for *common ties* by counting the unique partners with which both parties formed alliances in the five years since their joint alliance was announced. This accounts for the protecting party's social protection, which can limit knowledge spillover even in the absence of other forms of protection (Hallen et al., 2014). Next, we control for the number of *patent co-applications* by the firm and the partner during the five years following their announced alliance. These joint patents proxy for the common benefits derived from proactively sharing and co-producing knowledge during the alliance. Additionally, we control for the *joint venture* status of the alliance, given that an equity stake may mitigate knowledge spillover while facilitating learning between the parties (e.g., Oxley, 1997; 1999). We account for the value chain function of the alliance, using a variable coded "1" for upstream alliances that involve R&D activities, "-1" for downstream alliances that involve licensing, manufacturing, marketing, OEM, or supply activities, and "0" for alliances that combine both activity types (Lavie & Rosenkopf, 2006). Moreover, because of cross-national barriers to knowledge transfer (Lavie & Miller, 2008), we control for the cultural, administrative, geographical, and economic distances between the home countries of the firm and its partners. We use principal components analysis (obtaining an eigenvalue of 2.46 and a standardized Cronbach's alpha of 0.79) to construct an index of the *cross-national distance* between the firm and the partner in previous and subsequent alliances (Lavie & Miller, 2008). Additionally, to account for the diminished usefulness of the learned protection practices, we control for the *temporal gap between alliances*, measured as the number of years that have elapsed between the announcements of the previous and subsequent alliances. Moreover, because it is more difficult for the firm to apply the learned knowledge protection practices when the partner in the subsequent alliance is the same as in the previous alliance, we control for the *same partner in both alliances*. We also control for the firm's *aggregate knowledge absorbed in its previous alliances*, which accounts for the firm's cumulative experience in learning protection practices. We compute this as the average number of the firm's citations to all previous partners' patents during the five-year duration of their alliances, while excluding the previous alliance in question. Finally, we include fixed effects for the year, the firm's industry, and the firm's country.[12]

Analysis

We test our hypotheses using a two-stage model (Heckman, 1979) to account for the possibility that a firm self-selects into a subsequent alliance with limited spillover risk after gaining valuable knowledge in its previous alliance (Katila et al., 2008). The first-stage model estimates the probability of forming a subsequent alliance with a particular partner (e.g., Robinson & Stuart, 2007; Yang et al., 2015). In the first stage, we model partner selection as the firm's choice between the actual partner and a "counterfactual" partner from a control group of unformed alliances (e.g., Gulati, 1995; Rothaermel & Boeker, 2008). The counterfactual partner is the one closest in size to the actual partner among the publicly listed firms that were active in the same industry as the actual partner (Mowery, Oxley, & Silverman, 1998; Yang et al., 2015). To predict the formation of a subsequent alliance we use the same set of predictors as in the second-stage model, except for the subsequent alliance's status as a joint venture, its value chain scope, and value chain function, which lack counterfactuals for unformed alliances. As an exclusion restriction, we use the *partner relative size* comparing the actual partner with the counterfactual partner. The larger a counterfactual partner is compared to the actual one, the greater its visibility to the firm. Greater visibility increases the probability of the firm forming an alliance with that partner, without affecting knowledge spillover during the alliance. Accordingly, this variable had an impact in the first-stage model but not when introduced in the second-stage model.

[12] Firm fixed effects are excluded because of lack of variance for firms that formed a single pair of alliances. Instead, we cluster standard errors by the firm and its partners, which adjusts the standard errors for observations belonging to the same firm or partner in a way similar to a fixed effect, without losing degrees of freedom or observations (Guimarães & Portugal, 2010).

Our second-stage model uses a Poisson pseudo-maximum likelihood (PPML) regression model (Davies & Guy, 1987; Santos Silva & Tenreyro, 2006)[13] to predict knowledge spillover from the firm to its partner in the subsequent alliance. Because each subsequent alliance may be paired with multiple previous alliances and vice versa, we report three-way clustered standard errors by the firm, previous partner, and subsequent partner (Cameron, Gelbach, & Miller, 2011).

************* Insert Tables 2–4b and Figures 2–6 here *************

RESULTS

We report descriptive statistics and pairwise correlations in Table 2.[15] First-stage model results are reported in Table 3,[16] with second-stage model results reported in Table 4. Model 1 (Table 4a) is the baseline model including the control variables. It reveals that knowledge spillover to a partner in a subsequent alliance (SA) increases with the firm's GPE and scientific impact. Knowledge spillover to the subsequent partner also increases with that partner's age, its pre-alliance citations to the firm's patents, and its total backward citations. In turn, knowledge spillover in this alliance declines with the partner's GPE, patenting experience, and the strength of the partner's appropriability regime. Furthermore, knowledge spillover to the partner in the subsequent

---

[13] Unlike other count data estimators, PPML does not require an integer dependent variable (Correia, Guimarães, & Zylkin, 2020; Santos Silva & Tenreyro, 2006) but provides consistent estimates in the presence of overdispersion and zero inflation (Blackburn, 2015; Santos Silva & Tenreyro, 2006). Moreover, PPML estimates can be corrected for sampling-induced biases in a procedure analogous to that devised by Heckman (1979) (Terza, 1998). To compare the validity of PPML against alternate estimators (e.g., negative binomial or zero-inflated models), we relied on the HPC test procedure (Santos Silva, Tenreyro, & Windmeijer, 2015), which indicated a preference for PPML.

[15] Correlations between our explanatory variables in the second-stage model are mostly low, with few exceptions. Although maximum VIFs exceed 10, condition numbers remain well below 30, indicating no severe multicollinearity (Belsley, Kuh, & Welsh, 1980). The multicollinearity is driven by multiple instances of the independent variable as part of its quadratic and moderated functions (O'Brien, 2007), which is why we standardize all explanatory variables to zero mean and unit standard deviation (Iacobucci, Schneider, Popovich, & Bakamitsos, 2016) and rely on partial models for hypothesis testing. Our findings remain intact when we exclude high-VIF controls.

[16] The partner selection model reveals that firms form subsequent alliances with younger partners that have less GPE and patenting experience, and fewer patent co-applications. Firms also opt for partners that frequently cite or purchase the firms' patents, with whom they share technological overlap, common third-party ties, and partner-specific experience, and whose home countries are cross-nationally distant and have stronger appropriability regimes. Firms also opt for partners that are relatively larger than other prospective partners.

alliance increases with the technological overlap between the firm and that partner, their common ties to third parties, and their patent co-applications, but declines in equity joint ventures. When considering the influence of the previous alliance (PA) on knowledge spillover in the subsequent alliance, we observe negative effects of the previous partner's size and scientific impact. The firm's patent purchasing from the previous partner also yields a negative effect and so does an upstream alliance type. However, knowledge spillover in the subsequent alliance increases with the firm's patenting experience in the previous alliance and its patent co-applications with the previous partner. Finally, knowledge spillover in the subsequent alliance increases when the business similarity in that alliance is greater than in the previous alliance, when the same partner was involved in the previous alliance, and when the firm gained partnering experience between the previous and subsequent alliances. Most of these effects persist in the full model.

Model 2 (Table 4a) introduces the linear effect of knowledge absorbed from a previous partner, revealing a negative effect on knowledge spillover to the partner in the subsequent alliance ($\beta = -0.047$, $p = 0.011$). When its quadratic term is introduced in Model 3, we observe a negative linear effect ($\beta = -0.089$, $p < 0.001$) and a positive quadratic effect ($\beta = 0.014$, $p < 0.001$). Figure 2 further reveals a negative association that diminishes at higher levels of knowledge absorbed from the previous partner. To verify the shape of the curvilinear effect, we performed Lind and Mehlum's (2010) test for U-shaped relationships, which revealed a negative slope on the left of the inflection point (negative slope = -0.100, $p < 0.001$) with no positive slope on its right (positive slope = 0.031, $p = 0.114$). As predicted by Hypothesis 1, these findings suggest an L-shaped rather than a U-shaped association. To prevent one additional knowledge element (recently cited patent) from spilling to a subsequent partner, on average, a firm needs to absorb about 30 additional knowledge elements from a previous partner, but as more knowledge is absorbed from that partner, this ratio diminishes. At the maximum level of absorbed knowledge, preventing that spillover requires absorbing about 99 knowledge elements from a previous partner. These findings persist in Model 4, which relies on a lean specification with fewer control variables, suggesting that our findings are not mere artifacts of overfitting or specification errors.

Models 5–8 introduce the moderating effects.[17] Model 5 (Table 4b; Figure 3) reveals that the negative association between knowledge spillover in a subsequent alliance and the knowledge absorbed in a previous alliance is attenuated by an increase in the value chain scope of the previous alliance ($\beta = 0.011$, $p = 0.018$), in line with Hypothesis 2. Model 6 (Table 4b; Figure 4) reveals how a weaker appropriability regime in the firm's country relative to that in the previous partner's country reinforces that negative association, as per Hypothesis 3 ($\beta = -0.023$, $p = 0.003$). In line with Hypothesis 4, Model 7 (Table 4b; Figure 5) reveals that greater business overlap between the parties in the previous alliance relative to the subsequent alliance reinforces that negative association ($\beta = -0.008$, $p = 0.047$). Finally, Model 8 (Table 4b; Figure 6) lends support to Hypothesis 5, according to which the technological overlap between the parties in the previous alliance mitigates that negative association ($\beta = 0.040$, $p < 0.001$). Although the full model (Model 9) exhibits multicollinearity, all moderating effects persist in Model 10 which presents the full model with the lean specification.

We tested the robustness of our findings in several ways. For example, we dropped the minimum one-year lag between the previous and subsequent alliances, tested three- and seven-year windows for patent citations, inversed the dependent and independent variables to rule out reverse causality; recomputed patent-based measures using only USPTO patents, considered alternative

[17] We hypothesized that the moderators affect only the linear part of the negative association between the firm's knowledge absorption in a previous alliance and its knowledge spillover in a subsequent alliance (e.g., Duysters et al., 2020; Zollo & Reuer, 2010). Following Haans, Pieters, and He (2016), we tested a moderation of the entire curve in ancillary analysis but encountered severe multicollinearity (condition numbers > 30), which makes it difficult to interpret the corresponding results.

measures for knowledge spillover and absorption, replaced our measure of difference in business similarity with one capturing overlap of the parties' six-digit NAICS codes, introduced additional controls; ran a version of the first-stage model in which we relied on four counterfactual partners, tested different approaches for clustering standard errors, and tried alternative second-stage estimators. Overall, these additional analyses bestow confidence in our findings. We include detailed descriptions of the performed tests and their results in an online appendix.

