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Revisiting the Dynamics of Knowledge Spillover in Interfirm Alliances: Studies on Learning and Protection of Proprietary Knowledge in International Settings

Advisor: Dovev LAVIE

Co-advisor: Torben PEDERSEN

PhD Thesis by

Jens-Christian FRIEDMANN

ID number: 3050740

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THESIS ABSTRACT

This dissertation studies how firms cope with new challenges in absorbing and protecting knowledge from alliance partners. Chapter one examines how firms from emerging economies that assumed the “student” role in their prior alliances reverse roles and transition to the “teacher” role, while learning how to protect their own knowledge from spillover to prospective partners. It reveals that firms vicariously learn their partners’ knowledge protection practices to improve their own knowledge protection in subsequent alliances. Thereby it shows that learning and knowledge protection are interdependent activities not only within the same alliance but also across successive alliances. Chapter two studies how national innovation systems in the home countries of firms and their partners, respectively, influence firms’ knowledge acquisition from alliance partners. Whereas prior studies separately consider national systems and alliances, this study juxtaposes these aspects, showing that differences in national innovation systems help explain variability in firms’ learning. Finally, chapter three examines how knowledge spillover to an alliance partner can enable the firm to gain value as it observes its partner’s use of the spilled knowledge. It demonstrates that knowledge spillovers to partners can facilitate learning, as long as these spillovers do not become excessive, and if the partner recombines the firm’s spilled knowledge in non-redundant ways. Together, these studies contribute to the literature on learning in alliances by offering a new understanding of the dynamics of knowledge accumulation and protection.

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TABLE OF CONTENTS

1. INTRODUCTION

Interfirm alliances enable firms to combine their assets and realize synergies (Dyer & Singh, 1998) while absorbing each other's knowledge (Gomes-Casseres, Hagedoorn, & Jaffe, 2006; Mowery, Oxley, & Silverman, 1996). Traditionally, research on learning in alliances has ascribed the role of "teachers" to Western multinational enterprises, while regarding their partners from emerging economies as "students" that learn their knowledge and internalize it (e.g., Beamish, 1988; Child, Faulkner, & Tallman, 2005; Contractor & Lorange, 1988).[1] Accordingly, this research centers on how these "teachers" protect their knowledge from unwanted spillover as the "students" attempt to overcome their knowledge protection mechanisms (e.g., Hamel, 1991; Shenkar, 1990). However, this reality has changed, as by the turn of the 21st century, many technology leaders originate from (formerly) emerging economies. Moreover, increasing interdependence of knowledge and fast innovation cycles render it difficult for firms to protect proprietary knowledge from spillover to alliance partners (Contractor, 2019; Inkpen, Minbaeva, & Tsang, 2019). This reality poses new challenges for firms that enter alliances, while offering opportunities for scholars to revisit old truths and provide new theory and evidence in line with this changing reality.

This dissertation examines these challenges and their implications from the perspectives of both established multinationals that seek to maintain market leadership in the face of technological parity and interdependence, as well as from the perspective of their challengers that seek to learn how to protect their newly realized competitive positions. The objective of the dissertation is to understand how firms cope with emerging challenges of protecting and absorbing knowledge from partners. Throughout its three chapters, the dissertation examines how in alliances, contender firms

[1] Most alliances feature bi-directional knowledge flows (Mowery et al., 1996), even though one party may learn more than the other (Yang, Zheng, & Zaheer, 2015). Hence, in the present context, "student" designates a net receiver of knowledge flows, while "teacher" refers to a net provider of knowledge flows.

cope with the new reality of becoming technology leaders, how firms' learning from partners may be enhanced or constrained by their national contexts, and how "teacher" firms can improve their innovations by learning from their "students." In each chapter, I bring together established insights about learning in alliances with recent perspectives from the literatures on vicarious learning, national innovation systems, and knowledge management. My dissertation not only shows how firms reverse roles across successive alliances by learning knowledge protection practices from partners, but also explores how national contexts guide firms' learning in alliances, and finally demonstrates how spilled knowledge to a partner may benefit the originating firm by facilitating subsequent learning from the partner's inventions.