DISCUSSION

We study the extent to which a firm's ability to absorb the knowledge of its previous partners affects the spillover of its own knowledge to partners in subsequent alliances. Our findings reveal that firms in our sample managed to effectively reverse roles and limit knowledge spillover to their partners. We ascribe this to the firms' exposure to and vicarious learning of their previous partners' knowledge protection practices. Nevertheless, the protection of the firms' knowledge improves at a diminishing rate with increasing amounts of previously absorbed knowledge due to exhausted learning opportunities, encountering intricate practices, and specialization in the absorption role.

Furthermore, our findings suggest that the more challenging it is for a firm to overcome its previous partners' knowledge protection, the more effective its vicarious learning, and hence the protection of its own knowledge in a subsequent alliance, becomes. In particular, conditions that restrict the firm's opportunities and ability to absorb its previous partners' knowledge, and increase its motivation to absorb their knowledge, facilitate the learning of protection practices, and reinforce the firm's protection of its knowledge in a subsequent alliance. These conditions include (a) a narrow value chain scope in the previous alliances (restricting opportunities), (b) a weaker appropriability regime in the firm's country relative to its partners' countries in the previous alliances (restricting opportunities while increasing motivation), (c) greater business similarity in the previous alliances (increasing motivation while limiting ability), and (d) a weak relative absorptive capacity in these alliances (limiting ability to absorb knowledge). Hence, partners that deploy sophisticated knowledge protection practices may restrict knowledge spillover in the short term (e.g., Kale et al., 2000), while teaching the firm how to develop a long-lasting competence to protect its knowledge. Thus, a "hard practice" makes for an "easy game" in the subsequent alliance.

Our study offers several contributions to research on learning and knowledge protection in alliances. We extend research on the interplay of knowledge absorption and protection within a given alliance (e.g., Devarakonda & Reuer, 2018; Kale et al., 2000; Oxley & Sampson, 2004) by considering their interdependence across successive alliances. We reveal that besides engaging in experiential learning (Gulati et al., 2009), the firm engages in vicarious learning of its partners' knowledge protection practices, which enables it to improve its own knowledge protection in subsequent alliances. Although scholars have shown that vicarious learning of partners' practices contributes to a firm's innovation (Howard et al., 2016), we offer more direct evidence of knowledge flows between the parties and focus on alliance practices relating to knowledge absorption and protection. More importantly, whereas prior research has proposed vicarious learning of a particular practice and its application across distinct governance modes, such as alliances and acquisitions (e.g., Agarwal et al., 2012; Heimeriks, 2010; Meschi & Métais, 2013; Zollo, 2009; Zollo & Reuer, 2010), we study vicarious learning of counter practices or "flipside" activities (Doan, Sahib, & Witteloostuijn, 2018) within the same governance mode but across different instances. Unlike prior research showing that firms can learn by engaging in related activities (e.g., Agarwal et al., 2012; Bingham et al., 2015; Zollo & Reuer, 2010), we find that firms can learn counter activities, i.e., knowledge protection, when engaging in knowledge absorption. Whereas negative transfer learning (Ellis, 1965; Novick, 1988) from distinct yet related activities imposes a substantial risk (e.g., Ghosh, Martin, Pennings, & Wezel, 2014; Zollo, 2009), this risk is mitigated in vicarious learning so long as the firm can become immersed in its protective mindset.

By juxtaposing learning of partners' content knowledge and learning of their protection practices, we bring together two traditionally separate research streams (Inkpen & Tsang, 2007). Although recent research alludes to their interdependence (Duysters et al., 2020), little is known about their interplay. We posit that a firm that excels in knowledge absorption also becomes better at protecting its knowledge, so that learning the content knowledge (know-what) of partners goes hand in hand with learning procedural know-how about their protection practices. Finally, our study underscores the notion of role reversal. Prior research has revealed path dependence and challenges when firms seek to change immutable positions and modify their mindsets (Leonard-Barton, 1992; Levitt & March, 1988; Ocasio, 1997; Siggelkow, 2001). Yet we show that when reversing roles, as opposed to merely changing roles, firms can more easily transition to new positions and adapt their routines. In our context, East Asian firms that internalized their partners' knowledge also learned to protect their own knowledge and avoid the fate of their "prey."

Our study faces several limitations. Given our reliance on archival data sources, we could not directly measure the parties' knowledge protection practices and inferred their learning from patent citations. Future research may issue surveys and directly observe these practices in alliances. Moreover, whereas patent citations indicate that the firm may have absorbed tacit knowledge related to the observable knowledge embedded in its partners' patents (Narin, Noma, & Perry, 1987), some knowledge spillover may involve employee mobility and citations to scientific articles, among other means (Corsino et al., 2019). Although we identified several boundary conditions relating to learning opportunities, motivation, and ability, further research is needed to explain why firms are, on occasion, unable to reverse roles from absorption to protection, and thus fail to catch up (Lee & Malerba, 2017). It is possible that a firm would vicariously learn about the knowledge protection practices of its alliance partner even when having no interest in the partner's knowledge. However, such incidental learning may not be as effective given the firm's limited motivation to cope with the partner's protection practices. Alternatively, the partner may seek to proactively share some knowledge with the firm, e.g., to induce the firm's cooperation (Arora, Belenzon, & Patacconi, 2021). Future research may examine these boundary conditions.

Empirically, we disaggregated our data into pairs of previous-subsequent alliances in order to isolate the learning effect of each alliance. This leaves open the question of how firms integrate insights learned from multiple alliances and resolve potential discrepancies (Duysters et al., 2020). Besides studying this integration process, although only 10.47 percent of the alliances in our setting were multi-party alliances, future research may focus on role reversal in such alliances with more complex learning dynamics (e.g., Lavie, Lechner, & Singh, 2007). Future research may also generalize our findings to practices other than knowledge absorption and protection or to other governance modes besides alliances. A relevant question is whether role reversal is intentional or incidental, and how this may affect its implementation. By documenting actual practices, qualitative research can corroborate our proposed mechanisms and offer further insights into how firms change their mindset and manage this role reversal (e.g., Bingham et al., 2015).

Knowledge misappropriation in alliances remains an issue of concern to executives (Shih & Wang, 2013). Our study reinforces this concern by suggesting that when internalizing their partners' knowledge, firms become competent at protecting their proprietary knowledge in subsequent alliances. Hence, firms should actively engage in vicarious learning of knowledge protection practices. In turn, attempts at fending off a predatory partner using advanced practices can improve the partner's prospects of winning subsequent learning races. This requires managers to be mindful about the interplay of knowledge absorption and protection.

REFERENCES

Agarwal, R., Anand, J., Bercovitz, J., & Croson, R. 2012. Spillovers across organizational structures: The role of prior resource acquisition and communication in post-acquisition coordination outcomes. ***Strategic Management Journal,*** 33: 710–733.

Argote, L., McEvily, B., & Reagans, R. 2003. Managing knowledge in organizations: An integrative framework and review of emerging themes. ***Management Science***, 49: 571–582.

Argyris, C., & Schön, D. A. 1978. ***Organizational learning: A theory of action perspective***. New York: Addison-Wesley.

Arora, A., Belenzon, S., & Patacconi, A. 2021. Knowledge sharing in alliances and alliance portfolios. ***Management Science***, 67: 1569–1585.

Arslan, B. 2018. The interplay of competitive and cooperative behavior and differential benefits in alliances. ***Strategic Management Journal***, 39: 3222–3246.

Baughn, C. C., Denekamp, J. G., Stevens, J. H., & Osborn, R. N. 1997. Protecting intellectual capital in international alliances. ***Journal of World Business***, 32: 103–117.

Baum, J. A. C., Calabrese, T., & Silverman, B. S. 2000. Don't go it alone: Alliance network composition and startups' performance in Canadian biotechnology. ***Strategic Management Journal***, 21: 267–294.

Belsley, D. A., Kuh, E., & Welsch, R. E. 1980. ***Regression diagnostics***. New York: Wiley.

Berger, T., & Bristow, G. 2009. Competitiveness and the benchmarking of nations – A critical reflection. ***International Advances in Economic Research***, 15: 378–392.

Bingham, C. B., Heimeriks, K. H., Schijven, M., & Gates, S. 2015. Concurrent learning: How firms develop multiple dynamic capabilities in parallel. ***Strategic Management Journal***, 36: 1802–1825.

Blackburn, M. 2015. The relative performance of Poisson and negative binomial regression estimators. ***Oxford Bulletin of Economics and Statistics***, 77: 605–616.

Caballero, R. J., & Jaffe, A. B. 1993. How high are the giants' shoulders: An empirical assessment of knowledge spillovers and creative destruction in a model of economic growth. In O. Blanchard and S. Fischer (Eds.), ***NBER macroeconomics annual 1993***: 15–86. Cambridge, MA: MIT Press.

Cameron, A. C., Gelbach, J. B., & Miller, D. L. 2011. Robust inference with multiway clustering. ***Journal of Business & Economic Statistics***, 29: 238–249.

Castellaneta, F., Valentini, G., & Zollo, M. 2018. Learning or inertia? The impact of experience and knowledge codification on post-acquisition integration. ***Industrial and Corporate Change***, 27: 577–593.

Claessens, S., & Laeven, L. 2003. Financial development, property rights, and growth. ***Journal of Finance***, 58: 2401–2436.

Cohen, W. M., Goto, A., Nagata, A., Nelson, R., & Walsh, J. P. 2002. R&D spillovers, patents and the incentives to innovate in Japan and the United States. ***Research Policy***, 31: 1349–1369.

Cohen, W. M., & Levinthal, D. A. 1990. Absorptive capacity: A new perspective on learning and innovation. ***Administrative Science Quarterly***, 35: 128–152.

Cohen, W. M., Nelson, R. R., & Walsh, J. P. 2000. Protecting their intellectual assets: Appropriability conditions and why US manufacturing firms patent (or not). NBER Working Paper Series, WP 7552.

Contractor, F. J. 2019. Can a firm find the balance between openness and secrecy? Towards a theory of an optimum level of disclosure. ***Journal of International Business Studies***, 50: 261–274.

Corredoira, R. A., & Rosenkopf, L. 2010. Should auld acquaintance be forgot? The reverse transfer of knowledge through mobility ties. ***Strategic Management Journal***, 31: 159–181.

Correia, S., Guimarães, P., & Zylkin, T. 2020. Fast Poisson estimation with high-dimensional fixed effects. ***Stata Journal***, 20: 95–115.

Corsino, M., Mariani, M., & Torrisi, S. 2019. Firm strategic behavior and the measurement of knowledge flows with patent citations. ***Strategic Management Journal***, 40: 1040–1069.

Cui, V., Yang, H., & Vertinsky, I. 2018. Attacking your partners: Strategic alliances and competition between partners in product markets. ***Strategic Management Journal***, 39: 3316–3139.

Darr, E., Argote, L., & Epple, D. 1995. The acquisition, transfer and depreciation of knowledge in service organizations: Productivity in franchises. ***Management Science***, 41: 1750–1762.

Davies, R. B., & Guy, C. M. 1987. The statistical modeling of flow data when the Poisson assumption is violated. ***Geographical Analysis***, 19: 300–314.

De Rassenfosse, G., Palangkaraya, A., & Webster, E. 2016. Why do patents facilitate trade in technology? Testing the disclosure and appropriation effects. ***Research Policy***, 45: 1326–1336.

Devarakonda, S. V., & Reuer, J. 2018. Knowledge sharing and safeguarding in R&D collaborations: The role of steering committees in biotechnology alliances. ***Strategic Management Journal***, 39: 1912–1934.

Dickson, P. H., Weaver, K. M., & Hoy, F. 2006. Opportunism in the R&D alliances of SMEs: The roles of the institutional environment and SME size. ***Journal of Business Venturing***, 21: 487–513.

Dierickx, I., & Cool, K. 1989. An asset stock accumulation and the sustainability of competitive advantage. ***Management Science***, 35: 1504–1511.

Diestre, L., & Rajagopalan, N. 2012. Are all "sharks" dangerous? New biotechnology ventures and partner selection in R&D alliances. ***Strategic Management Journal***, 33: 1115–1134.

Doan, T. T., Sahib, P. R., & van Witteloostuijn, A. 2018. Lessons from the flipside: How do acquirers learn from divestitures to complete acquisitions? ***Long Range Planning***, 51(2): 252–266.

Duguet, E., & MacGarvie, M. 2005. How well do patent citations measure flows of technology? Evidence from French innovation surveys. ***Economics of Innovation and New Technology***, 14: 375–393.

Duysters, G., & de Man, A. P. 2003. Transitory alliances: An instrument for surviving turbulent industries? ***R&D Management***, 33 : 49–58.

Duysters, G., Jacob, J., Lemmens, C., & Jintian, Y. 2009. Internationalization and technological catching up of emerging multinationals: a comparative case study of China's Haier group. ***Industrial and Corporate Change***, 18: 325–349.

Duysters, G., Lavie, D., Sabidussi, A., & Stettner, U. 2020. What drives exploration? Convergence and divergence of exploration tendencies among alliance partners and competitors. ***Academy of Management Journal***, 63: 1425–1454.

Dyer, J. H., & Nobeoka, K. 2000. Creating and managing a high-performance knowledge-sharing network: The Toyota case. ***Strategic Management Journal***, 21: 345–367.

Dyer, J. H., & Singh, H. 1998. The relational view: Cooperative strategy and sources of interorganizational competitive advantage. ***Academy of Management Review***, 23: 660–679.

Ellis, H. C. 1965. ***The transfer of learning***. London: MacMillan Press.

Findikoglu, M., & Lavie, D. 2019. The contingent value of the dedicated alliance function. ***Strategic Organization***, 17: 177–209

Ghosh, A., Martin, X., Pennings, J. M., & Wezel, F. C. 2014. Ambition is nothing without focus: Compensating for negative transfer of experience in R&D. ***Organization Science***, 25: 572–590.

Gomes-Casseres, B., Hagedoorn, J., & Jaffe, A. B. 2006. Do alliances promote knowledge flows? ***Journal of Financial Economics***, 80: 5–33.

Guimarães, P., & Portugal, P. 2010. A simple feasible procedure to fit models with high-dimensional fixed effects. ***Stata Journal***, 10: 826–649.
Gulati, R. 1995. Does familiarity breed trust? The implications of repeated ties for contractual choice in alliances. ***Academy of Management Journal***, 38: 85–102.
Gulati, R., Lavie, D., & Singh, H. 2009. The nature of partnering experience and the gains from alliance. ***Strategic Management Journal***, 30: 1213–1233.
Haans, R. F., Pieters, C., & He, Z.-L. 2016. Thinking about U: Theorizing and testing U- and inverted U-shaped relationships in strategy research. ***Strategic Management Journal,*** 37: 1177–1195.
Hagedoorn, J., & Schakenraad, J. 1994. The effect of strategic technology alliances on company performance. ***Strategic Management Journal***, 15: 291–309.
Haleblian, J., & Finkelstein, S. 1999. The influence of organizational acquisition experience on acquisition performance: A behavioral learning perspective. ***Administrative Science Quarterly***, 44: 29–56.
Hall, B. H., Jaffe, A. B., & Trajtenberg, M. 2005. Market value and patent citations. ***RAND Journal of Economics***, 36: 16–38.
Hallen, B.L., Katila, R., & Rosenberger, J.D. 2014. How do social defenses work? A resource-dependence lens on technology ventures, venture capital investors, and corporate relationships. ***Academy of Management Journal***, 57: 1078-1101
Hamel, G. 1991. Competition for competence and inter-partner learning within international strategic alliances. ***Strategic Management Journal***, 12: 83–103.
Hamel, G., Doz, Y., & Prahalad, C. K. 1989. Collaborate with your competitors – and win. ***Harvard Business Review***, (January-February): 133–139.
Harhoff, D., Narin, F., Scherer, F. M., & Vopel, K. 1999. Citation frequency and the value of patented inventions. ***Review of Economics and Statistics***, 81: 511–515.
Haunschild, P. R. 1993. The impact of interlocks on corporate acquisition activity. ***Administrative Science Quarterly***, 38: 564–592.
Haveman, H. A. 1993. Follow the leader: Mimetic isomorphism and entry into new markets. ***Administrative Science Quarterly***, 38: 593–627.
Heckman, J. 1979. Sample selection bias as a specification error. ***Econometrica***, 47: 153–161.
Heimeriks, K. H. 2010. Confident or competent? How to avoid superstitious learning in alliance portfolios. ***Long Range Planning***, 43: 57–84.
Howard, M., Steensma, H. K., Lyles, M., & Dhanaraj, C. 2016. Learning to collaborate through collaboration: How allying with expert firms influences collaborative innovation within novice firms. ***Strategic Management Journal***, 27: 2092–2103.
Huang, K. G., & Li, J. 2019. Adopting knowledge from reverse innovations? Transnational patents and signaling from an emerging economy**.** ***Journal of International Business Studies***, 50: 1078–1102.
Huber, G. P. 1991. Organizational learning: The contributing processes and literatures. ***Organization Science***, 4: 325–341.
Iacobucci, D., Schneider, M. J., Popovich, D. L., & Bakamitsos, G. A. 2016. Mean centering helps alleviate "micro" but not "macro" multicollinearity. ***Behavioral Research Methods***, 48: 1308–1317.
Inkpen, A. C., & Tsang, E. W. K. 2007. Learning and strategic alliances. ***The Academy of Management Annals***, 1: 479–511.
Jaffe, A. B. 1986. Technological opportunity and spillovers of R&D: Evidence from firms' patents, profits and market value. ***American Economic Review***, 76: 984–999.

Jaffe, A. B., & Trajtenberg, M. 1999. International knowledge flows: Evidence from patent citations. ***Economics of Innovation and New Technology***, 8(1–2): 105–136.
Jaffe, A. B., Trajtenberg, M., & Fogarty, M. S. 2000. Knowledge spillovers and patent citations: Evidence from a survey of inventors. ***American Economic Review***, 90: 215–218.
Johnson, S., Kaufman, D., & Zoido-Lobaton, P. 1998. Government in transition: Regulatory discretion and the unofficial economy. ***American Economic Review***, 88: 387-392.
Kale, P., Dyer, J H., & Singh, H. 2002. Alliance capability, stock market response, and long-term alliance success: The role of the alliance function. ***Strategic Management Journal***, 23(8): 747–767.
Kale, P., Singh, H., & Perlmutter, H. 2000. Learning and protection of proprietary assets in strategic alliances: Building relational capital. ***Strategic Management Journal***, 21: 217–237.
Katila, R., Rosenberger, J. D., & Eisenhardt K. M. 2008. Swimming with sharks: Technology ventures, defense mechanisms and corporate relationships. ***Administrative Science Quarterly***, 53: 195–332.
Khanna, T. 1998. The scope of alliances. ***Organization Science***, 9: 340–355.
Khanna, T., Gulati, R., & Nohria, N. 1998. The dynamics of learning alliances: Competition, cooperation, and relative scope. ***Strategic Management Journal***, 19: 193–210.
Kuhn, J., Younge, K., & Marco, A. 2020. Patent citations reexamined. ***RAND Journal of Economics***, 51: 109–132.
Lane, P. J., & Lubatkin, M. 1998. Relative absorptive capacity and interorganizational learning. ***Strategic Management Journal***, 19: 461–447.
Larsson, R., Bengtsson, L., Henriksson, K., & Sparks, J. 1998. The interorganizational learning dilemma: Collective knowledge development in strategic alliances. ***Organization Science***, 9: 285–305.
Lavie, D. 2006. The competitive advantage of interconnected firms: An extension of the resource-based view. ***Academy of Management Review***, 31: 638–658.
Lavie, D. 2007. Alliance portfolios and firm performance: A study of value creation and appropriation in the U.S. software industry. ***Strategic Management Journal***, 28: 1187–1212.
Lavie, D., Lechner, C., & Singh, H. 2007. The performance implications of timing of entry and involvement in multipartner alliances. ***Academy of Management Journal***, 53(3): 578–604.
Lavie, D., & Miller, S. 2008. Alliance portfolio internationalization and firm performance. ***Organization Science***, 19: 623–646.
Lavie, D., & Rosenkopf, L. 2006. Balancing exploration and exploitation in alliance formation. ***Academy of Management Journal***, 49: 797–818.
Lee, K., & Malerba, F. 2017. Catch-up cycles and changes in industrial leadership: Windows of opportunity and responses of firms and countries in the evolution of sectoral systems. ***Research Policy***, 46: 338–351.
Leonard-Barton, D. 1992. Core capabilities and core rigidities: A paradox in managing new product development. ***Strategic Management Journal***, 14: 95–112.
Levin, R. C., Klevorick, A. K., Nelson, R. R., & Winter, S. G. 1987. Appropriating the returns from industrial research and development. ***Brookings Papers on Economic Activity***, 1987(3): 783–831.
Levitt, B., & March, J. G. 1988. Organizational learning. ***Annual Review of Sociology***, 14: 319–340.
Liebeskind, J. P. 1996. Knowledge, strategy, and the theory of the firm. ***Strategic Management Journal***, 17: 93–107.
Liebeskind, J. P. 1997. Keeping organizational secrets: Protective institutional mechanisms and their costs. ***Industrial and Corporate Change***, 6: 623–663.