Chapter one poses the question how firms from emerging economies that assumed the "student" role in prior alliances reverse roles and transition to the "teacher" role, while learning how to protect their proprietary knowledge from prospective partners. This study is grounded in the literature on learning and protecting knowledge in strategic alliances (e.g., Kale, Singh, & Perlmutter, 2000; Khanna, Gulati, & Nohria, 1998). Early work of this literature 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 focusing on protective practices that shield proprietary knowledge from spilling over to partners (e.g., Diestre & Rajagopalan, 2012; Katila, Rosenberger, & Eisenhardt, 2008). While prior research has centered on the interplay between knowledge absorption and protection in a given alliance, it is not well understood whether a firm that learns to absorb or protect knowledge in one alliance can then apply the learned practices in subsequent alliances. To solve this puzzle, chapter one examines whether firms that traditionally lacked proprietary knowledge but have become skilled at absorbing their partners' knowledge, manage to reverse roles, such that once they develop proprietary knowledge, they can effectively protect it from spilling over to partners in subsequent alliances. The theory advanced in chapter one contends that firms can vicariously learn their partners' knowledge protection practices by overcoming these protections as they attempt to absorb a partner's proprietary knowledge. Learning a partner's protection practice can then improve a firm's ability to develop and apply that practice when the "student" reverses its role to a "teacher" in subsequent alliances. Chapter one also examines commonly studied boundary conditions in the literature on learning in alliances that collectively influence the opportunities, motivation, and ability of the firm to absorb its partners' knowledge, and thus affect the effort the firm needs to invest in order to overcome its partners' knowledge protection. The more effort a firm needs to invest, the more likely it is that the firm can vicariously learn and successfully apply protection practices in later alliances, thus improving the firm's prospects of role reversal. By studying how absorbing knowledge from a partner influences a firm's ability to protect its proprietary knowledge from spilling over to a partner in a subsequent alliance, chapter one goes beyond prior research that has studied the interplay of knowledge absorption and protection in single alliance. It also contributes to the broader organizational learning literature by showing how firms learn counter activities, i.e., knowledge absorption and protection, as they reverse roles from "students" to "teachers" in successive alliances.

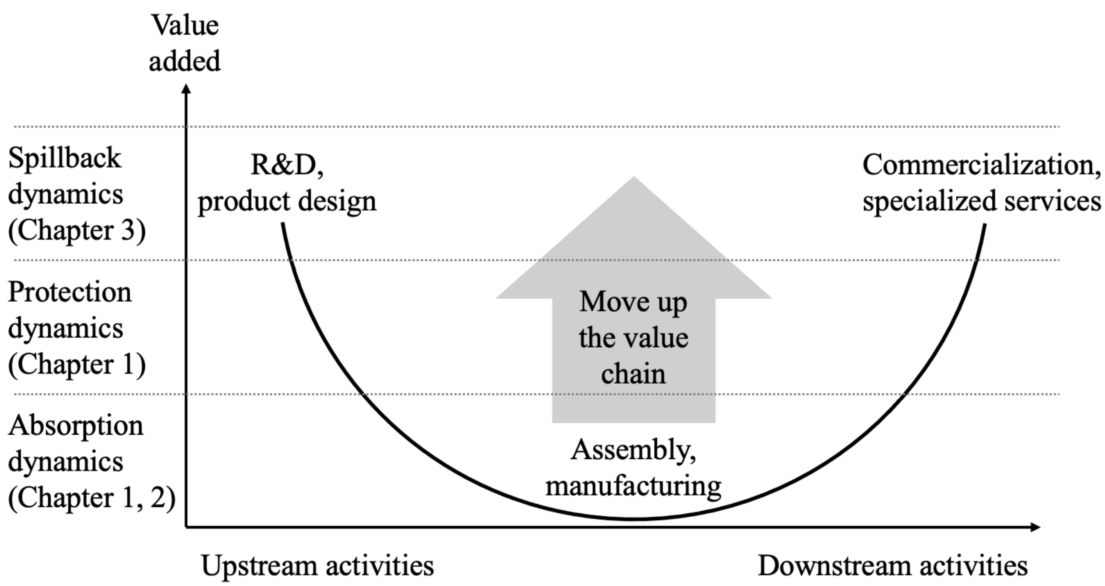
Whereas chapter one deals with "student" firms that reverse roles to become "teachers," chapter two raises the question why firms from certain countries tend to be better "students" in their alliances. Although the alliance literature acknowledges that firms' learning outcomes in alliances vary depending on their home countries, such differences have been conventionally attributed to firm-, knowledge-, and relationship-specific characteristics (e.g., Inkpen & Tsang, 2007; Lane, Salk, & Lyles, 2001; Simonin, 1999). Chapter two suggests that learning and knowledge acquisition in alliances can also be directly influenced by the home-country contexts of the partnering firms. Drawing on theories of national innovation systems (e.g., Lundvall, 1992; Nelson, 1993), chapter two proposes a contextual explanation for why firms' learning outcomes often vary depending on their home countries. It brings together theories on learning in alliances with theories on national innovation systems, asking how differences in national innovation systems contribute to firms' knowledge acquisition from partners in international alliances. To answer this question, chapter two focuses on innovation policies, which concern those components of national innovation systems that can be influenced by governmental actions. By invoking complementarities between internal R&D and external knowledge acquisition (e.g., Arora & Gambardella, 1990; Cassiman & Veugelers, 2006), the theory of chapter two contends that firms from countries with innovation policies that support domestic R&D have an improved ability and greater incentives to acquire their partners' knowledge. Moreover, by providing similar knowledge accumulation benefits to the partner in its home country, the innovation policy in the partner's country furnishes opportunities for the firm to acquire its partner's knowledge. While prior research has considered international alliances and national innovation systems separately, chapter two merges these research streams, contributing to both the literature on learning in alliances and to the literature on how innovation policies promote learning in firms. It shows that even though governments may not design innovation policies with interfirm alliances in mind, those policies can affect firms' learning in alliances. This suggests that in drafting innovation policies, governments can regulate knowledge inflows and outflows to their economy by influencing firms' learning from foreign alliance partners.

Finally, chapter three challenges the widely adopted claim in the alliance literature that exposing knowledge to alliance partners would restrict the source firm's appropriation of value from that knowledge (e.g., Hamel, 1991; Teece, 1986). This claim has led to scholars to conclude that firms would face disincentives to continue developing proprietary knowledge that was exposed to their partners (e.g., Diestre & Rajagopalan, 2012; Khanna et al., 1998; Lavie, 2006). Accordingly, the alliance literature has emphasized the importance of protecting of proprietary knowledge against spillover to partners (e.g., Deverakonda & Reuer, 2018; Kale et al., 2000; Norman, 2002; Oxley & Sampson, 2004). In chapter three I argue that although firms in alliances obviously need to invest in the protection of proprietary knowledge, once knowledge spillovers to partners have occurred, the source firms should also consider the possibility of learning from the partner's inventions that recombine hat spilled knowledge—which I term knowledge "spillback." Recognizing this possibility implies that by considering knowledge spilled to a partner a sunk cost, many firms restrict their potential for generating value from their alliances. If instead, these firms could learn from their partners' recombinations of their spilled knowledge, they would be able to regain some value which otherwise would have been considered lost. Perhaps due to its apparent contradiction of conventional wisdom, this possibility has not been theoretically developed nor empirically studied within the alliance context. To address this shortcoming, I examine how, and under which conditions, a firm's outbound knowledge spillovers to partners induce learning opportunities for the firm. My theory suggests that when spilling knowledge to an alliance partner, the source firm can benefit from the partner's complementary assets, which the partner may use to recombine the firm's spilled knowledge. In turn, learning from the partner's recombinations of the spilled knowledge can enable the firm to break the mold of rigidities and path dependencies entailed in its own knowledge development trajectory. Moreover, I contend that the firm's incentives to absorb knowledge spillback from partners are shaped by conditions that affect the extent to which partners can combine the spilled knowledge to develop inventions that are complementary to those of the firm. In the presence of such conditions, the partner's recombinations tend to encourage rather than stifle the firm's continued development of its spilled knowledge. Chapter three advances research on learning in alliances by introducing the notion of knowledge spillback, underscoring a previously neglected path for learning in alliances. Moreover, chapter three contributes to the debate concerning tradeoffs between knowledge absorption and protection in alliances, whereby greater protection of own assets restricts absorption of partners' assets and is rather costly (Contractor, 2019; Inkpen et al., 2019; Wadhwa, Bodas Freitas, & Sarkar, 2017). Indeed, as chapter one suggests, firms that invest in knowledge protection may inadvertently "teach" their protection practices to partners. Then, chapter three reveals that besides such caveats, knowledge protection can restrict firms' knowledge development by foreclosing knowledge spillback opportunities, and hence imposes opportunity costs.

Together, the three chapters offer a new understanding of the dynamics of knowledge accumulation and protection in alliances. Each chapter's implications pertain to different stages of a firm's advancement from the "student" role to that of the "teacher:" Firms from emerging economies typically start out in the "student" role while performing mostly low value-added manufacturing activities, which often rely on established, commoditized knowledge. As these firms catch up and move into higher value-added R&D activities, they face increasing needs to upgrade their knowledge bases and accumulate proprietary knowledge (Mudambi, 2008). To this purpose, "student" firms can benefit from alliances with partners from advanced economies, which enable them to access complementary knowledge that is otherwise unavailable in their home countries.

Against this background, chapter two suggests that a firm's effectiveness at being a "student" is contingent on the extent to which its home-country innovation system supports the firm's investments in internal R&D and, in turn, the acquisition of complementary external knowledge from international alliance partners. Moreover, it reveals that the firm can benefit by forming alliances with partners who themselves rely on advanced innovation systems in their countries of origin. As the firm accumulates proprietary knowledge and transitions from the "student" role to that of a "teacher," it faces the need to safeguard its recently attained competitive position by protecting its knowledge against spillover to alliance partners. Chapter one offers guidance to firms in this transitory phase, suggesting that firms which reverse roles from "student" to "teacher" can vicariously learn knowledge protection practices as they keep applying their well-honed skills at internalizing their partners' technological knowledge. Eventually, once the firm evolves into a technology leader, it would have accumulated a substantial base of proprietary knowledge. At this stage, the firm may increasingly encounter competency traps that hamper its continued knowledge development. As chapter three suggests, a firm facing this predicament can benefit from observing how its partners use its knowledge spillovers to generate valuable recombinations, whereby the firm can overcome rigidities in its own knowledge development process as it absorbs knowledge spillback. The dynamics of knowledge spillover prevailing at each stage of the firm's upward movement along the global value chain is displayed in Figure 1.1.