Lind, J. T., & Mehlum, H. 2010. With or without U? The appropriate test for a U-shaped relationship. ***Oxford Bulletin of Economics and Statistics***, 72: 109–118.
Lioukas, C. S., & Reuer, J. J. 2020. Choosing between safeguards: Scope and governance decisions in R&D alliances. ***Journal of Management***, 46: 359–384.
Liu, X., & Buck, T. 2007. Innovation performance and channels for international technology spillovers: Evidence from Chinese high-tech industries. ***Research Policy***, 36(3): 355–366.
Martin de Holan, P., & Phillips, N. 2004. Remembrance of things past? The dynamics of organizational forgetting. ***Management Science***, 50: 1603–1613.
Mathews, J. A. 2006. Dragon multinationals: New players in 21st century globalization. ***Asia Pacific Journal of Management***, 23: 5–27.
Meschi, P-X., & Métais, E. 2013. Do firms forget about their past acquisitions? Evidence from French acquisitions in the United States (1988–2006). ***Journal of Management***, 39: 469–495.
Monteiro, L. F., Mol, M. J., & Birkinshaw, J. 2017. Ready to be open? Explaining the firm level barriers to benefiting from openness to external knowledge. ***Long Range Planning***, 50: 282–295.
Mowery, D. C., Oxley, J. E., & Silverman, B. S. 1996. Strategic alliances and interfirm knowledge transfer. ***Strategic Management Journal***, 17: 77–91.
Mowery, D. C., Oxley, J. E., & Silverman, B. S. 1998. Technological overlap and interfirm cooperation: Implications for the resource-based view of the firm. ***Research Policy***, 27: 507–523.
Narin, F., Noma, E., & Perry, R. 1987. Patents as indicators of corporate technological strength. ***Research Policy***, 16: 143–155.
Novick, L. R. 1988. Analogical transfer, problem similarity, and expertise. ***Journal of Experimental Psychology: Learning, Memory, and Cognition***, 14: 510–520.
O'Brien, R. M. 2007. A caution regarding rules of thumb for variance inflation factors. ***Quality & Quantity***, 41: 673–690.
Ocasio, W. 1997. Towards an attention-based view of the firm. ***Strategic Management Journal***, 18: 187–206.
OECD. 2009. ***OECD Patent Statistics Manual***. Paris: OECD Publishing.
Oxley, J. E. 1997. Appropriability hazards and governance in strategic alliances: A transaction cost approach. ***Journal of Law, Economics, and Organization***, 13: 387–409.
Oxley, J. E. 1999. Institutional environment and the mechanisms of governance: The impact of intellectual property protection on the structure of interfirm alliances. ***Journal of Economic Behavior & Organization***, 38: 283–309.
Oxley, J. E., & Sampson, R. C. 2004. The scope and governance of international R&D alliances. ***Strategic Management Journal***, 25: 723–749.
Oxley, J. E., & Wada, T. 2009. Alliance structure and the scope of knowledge transfer: Evidence from U.S.-Japan agreements. ***Management Science***, 55: 635–649.
Palomeras, N., & Wehrheim, D. 2020. The strategic allocation of inventors to R&D collaborations. ***Strategic Management Journal***, 42: 144–169.
Porrini, P. 2004. Can a previous alliance between an acquirer and a target affect acquisition performance? ***Journal of Management***, 30: 545–562.
Puranam, P., & Srikanth, K. 2007. What they know vs. what they do: How acquirers leverage technology acquisitions. ***Strategic Management Journal***, 28: 805–825.
Robinson, D. T., & Stuart, T. E. 2007. Network effects in the governance of strategic alliances. ***Journal of Law, Economics, & Organization***, 23: 242–273.
Rosenkopf, L., & Almeida, P. 2003. Overcoming local search through alliances and mobility. ***Management Science***, 49: 751–766.
Rosenkopf, L., & Nerkar, A. 2001. Beyond local search: Boundary-spanning exploration, and impact

in the optical disk industry. ***Strategic Management Journal***, 22: 287–306.
Rothaermel, F. T., & Boeker, W. 2008. Old technology meets new technology: Complementarities, similarities, and alliance formation. ***Strategic Management Journal***, 29: 47–77.
Sampson, R. C. 2007. R&D alliances and firm performance: The impact of technological diversity and alliance organization on innovation. ***Academy of Management Journal***, 50: 364–386.
Santos Silva, J. M. C., & Tenreyro, S. 2006. The log of gravity. ***Review of Economics and Statistics***, 88: 641–658.
Santos Silva, J. M. C., Tenreyro, S., & Windmeijer, F. 2015. Testing competing models for non-negative data with many zeros. ***Journal of Econometric Methods***, 4: 29–46.
Schilling, M. A. 2009. Understanding the alliance data. ***Strategic Management Journal***, 30: 233–260.
Schotter, A., & Teagarden, M. 2014. Protecting intellectual property in China. ***Sloan Management Review***, 55(4): 41–48.
Shih, W. C., & Wang, J. C. 2013. Will our partner steal our IP? ***Harvard Business Review*** (February): 137–141.
Siggelkow, N. 2001. Change in the presence of fit: The rise, the fall, and the renaissance of Liz Claiborne. ***Academy of Management Journal***, 44: 838–857.
Simonin, B. L. 1999. Ambiguity and the process of knowledge transfer in strategic alliances. ***Strategic Management Journal***, 20: 595–623.
Simonin, B. L. 2004. An empirical investigation of the process of knowledge transfer in international strategic alliances. ***Journal of International Business Studies***, 35: 407–427.
Stettner, U., & Lavie, D. 2014. Ambidexterity under scrutiny: Exploration and exploitation via internal organization, and acquisitions. ***Strategic Management Journal***, 35: 1903–1929.
Szulanski, G. 1996. Exploring internal stickiness: Impediments to the transfer of best practice within the firm. ***Strategic Management Journal,*** 17: 27–43.
Teece, D. J. 1986. Profiting from technological innovation: Implications for integration, collaboration, licensing, and public policy. ***Research Policy***, 15: 285–305.
Terza, J. V. 1998. Estimating count data models with endogenous switching, sample selection and endogenous treatment effects. ***Journal of Econometrics***, 84: 129–154.
Terza, J. V. 2017. Two-stage residual inclusion estimation: A practitioners guide to Stata implementation. ***Stata Journal***, 17: 916–938.
Tsang, E. W. K. 2002. Acquiring knowledge by foreign partners from international joint ventures in a transition economy: Learning-by-doing and learning myopia. ***Strategic Management Journal***, 23: 835–854.
Vasudeva, G., & Anand, J. 2011. Unpacking absorptive capacity: A study of knowledge utilization from alliance portfolios. ***Academy of Management Journal***, 54: 611–623.
Villalonga, B., & McGahan, A. M. 2005. The choice among acquisitions, alliances, and divestitures. ***Strategic Management Journal***, 26: 1183–1208.
von Wartburg, I., Teichert, T., & Rost, K. 2005. Inventive progress measured by multi-stage patent citation analysis. ***Research Policy,*** 34: 1591–1607.
Wadhwa, A., Bodas Freitas, I. M., & Sarkar, M. B. 2017. The paradox of openness and value protection strategies: Effect of extramural R&D on innovative performance. ***Organization Science***, 28: 873–893.
Yang, H., Phelps, C., & Steensma, H. K. 2010. Learning from what others have learned from you: The effects of knowledge spillovers on originating firms. ***Academy of Management Journal***, 53: 371–389.
Yang, H., Zheng, Y., & Zaheer, A. 2015. Asymmetric learning capabilities and stock market

returns. ***Academy of Management Journal***, 58: 356–374.
Zahra, S. A., & George, G. 2002. Absorptive capacity: A review, reconceptualization, and extension. ***Academy of Management Review***, 27: 185–203.
Zhang, Y. A., Li, H., Li, Y., & Zhou, L. A. 2010. FDI spillovers in an emerging market: The role of foreign firms' country origin diversity and domestic firms' absorptive capacity. ***Strategic Management Journal***, 31: 969–989.
Zhao, M. 2006. Conducting R&D in countries with weak intellectual property rights protection. ***Management Science***, 52: 1185–1199.
Zollo, M. 2009. Superstitious learning with rare strategic decisions: Theory and evidence from corporate acquisitions. ***Organization Science***, 20: 894–908.
Zollo, M., & Reuer, J. J. 2010. Experience spillovers across corporate development activities. ***Organization Science***, 21: 1195–1212.

Table 1: Patent applications of firms and partners until 2020

Patent applications	Firms (N = 87)	Partners (N = 381)
Patent applications worldwide	3,116,085 (n = 87)	15,361,229 (n = 381)
USPTO patent applications	524,995 (n = 86)	2,446,068 (n = 309)
EPO patent applications	78,612 (n = 85)	609,649 (n = 289)
JPO patent applications	112,504 (n = 82)	5,142,355 (n = 267)
Patent families (USPTO/EPO/JPO)	366,144 (n = 87)	5,214,995 (n = 371)