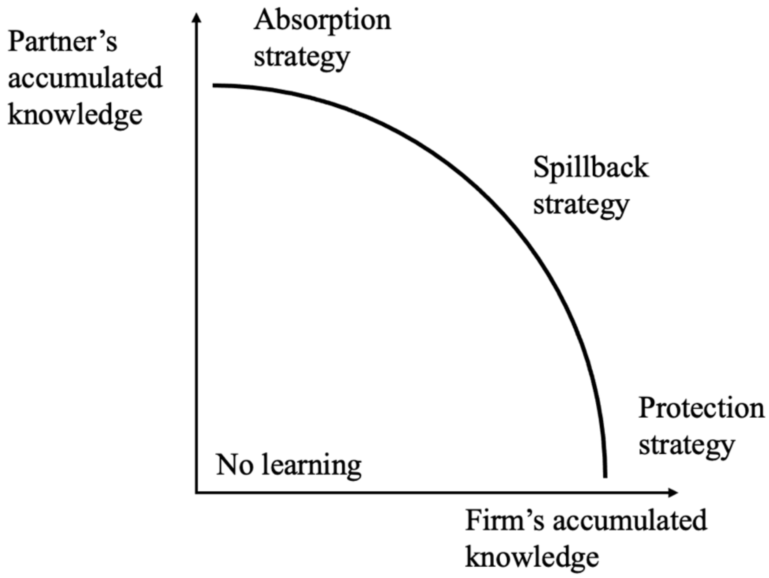
Figure 1.1: Dynamics of knowledge spillover in alliances as the firm moves up the value chain



Value-chain curve representation adapted from Mudambi (2008).

While Figure 1.1 shows how the dynamics of knowledge spillover in alliances vary with the firm's accumulation of proprietary knowledge as it moves up the value chain, the firm's chosen knowledge management strategy in a given alliance would also depend on the position of the partner within that value chain and, consequently, on the knowledge held by that partner. Consider a scenario in which the amount and quality of a partner's accumulated knowledge vastly exceeds the amount and quality of the firm's knowledge: Under these conditions, the firm faces incentives to internalize the partner's knowledge while the partner would seek to protect its knowledge against spilling over to the firm. Now, consider the opposite scenario in which the partner's accumulated knowledge substantially exceeds that of the firm. The firm would direct its efforts toward protecting its knowledge against spillover while the partner would focus on absorbing the firm's knowledge. In fact, the more the firm keeps advancing from "student" to "teacher," the more frequently it will encounter partners that require it to adopt a protective role. Finally, consider the scenario in which the firm has accumulated enough valuable knowledge to incentivize the partner's absorption of the firm's knowledge spillovers, yet the partner also holds sufficient knowledge to enable it to recombine the firm's spilled knowledge in meaningful ways. In this scenario the firm may encounter opportunities for leveraging knowledge spillback. Together, these different scenarios constitute a choice set of knowledge management strategies firms have at their disposal as they move up the value chain and are confronted with managing increasingly complex learning dynamics in their alliances. The preferred strategy would depend on the amount and quality of both the firm's accumulated knowledge and of the partner's knowledge. This is illustrated in Figure 1.2. It integrates insights offered by this dissertation while providing a new way of conceptualizing the dynamics of knowledge spillover and knowledge protection in alliances. The framework conceives of knowledge absorption, knowledge protection, and knowledge spillback strategies as options along a continuum. Rather than considering these options as mutually exclusive alternatives, firms may utilize combinations of these strategies as they manage their alliance portfolios, whereby the relative weight given to each option would depend on the firm's broader strategic objectives and on its position within the global value chain. Firms should learn to combine these options strategically in order to maximize the value gain from their alliance portfolios.

Figure 1.2: Choice set of knowledge management strategies in alliances



Future research may expand on these ideas by investigating conditions that would influence firms' choice among these strategic options. For instance, it is possible that the firm's choice between a knowledge absorption/protection strategy and a knowledge spillback strategy relates to the overlap or complementarity between the partnering firms' knowledge bases, the degree of their product-market competition, and the extent to which both parties consider their alliance to be a one-off transaction versus a longer-lasting relationship. Furthermore, the dynamics of knowledge spillover and knowledge protection may vary depending on the type of alliance the firm engages in. For instance, multiparty alliances (e.g., Lavie, Lechner, & Singh, 2007) and voluntary standard-setting consortia (e.g., Leiponen, 2008; Rysman & Simcoe, 2008; Vasudeva, Alexander, & Jones, 2015) feature knowledge dynamics that differ from those prevailing in dyadic alliances. Hence, it is conceivable that firms adopt different strategies depending on the form of collaboration they engage in, even under otherwise similar conditions. Future research may explore these boundary conditions of the insights furnished by this dissertation.

2. CHAPTER ONE:

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

(co-authored with Dovev Lavie and Linda Rademaker)

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 between 1999 and 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.