Table 2: Descriptive statistics and pairwise correlations for second-stage model

Variables	Mean	Std.Dev.	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.
1. SA knowledge spillover	439.33	1290.69										
2. PA knowledge absorbed	456.46	1190.49	0.12									
3. Firm age	30.95	12.26	0.12	0.20								
4. Firm size	85863.13	73527.70	0.01	0.19	0.24							
5. Firm GPE	48.39	35.11	0.08	0.03	0.01	-0.07						
6. Firm R&D intensity	0.08	0.22	0.33	0.39	0.52	0.42	0.13					
7. SA firm DAF	0.22	0.41	-0.13	0.16	0.40	0.52	-0.06	0.29				
8. SA firm scientific impact	11.31	7.89	0.30	0.15	0.05	-0.25	0.16	0.55	-0.32			
9. SA partner age	34.36	37.07	0.09	0.04	0.07	0.17	-0.02	0.08	0.09	-0.06		
10. SA partner size	33757.72	134444.44	0.01	-0.05	-0.05	-0.08	-0.03	-0.10	-0.09	-0.01	0.17	
11. SA partner GPE	28.60	65.18	0.25	-0.01	-0.02	-0.14	0.09	0.10	-0.18	0.30	0.10	0.10
12. SA pre-alliance citations	282.49	921.13	0.61	0.12	0.14	0.06	0.04	0.28	-0.05	0.20	0.06	-0.01
13. SA partner patenting experience	6341.77	18808.61	0.26	0.02	0.02	-0.08	0.08	0.14	-0.13	0.24	0.34	0.06
14. SA partner total backward citations	55997.97	130333.86	0.54	0.04	0.04	-0.11	0.08	0.14	-0.17	0.25	0.07	0.08
15. SA partner patent purchasing	23.52	261.07	-0.02	-0.00	0.04	-0.01	-0.02	-0.06	-0.01	-0.05	0.10	-0.01
16. SA value chain scope	0.11	0.11	0.25	-0.00	0.01	-0.22	0.12	0.14	-0.30	0.37	0.12	-0.05
17. SA diff. in appropriability regimes	10.36	23.13	-0.00	0.02	-0.36	0.30	0.00	-0.04	-0.01	-0.12	0.02	0.04
18. SA technological overlap	0.36	0.28	0.30	0.11	0.03	0.01	0.13	0.28	-0.09	0.36	0.09	0.00
19. SA common ties	0.47	1.51	0.18	-0.04	-0.04	-0.04	0.10	0.16	-0.16	0.32	0.14	0.04
20. SA joint venture	0.34	0.48	-0.14	-0.08	-0.11	0.13	-0.13	-0.25	0.14	-0.34	0.20	0.14
21. SA value chain function	-0.28	0.61	-0.13	0.04	0.03	0.05	0.05	0.07	-0.00	0.04	0.05	0.02
22. SA joint partnering experience	0.65	1.57	0.32	0.04	0.08	-0.00	0.02	0.15	-0.14	0.15	0.15	0.09
23. SA cross-national distance	-0.25	1.23	-0.02	-0.06	-0.21	-0.02	0.03	-0.12	-0.10	-0.04	-0.12	0.02
24. SA patent co-applications	1.29	8.51	0.04	0.04	0.08	0.05	0.01	0.11	0.16	0.05	0.02	-0.00
25. PA partner age	31.57	38.87	-0.04	0.34	0.00	0.05	-0.06	-0.10	0.04	-0.18	0.02	-0.01
26. PA partner size	33218.10	85787.29	-0.05	0.08	-0.00	-0.03	-0.02	-0.12	-0.06	-0.11	-0.02	0.02
27. PA partner GPE	55.01	95.96	0.06	0.40	0.01	-0.06	0.02	0.13	-0.03	0.17	-0.02	0.02
28. PA partner DAF	0.15	0.15	-0.04	-0.05	-0.05	0.07	-0.03	-0.11	-0.03	-0.12	0.04	-0.01
29. PA partner scientific impact	17.10	15.35	0.16	0.03	0.12	-0.02	0.10	0.40	-0.03	0.45	-0.02	-0.02
30. PA pre-alliance citations	181.67	507.17	0.09	0.54	0.17	0.19	0.02	0.31	0.18	0.08	0.03	-0.04
31. PA firm patenting experience	6760.64	8190.56	0.17	0.29	0.46	0.55	0.07	0.63	0.49	0.16	0.08	-0.10
32. PA firm total backward citations	176080.77	185783.71	0.27	0.42	0.50	0.53	0.10	0.86	0.45	0.34	0.09	-0.12
33. PA firm patent purchasing	4.47	39.26	-0.02	0.00	0.09	0.14	-0.01	0.01	0.15	-0.08	0.01	-0.01
34. PA value chain scope	0.15	0.12	0.10	0.37	0.15	0.03	0.05	0.26	0.01	0.16	0.02	-0.06
35. PA diff. in appropriability regimes	6.89	20.72	-0.07	-0.13	-0.43	0.25	-0.04	-0.20	0.02	-0.29	0.04	-0.03
36. PA technological overlap	0.39	0.27	0.06	0.45	0.06	0.07	0.03	0.18	0.07	0.08	-0.02	-0.02
37. PA common ties	1.55	2.85	0.11	0.40	0.10	-0.00	0.05	0.28	-0.07	0.31	0.01	0.01
38. PA joint venture	0.28	0.48	-0.12	-0.09	-0.13	0.05	-0.09	-0.30	-0.06	-0.33	0.04	0.02
39. PA value chain function	-0.37	0.62	0.01	0.08	0.04	0.01	0.04	0.04	0.09	-0.00	-0.02	0.02
40. PA joint partnering experience	0.62	1.52	0.02	0.50	0.19	0.10	-0.02	0.14	0.09	-0.01	0.01	-0.02
41. PA cross-national distance	0.04	1.29	0.04	-0.22	-0.19	0.02	0.03	0.07	-0.09	0.08	0.00	-0.05
42. PA patent co-applications	0.94	7.78	0.02	0.33	0.06	0.05	0.01	0.07	0.05	0.03	0.00	-0.02
43. Diff. in business similarity PA – SA	-0.03	0.52	-0.12	0.13	-0.04	0.14	-0.05	-0.14	0.11	-0.25	-0.05	0.04
44. Intermediate firm GPE	12.92	12.07	0.23	0.19	0.36	0.33	0.06	0.69	0.23	0.36	0.08	-0.06
45. Temporal gap between alliances	4.66	2.80	-0.10	0.03	0.17	0.41	-0.11	0.04	0.47	-0.44	0.07	0.01
46. Same partner in both alliances	0.02	0.13	0.00	-0.00	-0.04	-0.05	-0.07	-0.01	-0.06	-0.02	-0.01	0.06
47. Aggregate PA knowledge absorption	732.08	768.61	0.29	0.35	0.46	0.40	0.11	0.68	0.31	0.46	0.09	-0.11

N = 3,408 pairs of previous-subsequent alliances.

Table 2: Descriptive statistics and pairwise correlations for second-stage model (continued)

	11.	12.	13.	14.	15.	16.	17.	18.	19.	20.	21.	22.	23.	24.	25.	26.	27.	28.
12.	0.11																	
13.	0.44	0.15																
14.	0.73	0.42	0.43															
15.	-0.01	-0.01	0.11	0.02														
16.	0.25	0.17	0.37	0.22	-0.00													
17.	-0.06	0.00	-0.11	0.01	-0.01	-0.07												
18.	0.20	0.23	0.40	0.27	0.02	0.26	0.11											
19.	0.54	0.04	0.34	0.30	-0.02	0.29	-0.06	0.22										
20.	-0.11	-0.12	0.03	-0.13	0.10	0.04	-0.04	-0.13	-0.10									
21.	-0.00	-0.04	0.06	-0.09	-0.05	-0.28	0.01	0.02	-0.05	-0.35								
22.	0.30	0.32	0.47	0.26	0.01	0.32	-0.09	0.38	0.24	0.07	0.02							
23.	0.07	-0.09	-0.19	0.03	-0.09	-0.01	0.43	-0.07	0.03	-0.18	-0.16	-0.21						
24.	0.04	0.03	0.20	0.12	0.05	0.08	-0.05	0.11	0.04	0.13	-0.07	-0.01	-0.22					
25.	-0.08	-0.02	-0.06	-0.06	-0.01	-0.06	0.02	-0.09	-0.07	0.11	-0.05	-0.01	0.00	-0.00				
26.	-0.02	-0.04	-0.04	-0.02	0.02	-0.05	-0.08	-0.09	-0.04	0.08	-0.02	0.01	-0.00	-0.03	0.11			
27.	0.05	0.04	0.03	0.05	-0.01	0.01	-0.05	0.07	0.00	-0.06	0.04	0.02	-0.04	0.03	0.06	0.15		
28.	-0.04	-0.03	-0.01	-0.03	0.11	-0.04	0.07	-0.03	-0.02	0.09	-0.02	-0.02	0.01	-0.02	0.01	0.02	-0.04	
29.	0.15	0.12	0.14	0.12	-0.03	0.17	-0.06	0.21	0.17	-0.20	0.05	0.09	-0.04	0.07	-0.26	-0.07	0.41	-0.07
30.	-0.03	0.10	-0.00	0.02	0.00	-0.04	0.02	0.09	-0.05	-0.07	0.04	0.02	-0.04	0.04	0.33	0.07	0.27	-0.04
31.	-0.02	0.19	0.04	0.02	0.02	-0.06	0.03	0.20	0.01	-0.22	0.11	0.04	-0.08	0.08	0.00	-0.12	-0.01	-0.00
32.	0.01	0.26	0.08	0.08	0.00	0.01	0.02	0.27	0.03	-0.24	0.10	0.08	-0.12	0.10	-0.01	-0.13	0.10	-0.05
33.	-0.04	-0.00	-0.02	-0.03	-0.01	-0.07	0.01	-0.00	-0.03	-0.02	0.02	-0.02	0.01	0.01	0.03	-0.02	-0.04	-0.00
34.	0.02	0.08	0.05	0.06	-0.00	0.10	0.02	0.11	0.01	-0.07	-0.03	0.06	-0.01	0.04	0.16	-0.02	0.29	-0.06
35.	-0.11	-0.05	-0.06	-0.09	0.01	-0.07	0.44	-0.07	-0.02	0.16	-0.02	-0.05	0.15	-0.02	0.08	0.04	-0.09	0.14
36.	-0.02	0.07	0.00	0.02	-0.01	0.02	0.04	0.13	-0.03	-0.10	0.03	0.05	-0.03	0.01	0.17	0.11	0.16	-0.03
37.	0.11	0.08	0.09	0.08	-0.03	0.12	-0.06	0.12	0.10	-0.07	0.01	0.10	-0.04	0.02	0.11	0.09	0.49	-0.05
38.	-0.08	-0.10	-0.06	-0.09	0.06	-0.08	0.05	-0.21	-0.04	0.22	-0.07	-0.06	0.05	-0.03	0.18	0.15	-0.11	0.02
39.	-0.03	0.02	-0.04	-0.02	-0.04	-0.08	-0.03	0.02	-0.05	-0.04	0.06	-0.04	-0.04	0.00	0.01	-0.01	0.07	-0.03
40.	-0.01	0.02	-0.02	0.01	-0.02	-0.01	-0.06	-0.04	-0.06	0.01	-0.03	0.01	-0.03	0.00	0.16	0.22	0.22	-0.04
41.	0.03	0.02	0.05	0.03	-0.03	0.11	0.20	0.05	0.09	-0.01	-0.00	0.03	0.09	0.00	-0.20	-0.02	0.08	0.08
42.	0.01	0.02	0.01	0.02	-0.00	0.00	-0.00	0.04	-0.01	-0.02	0.01	0.01	-0.00	0.00	0.08	0.03	0.08	0.04
43.	0.02	-0.15	-0.18	0.00	-0.00	-0.27	0.18	-0.25	-0.13	-0.05	-0.00	-0.24	0.15	-0.10	0.15	0.05	-0.13	0.03
44.	0.01	0.21	0.08	0.08	-0.03	0.06	-0.01	0.17	0.01	-0.09	0.04	0.12	-0.14	0.10	-0.13	-0.09	0.12	-0.09
45.	-0.23	-0.02	-0.16	-0.15	-0.02	-0.30	0.06	-0.14	-0.23	0.14	0.07	-0.10	-0.13	0.06	0.01	-0.02	0.00	-0.05
46.	0.11	-0.02	0.02	0.07	-0.01	0.04	0.01	0.09	0.04	0.06	-0.06	0.26	0.02	-0.02	-0.01	0.08	0.04	0.00
47.	-0.01	0.27	0.09	0.09	-0.01	0.05	0.01	0.30	-0.03	-0.22	0.07	0.11	-0.12	0.08	-0.08	-0.14	0.11	-0.09

	29.	30.	31.	32.	33.	34.	35.	36.	37.	38.	39.	40.	41.	42.	43.	44.	45.	46.
30.	-0.06																	
31.	0.15	0.33																
32.	0.26	0.39	0.89															
33.	-0.07	0.05	0.30	0.15														
34.	0.08	0.34	0.10	0.24	-0.01													
35.	-0.04	-0.13	-0.07	-0.11	-0.02	-0.07												
36.	0.12	0.43	0.17	0.23	-0.01	0.24	0.13											
37.	0.27	0.25	0.04	0.17	-0.06	0.23	-0.14	0.22										
38.	-0.37	-0.02	-0.16	-0.26	0.13	-0.04	0.06	-0.15	-0.21									
39.	0.01	0.08	0.05	0.07	-0.07	-0.24	0.01	0.05	0.03	-0.28								
40.	-0.09	0.55	0.10	0.13	-0.00	0.23	-0.14	0.36	0.21	0.07	-0.02							
41.	0.33	-0.28	-0.12	-0.03	-0.19	0.01	0.42	-0.04	-0.10	-0.07	-0.17	-0.20						
42.	-0.06	0.22	0.12	0.12	0.11	0.03	-0.03	0.15	0.06	-0.00	0.14	0.01	-0.14					
43.	-0.23	0.19	0.04	-0.03	0.09	0.07	0.11	0.31	-0.03	0.07	-0.00	0.26	-0.07	0.04				
44.	0.39	0.12	0.25	0.46	-0.07	0.20	-0.18	0.08	0.33	-0.22	-0.02	0.02	0.13	0.03	-0.20			
45.	-0.02	0.03	0.00	0.04	-0.02	-0.03	0.08	0.01	-0.04	-0.02	0.05	0.02	0.04	-0.02	0.07	0.40		
46.	-0.01	-0.01	-0.07	-0.08	-0.01	0.04	0.01	0.07	0.06	0.02	-0.03	0.02	-0.00	0.01	0.01	-0.05	-0.07	
47.	0.36	0.29	0.71	0.88	0.07	0.25	-0.15	0.18	0.24	-0.30	0.04	0.07	0.04	0.08	-0.14	0.70	0.06	-0.08

Table 3: First-stage probit models for partner selection

Variables	Model (1)		Model (2)	
PA knowledge absorbed	0.001	(0.047)	0.010	(0.044)
Firm age	-0.109*	(0.054)	-0.004	(0.052)
Firm size	0.084	(0.053)	0.020	(0.051)
Firm GPE	0.003	(0.059)	-0.040	(0.049)
Firm R&D intensity	-0.001	(0.017)		
SA firm DAF	0.101	(0.080)		
SA firm scientific impact	0.001	(0.050)		
SA partner age	-0.157***	(0.018)	-0.224***	(0.017)
SA partner size	-0.022	(0.013)	-0.008	(0.013)
SA partner GPE	-0.109***	(0.022)		
SA partner pre-alliance citations	0.075***	(0.020)	0.156***	(0.018)
SA partner patenting experience	-0.062**	(0.023)	0.039*	(0.019)
SA partner total backward citations	0.030	(0.021)	-0.029+	(0.016)
SA partner patent purchasing	0.212***	(0.032)		
SA difference in appropriability regimes	0.128***	(0.028)	0.161***	(0.026)
SA technological overlap	0.050**	(0.019)	0.080***	(0.018)
SA common ties	0.061**	(0.021)	0.061***	(0.017)
SA joint partnering experience	0.508***	(0.037)		
SA cross-national distance	0.111***	(0.020)		
SA patent co-applications	-0.035*	(0.017)		
PA partner age	-0.002	(0.019)	0.000	(0.018)
PA partner size	0.002	(0.017)	0.002	(0.017)
PA partner GPE	0.007	(0.023)		
PA partner DAF	0.077	(0.141)		
PA partner scientific impact	0.013	(0.022)		
PA firm pre-alliance citations	-0.004	(0.045)	-0.011	(0.042)
PA firm patenting experience	-0.038	(0.095)	-0.008	(0.085)
PA firm total backward citations	-0.185*	(0.082)	-0.041	(0.061)
PA firm patent purchasing	-0.017	(0.017)		
PA value chain scope	-0.000	(0.020)	-0.004	(0.018)
PA difference in appropriability regimes	0.009	(0.027)	0.007	(0.024)
PA technological overlap	-0.019	(0.022)	-0.017	(0.020)
PA common ties	0.007	(0.023)	-0.003	(0.019)
PA joint venture	0.038	(0.045)		
PA value chain function	0.002	(0.019)		
PA joint partnering experience	-0.004	(0.021)		
PA cross-national distance	-0.003	(0.023)		
PA patent co-applications	0.004	(0.019)		
Difference in business similarity PA – SA	0.063**	(0.022)	0.052*	(0.021)
Intermediate firm GPE	-0.104+	(0.056)	-0.008	(0.031)
Temporal gap between alliances	0.014	(0.032)		
Same partner in both alliances	-0.500***	(0.150)		
Aggregate PA knowledge absorption	0.063	(0.090)		
SA partner relative size	0.259***	(0.020)	0.252***	(0.019)
Constant	-0.099	(0.486)	-0.247	(0.481)
Year, Industry, & Country fixed effects	Included		Included	
N population	6,816		6,816	
N selected	3,408 (50%)		3,408 (50%)	
Pseudo R^2	0.107		0.058	
Log-likelihood	-4217.9		-4461.1	

Standard errors in parentheses. Significance: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, + $p < 0.10$.

Table 4a: PPML regression for knowledge spillover in a subsequent alliance

Variables	Model (1)		Model (2)		Model (3)		Model (4)	
PA knowledge absorbed			-0.047*	(0.018)	-0.089***	(0.021)	-0.051*	(0.023)
PA knowledge absorbed^2					0.014***	(0.003)	0.015***	(0.002)
Firm age	0.032	(0.302)	0.044	(0.297)	0.057	(0.291)	0.487	(0.367)
Firm size	-0.976+	(0.573)	-0.983+	(0.577)	-0.993+	(0.583)	-1.590***	(0.286)
Firm GPE	1.085***	(0.128)	1.119***	(0.132)	1.142***	(0.134)	1.379***	(0.133)
Firm R&D intensity	-0.287	(0.556)	-0.278	(0.549)	-0.266	(0.546)		
SA firm DAF	0.668	(0.640)	0.675	(0.642)	0.687	(0.645)		
SA firm scientific impact	0.559*	(0.221)	0.565*	(0.220)	0.565*	(0.220)		
SA partner age	0.831***	(0.108)	0.831***	(0.108)	0.832***	(0.108)	0.897***	(0.113)
SA partner size	0.092	(0.079)	0.092	(0.079)	0.090	(0.079)	-0.425	(0.440)
SA partner GPE	-0.384***	(0.056)	-0.386***	(0.056)	-0.388***	(0.056)		
SA partner pre-alliance citations	0.259***	(0.025)	0.259***	(0.024)	0.260***	(0.024)	0.070*	(0.028)
SA partner patenting experience	-0.559***	(0.024)	-0.561***	(0.024)	-0.561***	(0.024)	-0.434***	(0.025)
SA partner total backward citations	1.324***	(0.085)	1.327***	(0.085)	1.329***	(0.085)	0.931***	(0.078)
SA partner patent purchasing	0.233	(0.157)	0.232	(0.157)	0.233	(0.157)		
SA value chain scope	0.075+	(0.041)	0.076+	(0.042)	0.075+	(0.042)	-0.035	(0.054)
SA difference in appropriability regimes	-0.375*	(0.183)	-0.379*	(0.184)	-0.381*	(0.182)	0.086	(0.221)
SA technological overlap	1.140***	(0.121)	1.140***	(0.121)	1.143***	(0.122)	1.326***	(0.092)
SA common ties	0.104*	(0.043)	0.103*	(0.044)	0.103*	(0.043)	0.098***	(0.012)
SA joint venture	-0.495**	(0.177)	-0.496**	(0.178)	-0.500**	(0.178)		
SA value chain function	-0.012	(0.033)	-0.012	(0.033)	-0.012	(0.033)		
SA joint partnering experience	0.012	(0.046)	0.011	(0.046)	0.013	(0.045)		
SA cross-national distance	-0.033	(0.239)	-0.034	(0.239)	-0.030	(0.239)		
SA patent co-applications	0.149***	(0.020)	0.149***	(0.020)	0.148***	(0.020)		
PA partner age	0.016+	(0.009)	0.029+	(0.015)	0.036*	(0.016)	0.026+	(0.014)
PA partner size	-0.113**	(0.041)	-0.101**	(0.037)	-0.098**	(0.038)	-0.112*	(0.045)
PA partner GPE	0.012	(0.011)	0.022	(0.015)	0.029+	(0.016)		
PA partner DAF	-0.013	(0.047)	0.010	(0.051)	-0.002	(0.051)		
PA partner scientific impact	-0.008*	(0.003)	-0.006+	(0.003)	-0.006+	(0.003)		
PA firm pre-alliance citations	0.014	(0.012)	0.042*	(0.017)	0.033*	(0.016)	0.021	(0.018)
PA firm patenting experience	0.632***	(0.078)	0.636***	(0.078)	0.656***	(0.082)	0.781***	(0.072)
PA firm total backward citations	0.118	(0.101)	0.116	(0.097)	0.111	(0.100)	0.087	(0.076)
PA firm patent purchasing	-0.015***	(0.004)	-0.016***	(0.004)	-0.015***	(0.004)		
PA value chain scope	-0.014*	(0.006)	-0.016*	(0.007)	-0.016*	(0.006)	0.002	(0.005)
PA difference in appropriability regimes	0.034	(0.024)	0.039	(0.028)	0.033	(0.025)	0.020	(0.014)
PA technological overlap	0.017*	(0.008)	0.026*	(0.011)	0.033**	(0.012)	0.027	(0.018)
PA common ties	0.002	(0.006)	0.002	(0.007)	0.007	(0.006)	0.020***	(0.004)
PA joint venture	-0.013	(0.012)	-0.022	(0.013)	-0.025*	(0.012)		
PA value chain function	-0.021***	(0.006)	-0.027***	(0.006)	-0.028***	(0.005)		
PA joint partnering experience	0.005	(0.005)	0.008	(0.005)	-0.001	(0.007)		
PA cross-national distance	-0.006	(0.006)	-0.011	(0.008)	-0.009	(0.007)		
PA patent co-applications	0.008***	(0.002)	0.016***	(0.004)	0.009*	(0.004)		
Difference in business similarity PA – SA	-0.129***	(0.015)	-0.133***	(0.017)	-0.130***	(0.017)	-0.163***	(0.025)
Intermediate firm GPE	0.359***	(0.038)	0.370***	(0.038)	0.376***	(0.038)	0.419***	(0.056)
Temporal gap between alliances	0.007	(0.080)	-0.006	(0.080)	-0.010	(0.082)		
Same partner in both alliances	0.223***	(0.064)	0.220***	(0.061)	0.216***	(0.061)		
Aggregate PA knowledge absorption	-0.132	(0.150)	-0.154	(0.141)	-0.168	(0.139)		
λ partner selection	-0.786**	(0.287)	-0.790**	(0.287)	-0.789**	(0.285)	-1.198***	(0.254)
Constant	2.516***	(0.495)	2.489***	(0.497)	2.441***	(0.502)	3.365***	(0.406)
Year, Industry, & Country fixed effects	Included		Included		Included		Included	
N pairs of previous-subsequent alliances	3,408		3,408		3,408		3,408	
Log pseudo-likelihood	-73158		-73030		-72933		-96441	
Condition number	16.80		17.17		17.58		15.77	