2.1. INTRODUCTION

Alliances enable firms to combine 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 of concern to managers who seek to protect their firms from imitation that can diminish the firm's appropriated value in alliances (Lavie, 2006; Shih & Wang, 2013). With such undesirable knowledge spillover, firms may lose their competitive advantage and give more than they gain in alliances, while their partners not only imitate but also outmaneuver them (Hamel, Doz, & Prahalad, 1989). 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 et al., 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). However, 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 overcome its partners' knowledge protection and absorbed their knowledge reverse roles[1] and learn to 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 gained 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 contrast, we study learning across alliances by drawing 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 proprietary knowledge, shifts its attention to protecting its own 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' content knowledge (Argote, McEvily, & Reagans, 2003) and thus affect its vicarious leaning 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. While Western firms have traditionally been concerned with protecting their proprietary knowledge from involuntary spillovers in Asia (Liu & Buck, 2007; Schotter & Teagarden, 2014; Zhang, Li, Li, & Zhou, 2010), the last decades have been marked by Asian firms' development of proprietary knowledge (Huang & Li, 2019; Mathews, 2006), and consequently their need to protect it. 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 firms' knowledge in subsequent alliances.

2.2. 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 content 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.

2.2.1. Knowledge absorption and protection across alliances

Knowledge absorption and protection involve different practices. For example, knowledge absorption involves practices such as reverse-engineering, hacking, copying, and codifying information. In contrast, knowledge protection relates to practices such as secrecy, contractual safeguards, strategic staffing, process fragmenting, and use of network firewalls (Contractor, 2019; Liebeskind, 1996; 1997; Palomeras & Wehrheim, 2020; Zhao, 2006). A manager we interviewed elaborates:

We had to strengthen our security system…secured USBs, encrypting all the files,…tracking all the documents, tracking all the printouts;…making sure that one employee doesn't get to work on the full internal manufacturing chain…so that one person cannot understand the whole process; The strategy team does regular scanning…we just go at people's desks randomly to see if there's any secure documents lying around; We make sure that for all the confidential documents it's rightfully noted on the top of the document; We make sure that after an important meeting people leave their documents at the meeting room so then we can collect them and scrap them; We also have a layer of meeting rooms where outside people will come and have a meeting, but they are not exposed to our office space where there could be documents lying around." (President of a specialty chemicals firm, South Korea)

Because the corresponding practices differ, absorbing knowledge may not necessarily assist

[3] Our theory does not require alliances to be formed with the intent to absorb the partners' knowledge or to learn their 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).

a firm's direct learning of protection practices. Furthermore, preexisting structures and schemata that favor allocating attention to familiar activities may restrict the learning of new activities (Ocasio, 1997), which constrain the firm's learning of practices for knowledge protection based on its experience with practices used for absorbing its partner's content knowledge. Nevertheless, knowledge absorption and protection are related activities, so while absorbing the partner's content knowledge, the firm observes its partner's protection practices and can vicariously learn them.

The firm's absorption of its partner's content knowledge suggests that it has managed to familiarize itself with that partner's knowledge protection practices and overcome them. Although the partner may share some knowledge per the alliance agreement, it otherwise seeks to conceal its proprietary knowledge when interacting with the firm during their alliance (Lavie, 2006), but by protecting this knowledge it reveals to the firm its 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 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. As the firm becomes competent at neutralizing protection practices and absorbs its partner's knowledge, it learns to apply similar or improved practices to protect its own knowledge from spilling over to a partner in a subsequent alliance. 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, that spillover prevention improves at a diminishing rate with the extent to which the firm absorbed its previous partner's knowledge.

First, basic protection practices such as secrecy and contract design are relatively generic and thus easy to learn to the extent that the firm is unfamiliar with these practices. In this case, exposure to these practices can greatly improve the firm's 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 more intricate means of protection after absorbing some of that partner's knowledge. 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 of intricate practices 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

[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. An analogy is that of the locksmith: If unsuccessful at opening a lock, they are less likely to learn how to design better locks in the future. If successful, they can identify weaknesses and correct them when designing new locks.

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 practices 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 2.1).

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 2.1 here *************

2.2.2. Boundary conditions for the association between knowledge absorption and protection

We contend that the firm's absorption of a previous partner's content knowledge indicates vicarious learning of the partner's knowledge protection practices, which enhances the firm's 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 the firm's learning effort depends on its *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 (creating opportunities), (b) the relative strength of the appropriability regimes in the parties' home countries (increasing motivation while restricting opportunities), (c) the business similarity between the firm and its previous and subsequent partners (increasing motivation while limiting ability), and (d) the firm's relative absorptive capacity (increasing ability to absorb knowledge). By influencing the motivation, ability, and opportunities to absorb the previous partner's content knowledge (i.e., the partner's inventions), these conditions affect the efforts to overcome this partner's knowledge protection, which in turn affects the firm's 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 greater 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 the effectiveness at which the firm vicariously learns these practices.[5] This undermines the firm's adoption and deployment of these practices when seeking to protect its own knowledge in a subsequent alliance. Thus, the firm's restriction of knowledge spillover in a subsequent alliance is constrained by the value chain

[5] Even if a broad-scope alliance exposes the firm to a wider range of protection practices, the firm would encounter more opportunities to overcome them incidentally, and thus engage with each practice less diligently. This may result in negative transfer learning (Zollo, 2009), which reduces the firm's effectiveness at learning protection practices.

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 subsequent partner.

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 a combination of more advanced practices for knowledge protection to fend off the firm's attempts to absorb its knowledge (Cohen, Nelson, & Walsh, 2000; Srikanth, Nandkumar, Mani, & Kale, 2020; Zhao, 2006). 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 vicariously learned insights to improve its own knowledge protection in a subsequent alliance, which can further restrict knowledge spillover to the partner in that alliance. Therefore, the effectiveness at which the firm restricts knowledge spillover in a subsequent alliance improves with the absorption of its previous partner's knowledge, but that restriction effect becomes 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 is because that knowledge can help the firm anticipate the partner's innovations and respond by developing substitute products that compete with those of the partner (Cui et al., 2018). Yet, to prevent this scenario, the partner is likely to invest more in protecting its proprietary knowledge (Oxley & Sampson, 2004) and thus limit the firm's *ability* to absorb its content knowledge. The partner's reliance on stronger protection practices suggests that the competitive tension encourages the firm to be more tenacious in its attempts to overcome its partner's knowledge protection. This reinforces vicarious learning of the partner's protection practices, supporting their application for protecting the firm's 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). As a result, 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 vicariously 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 effectiveness in preventing knowledge spillover to a partner in a subsequent alliance. Overall, this reinforces the negative association between the firm's absorption of 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 absorption of 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 for the previous partner's content knowledge constrains vicarious learning of that 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.

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.*

2.3. METHODS

2.3.1. 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):

"The Asian corporations have become pretty sophisticated in terms of how they protect their work…A good example would be TSMC, the chip manufacturer based in Taiwan. They have very aggressive operating practices to prevent their proprietary operating knowledge from being leaked…they don't allow smartphone devices to be inside their premises…TSMC probably learned some of these practices from some of the Western early chip manufacturers. Intel probably would be one of them… and then they just built it from there. They are leaders now, so today it would be very very difficult for any other country or company to catch up with them, although many are desperately trying, also Western companies. Even a company like Intel finds it hard to compete with them. They have mastered a culture of protecting their know-how." (CFO of a technology firm, Hong Kong)

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 et al., 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.[6] 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. By studying pairs of the firm's previous and subsequent alliances we account for the fact that different alliances expose the firm to different protection practices, and that the firm's learning varies from one previous partner to another. Considering pairs of a previous alliance and a subsequent alliance also enables us to distinguish the firm's vicarious learning of a particular partner's protection

[6] 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.

practices from the potentially confounding effect of the firm's accumulated alliance experience. 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.[7] We consider an alliance to be subsequent if it was announced between one to ten years after the launch of a previous alliance.[8] 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.

Because information about learned knowledge protection practices is unavailable from archival sources, we measure the observed flows of content knowledge that indicate the extent to which firms have managed to overcome the knowledge protection practices used by their partners. 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 effectively 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 complement patents with other safeguards to protect their knowledge (Contractor, 2019; Schotter & Teagarden, 2014; Srikanth et al., 2020). Moreover, although patent filings are widely accessible, incorporating the underlying knowledge embedded in a partner's patent and

[7] 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.
[8] 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 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 ancillary analyses, we consider alternative time windows.

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, citations to a partner's patents that aim to exploit its underlying knowledge for the firm's private gain indicate a spillover which the partner seeks to avoid (Devarakonda & Reuer, 2018) despite potentially favorable implications of patent citations for the partner (e.g., Hall, Jaffe, & Trajtenberg, 2005). Although knowledge spillover could benefit the partner in some instances, its undesirable implications are a sufficient reason for the partner to protect against knowledge spillover in its alliances.

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).[9] 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).[10] 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 2.1 exhibits the number of patent applications since the earliest applications in 1899 and until 2020.

************ Insert Table 2.1 here ************

[9] 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.

[10] The patent offices with which the citing patents were filed—the USPTO, JPO, and EPO—are 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).

2.3.2. 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 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 inventions that the firm and its partner jointly developed during 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.

2.3.2.1. Control variables

Our moderators served also as control variables in addition to their equivalents in the subsequent alliance. Moreover, 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,[11] and partnering experience at the time of announcing the previous and subsequent alliances. Mature firms (*Age*) typically accumulate broader knowledge (Cohen & Levinthal, 1990). *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 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 proxies for direct experiential learning of 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

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

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., 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 furthermore 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.[12] 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 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). 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).

[12] 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."

Since the usefulness of the learned protection practices may diminish over time, 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.[13]

2.3.3. 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

[13] 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 for observations relating to the same firm or partner in a way similar to a fixed effect, without losing degrees of freedom (Guimarães & Portugal, 2010).

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 the actual partner is compared to the counterfactual partner, 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.

Our second-stage model uses a Poisson pseudo-maximum likelihood (PPML) regression model (Davies & Guy, 1987; Santos Silva & Tenreyro, 2006)[14] 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 2.2–2.4b and Figures 2.2–2.6 here *************

2.4. RESULTS

We report descriptive statistics and pairwise correlations in Table 2.2.[15] First-stage model results are reported in Table 2.3,[16] with second-stage model results reported in Table 2.4. Model 1

[14] Unlike other count data estimators, PPML does not require an integer dependent variable (Correia, Guimarães, & Zylkin, 2020; Santos Silva & Tenreyro, 2006) and 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. We observed no adverse effects on the variable estimates in Table 2.4. While 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

(Table 2.4a) 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 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 2.4a) 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

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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.