Standardized coefficients. Clustered standard errors in parentheses. Significance: *** p < 0.001, ** p < 0.01, * p < 0.05, + p < 0.10.

Table 4b: PPML regression for knowledge spillover in a subsequent alliance (moderators)

Variables	Model (5)	Model (6)	Model (7)	Model (8)	Model (9)	Model (10)
PA knowledge absorbed	-0.092***	-0.079***	-0.097***	-0.078***	-0.084***	-0.062*
	(0.021)	(0.018)	(0.021)	(0.017)	(0.014)	(0.025)
PA knowledge absorbed^2	0.013***	0.010**	0.016***	-0.001	0.002	0.005
	(0.004)	(0.004)	(0.004)	(0.004)	(0.006)	(0.004)
PA value chain scope	-0.023***	-0.012+	-0.015*	-0.019**	-0.020***	0.001
	(0.006)	(0.006)	(0.007)	(0.006)	(0.006)	(0.005)
PA difference in appropriability regimes	0.022	0.041	0.032	0.036	0.029	0.029
	(0.022)	(0.035)	(0.025)	(0.028)	(0.035)	(0.024)
Difference in business similarity PA – SA	-0.128***	-0.133***	-0.131***	-0.131***	-0.135***	-0.168***
	(0.016)	(0.018)	(0.017)	(0.017)	(0.018)	(0.023)
PA technological overlap	0.033**	0.029**	0.033**	0.038***	0.026*	0.026
	(0.011)	(0.010)	(0.012)	(0.010)	(0.011)	(0.018)
PA value chain scope	0.011*				0.021**	0.011**
× PA knowledge absorbed (H2)	(0.004)				(0.007)	(0.004)
PA difference in appropriability regimes		-0.023**			-0.055***	-0.051***
× PA knowledge absorbed (H3)		(0.008)			(0.012)	(0.008)
Difference in business similarity PA – SA			-0.008*		-0.013*	-0.024**
× PA knowledge absorbed (H4)			(0.004)		(0.005)	(0.007)
PA technological overlap				0.040***	0.005	0.023***
× PA knowledge absorbed (H5)				(0.011)	(0.016)	(0.007)
Constant	2.397***	2.442***	2.449***	2.418***	2.366***	3.326***
	(0.504)	(0.502)	(0.501)	(0.504)	(0.506)	(0.389)
Controls	Included	Included	Included	Included	Included	Included[1]
Year, Industry, & Country fixed effects	Included	Included	Included	Included	Included	Included
N pairs of previous-subsequent alliances	3,408	3,408	3,408	3,408	3,408	3,408
Log pseudo-likelihood	-72830	-72872	-72905	-72845	-72521	-95867
Condition number	17.86	17.97	17.73	21.27	22.94	20.64

Standardized coefficients. Clustered standard errors in parentheses. Significance: *** p < 0.001, ** p < 0.01, * p < 0.05, + p < 0.10.
[1] Simplified set of controls in Model 10, as in Model 4 (Table 4a).

Figure 1: Knowledge spillover in a subsequent alliance by knowledge absorbed in a previous alliance

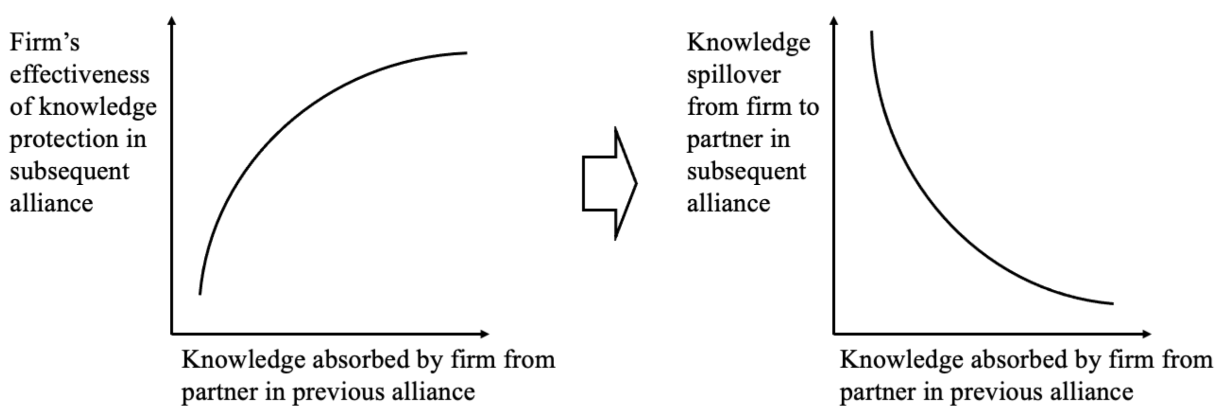


Figure 2: Knowledge spillover in a subsequent alliance by knowledge absorbed in a previous alliance

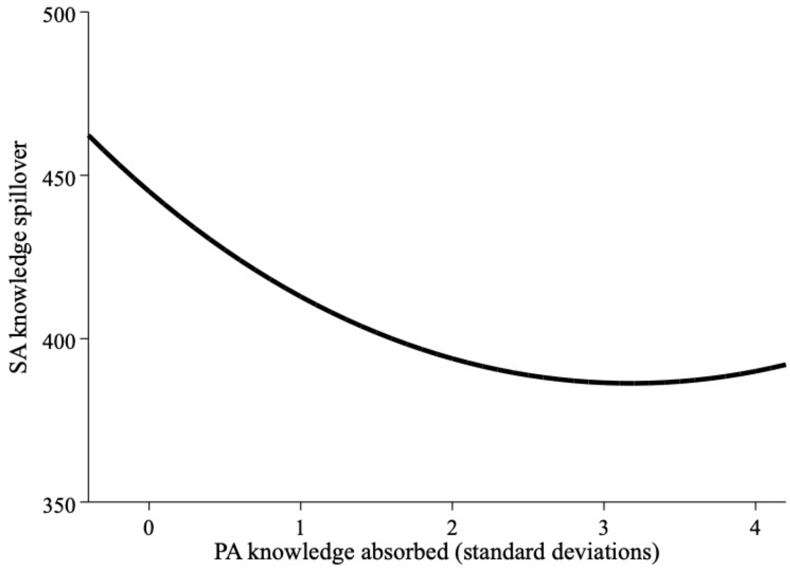


Figure 3: Moderating effect of value chain scope in a previous alliance

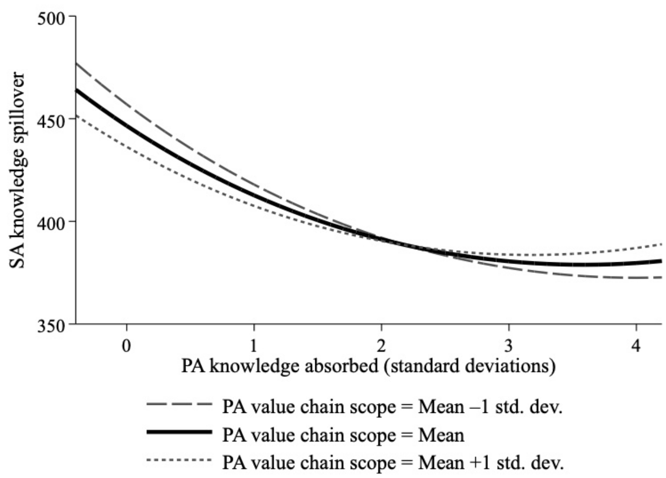


Figure 4: Moderating effect of firm's weaker appropriability regime in a previous alliance

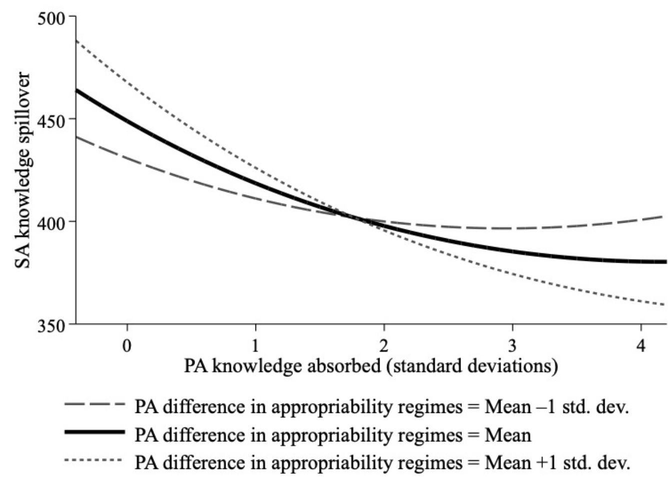


Figure 5: Moderating effect of stronger business similarity in a previous alliance