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 2.4b; 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 2.4b; 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 2.4b; Figure 5) shows 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 2.4b; Figure 6) lends support to Hypothesis 5, according to which the technological overlap between the parties in the previous

[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 but encountered severe multicollinearity (condition numbers > 30), which hinders interpretation of corresponding results.

alliance mitigates that negative association ($\beta = 0.040$, $p < 0.001$). Model 9 (the full model) exhibits multicollinearity, but all moderating effects persist in Model 10 (a lean specification of the full model).

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 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 Table 2.5.

************* Insert Table 2.5 here *************

2.5. 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 a previous partner's 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 a previous partner's knowledge and increase its motivation to absorb the partner's 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 alliance, (b) a weaker appropriability regime in the firm's country relative to its partner's country in that alliance, (c) greater business similarity in the previous alliance, and (d) a weak relative absorptive capacity in that alliance. 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 suggest that besides engaging in experiential learning of content knowledge (Gulati et al., 2009), the firm engages in vicarious learning of its partners' knowledge protection practices, which can 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 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 counter activities so long as the firm can become immersed in its protective mindset. The reason is that negative transfer learning occurs when managers erroneously generalize their learnings across activities that appear to be superficially similar, but which are intrinsically different (Ghosh et al., 2014). However, such erroneous generalizations are unlikely to occur across counter activities such as knowledge absorption and knowledge protection, for a lack of superficial resemblance among them.

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 own 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 managerial 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 becoming 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. While a sensitive topic, 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 may explain why firms are, on occasion, unable to reverse roles from absorption to protection, and thus fail to catch up (Lee & Malerba, 2017). In particular, it is worth studying the obstacles that firms face when applying practices that they learned in previous alliances (e.g., Lavie & Singh, 2012). In contrast, 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 in their alliance, 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 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, including standard-setting consortia that motivate knowledge sharing and exhibit 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, to other governance modes besides alliances, and to other country contexts. 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). Such data can also reveal how a firm selects specific protection practices from its collection of practices.

Knowledge misappropriation in alliances remains an issue of concern to managers (Shih & Wang, 2013). Our study reinforces this concern by suggesting that when internalizing their partners' knowledge, firms become competent at protecting their own 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 that partner's prospects of winning subsequent learning races in alliances. This requires managers to be mindful about the interplay of knowledge absorption and protection.

2.6. FIGURES AND TABLES

Table 2.1: 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 2.2: 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 2.2: 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 2.3: 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 2.4a: 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 2.4b: PPML regression for knowledge spillover in a subsequent alliance (moderation analysis)

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 2.1: Knowledge spillover in a subsequent alliance by knowledge absorbed in a previous alliance

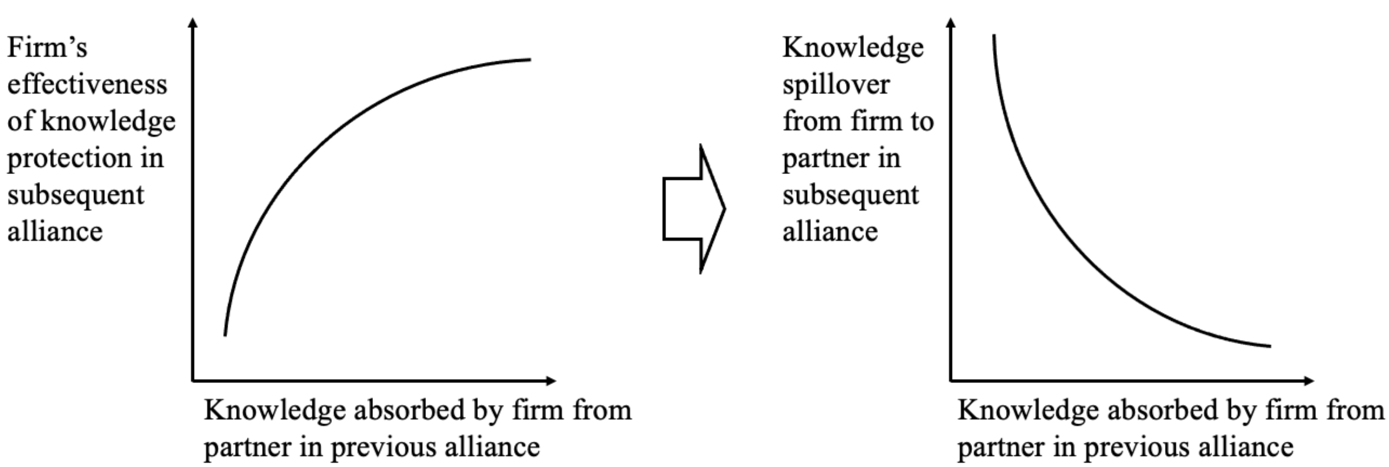

Figure 2.2: Knowledge spillover in a subsequent alliance by knowledge absorbed in a previous alliance