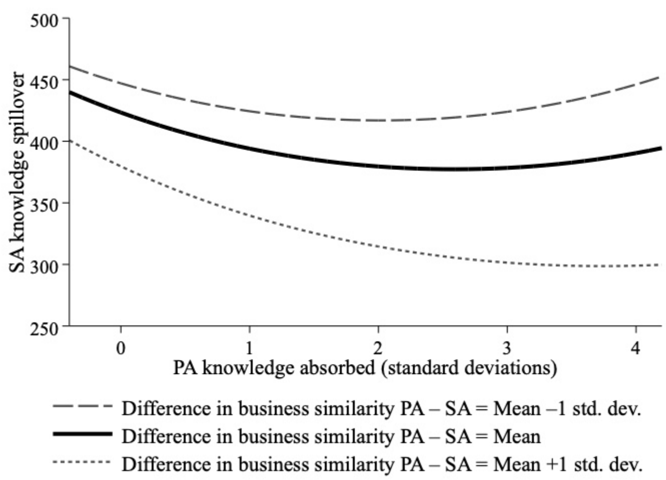
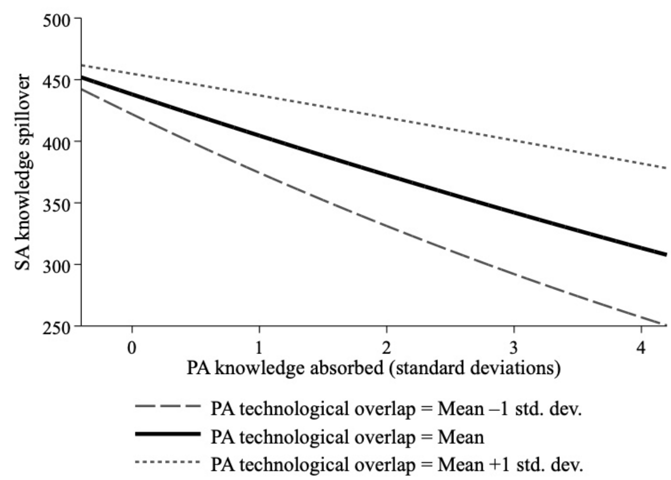


Figure 6: Moderating effect of relative absorptive capacity in a previous alliance



ONLINE APPENDIX: ROBUSTNESS TESTS

Table A1: Summary of robustness tests

Description of test and rationale		**Findings**
1.	Drop the minimum lag between previous and subsequent alliances to account for the possibility that firms may internalize and apply knowledge protection practices in subsequent alliances that are separated by less than one year.	Consistent findings.
2.	Drop pairs of alliances with temporal overlap, to account for the possibility that the firm needs to complete the previous alliance before applying learned practices in a subsequent alliance.	Consistent findings except for H5; loss of 2,089 (61.3%) observations.
3.	Switch previous and subsequent alliances, so the dependent variable captures knowledge spillover from the firm to the previous partner and the independent variable captures knowledge absorbed by the firm from the subsequent partner. If findings hold, this may suggest reverse causality concerns.	No indication of reverse causality.
4.	Test (a) three-year and (b) seven-year windows for patent citations, to test the findings' sensitivity to different windows for patent citations.	a) & b) Consistent findings, except H4 (consistent sign).
5.	Assume (a) three-year and (b) seven-year alliance duration, to test the findings' sensitivity to different assumptions about alliance duration.	a) & b) Consistent findings.
6.	Recompute all patent-based variables using only USPTO patents, to rule out concerns that different standards for patent citations by different patent offices may confound the findings.	Consistent findings, except H3 and H4 (consistent signs).
8.	Use non-discounted measures of knowledge spillover and knowledge absorption, to test the findings' sensitivity to discounting of patent citations.	Consistent findings.
9.	Consider only unique patent citations in the measures for knowledge spillover and knowledge absorption, to rule out the possibility that the findings are driven by the absorbing party's repeated citations to the same patents.	Consistent findings.
10.	Consider citations only by patents that list fewer than 100 backward citations, to rule out the possibility that the findings are driven by firms citing excessively only to avoid their patents' rejection by the patent office (Kuhn, Younge, & Marco, 2020).	Consistent findings.
11.	Consider citations only to patents that the absorbing party cited for the first time after the alliance announcement, to rule out the possibility that the findings are driven by citations to patents already known to the absorbing party prior to the alliance.	Consistent findings.
12.	Discount knowledge absorbed in the previous alliance based on the years that have passed between the previous and subsequent alliances, to account for the possibility that the firm may forget learned knowledge protection practices after a certain time, or that these practices may become less effective as time passes.	Consistent findings, except H4 (consistent sign).
13.	Measure the strength of the appropriability regime based on countries' ordinal ranking in the Property Rights Index, to rule out the possibility that the findings are exaggerated by features of the distribution of countries along the index's scale.	Consistent findings.

14.	Measure business similarity using the overlap of six-digit NAICS codes, to test the findings' sensitivity to differences in industry definitions.	Consistent findings, except H3 (consistent sign).
15.	Measure technological overlap using a Jaccard index of the extent to which the parties' patents cover different patent classes (e.g., von Wartburg, Teichert, & Rost, 2005). The index is defined as $S_{i,j} = \frac{\lvert C_i \cap C_j \rvert}{\lvert C_i \cup C_j \rvert}$, where C_i and C_j represent the numbers of IPC subclasses in the patents of firm i and firm j.	Consistent findings, except H2 and H4 (consistent signs).
16.	Measure technological overlap using the standardized Euclidean Distance between the patent classes in the parties' patents (e.g., Rosenkopf & Almeida, 2003). The measure is defined as $S_{i,j}=\sqrt{\sum_k (f_{ik} - f_{jk})^2}$, where f_{ik} is the percentage share of firm i's patents allocated to IPC subclass k.	Consistent findings, except H4 (consistent sign).
17.	Measure technological overlap using the common citation rate of the parties' patents (Mowery et al.,1998). The common citation rate is defined as: $S_{i,j}$ = (Citations in patents of firm i to patents cited in patents of firm j / Total citations in patents of firm i) + (Citations in patents of firm j to patents cited in patents of firm i / Total citations in patents of firm j).	Consistent findings, except H2 (consistent sign).
18.	Measure technological overlap using a refined cosine index (Jaffe, 1986), defining the patent class at the five-, to seven-digit (group) level of the IPC instead of the four-digit (subclass) level.	Consistent findings.
19.	Specify additional controls, including: a) Protecting party's patent applications during the alliance b) Rate of cross-citations (Mowery et al., 1996) in previous and subsequent alliances c) Firm's knowledge spillover in previous alliance and knowledge absorption in subsequent alliance d) Firm's activity load in previous alliance (simultaneous alliances) e) Firm's and partners' vertical integration f) Firm's and partners' financial solvency g) Firm's and partners' status as state-owned enterprises h) Partners' R&D intensity i) Indicator of technology transfer agreement j) Indicator of licensing agreement k) Indicator of horizontal (same-industry) alliance l) Number of joint alliances formed by previous and subsequent partners.	a) Consistent findings, except H2 and H5 (consistent signs) b) Consistent findings c) Consistent findings d) Consistent findings e) Consistent findings; loss of 649 (19.04%) observations f) Consistent findings g) Consistent findings h) Consistent findings; loss of 539 (15.82%) observations i) Consistent findings, except H4 (consistent sign) j) Consistent findings k) Consistent findings, except H4 (consistent sign) l) Consistent findings.
20.	Exclude observations if a) the same partner was featured in the previous and the subsequent alliance b) the firm held a minority investment in the previous partner or in the subsequent partner (and vice versa).	a) Consistent findings; loss of 58 observations (1.9%) b) Consistent findings; loss of 150 (4.4%) observations
21.	Explore additional boundary conditions that moderate the negative association between knowledge spillover in a subsequent alliance and knowledge absorbed in a previous alliance: a) Value chain function in previous alliance	a) Weaker negative association in previous upstream alliances (β=0.011, p<0.001) b) Insignificant interaction c) Insignificant interaction

	b) Joint-venture governance of previous alliance c) Horizontal previous alliance d) Firm's activity load in previous alliance e) Firm's GPE in previous alliance f) Firm's joint partnering experience with previous partner g) Firm's cumulated knowledge absorption in all previous alliances (except previous alliance under consideration) h) Previous partner's R&D intensity.	d) Weaker negative association with greater activity load in previous alliance (β=0.013, p=0.014) e) Weaker negative association with greater firm GPE (β=0.052, p=0.096) f) Weaker negative association with greater joint experience with previous partner (β=0.029, p<0.001) g) Stronger negative association with firm's greater cumulated knowledge absorption (β=-0.004, p=0.035) h) Stronger negative association with greater R&D intensity of previous partner (β=-0.073, p=0.077).
22.	Test how the moderators affect the quadratic term of knowledge absorbed in the previous alliances (Haans, Pieters, & He, 2016).	Consistent findings, except H5, but severe multicollinearity.
23.	Test different approaches for clustering standard errors: a) Cluster by observation (robust standard errors) b) Cluster by firm c) Cluster two-way by previous alliance and subsequent alliances d) Cluster three-way by firm and previous and subsequent alliances e) Cluster five-way by firm, partners, and previous and subsequent alliances.	a) Consistent findings, except H4 (consistent sign) b) Consistent findings c) Consistent findings, except H4 (consistent sign) d) Consistent findings e) Consistent findings.
24.	Estimate the second-stage model using Negative Binomial.	Consistent findings, except H2.
25.	Estimate the second-stage model using zero-inflated Poisson. Non-zero knowledge spillover was predicted using the firm's patent applications during the subsequent alliance, the subsequent partner's patenting experience, their technological overlap, and their cross-national distance.	Consistent findings, except H4 (consistent sign).
26.	Consider a first-stage model in which partner-selection is estimated by using four (instead of one) counterfactual partners per formed alliance (Robinson & Stuart, 2007).	Consistent findings.
27.	Include a sample-selection first-stage model that estimates the probability of sampling a firm (out of all listed firms from China, South Korea, Taiwan, and Singapore active in the sampled industries: 4,746 firms, 34,807 firm-years), using the firms' age, size, R&D intensity, GPE, and patenting experience as predictors. As exclusion restriction, we used the extent of annual alliance formation in a firm's industry.	Consistent findings.
28.	Estimate the second-stage models without first-stage model.	Consistent findings.
29.	Estimate models without fixed effects.	Consistent signs (all hypotheses).
30.	Drop potential outliers of variables of interest, identified via the Extreme Studentized Deviate Method and the Chi-Squared Test.	Consistent findings; loss of 93 (2.73%) observations.