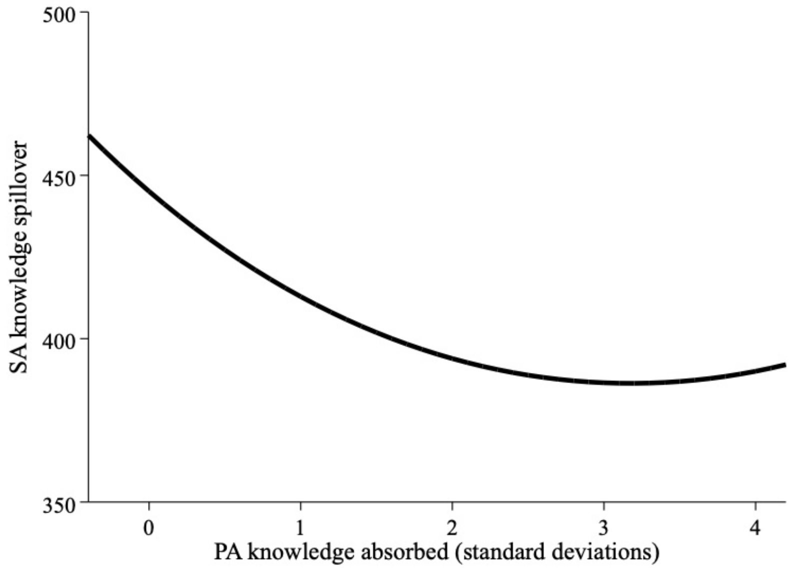

Figure 2.3: Moderating effect of value chain scope in a previous alliance

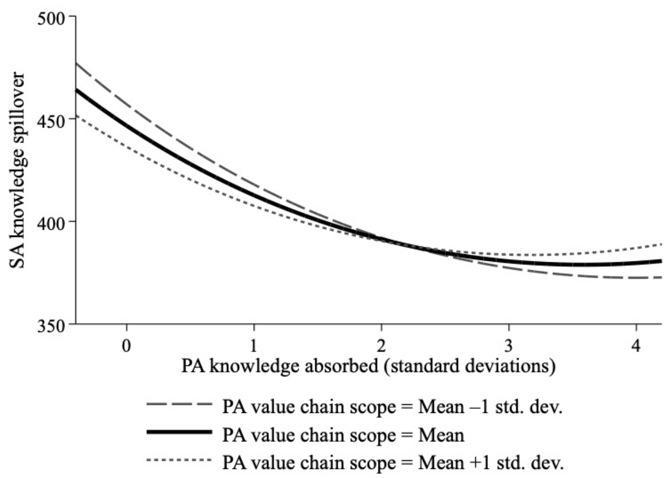

Figure 2.4: Moderating effect of firm's weaker appropriability regime in a previous alliance

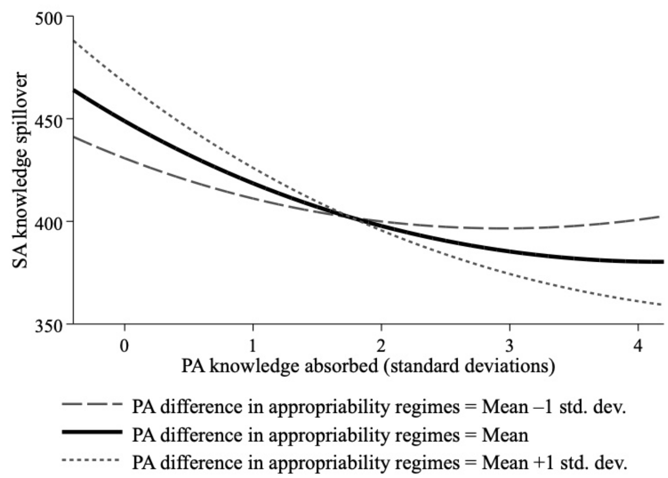

Figure 2.5: Moderating effect of stronger business similarity in a previous alliance

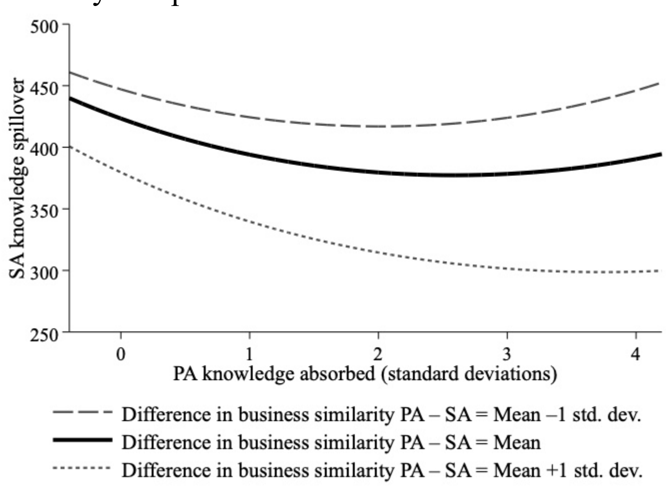

Figure 2.6: Moderating effect of relative absorptive capacity in a previous alliance

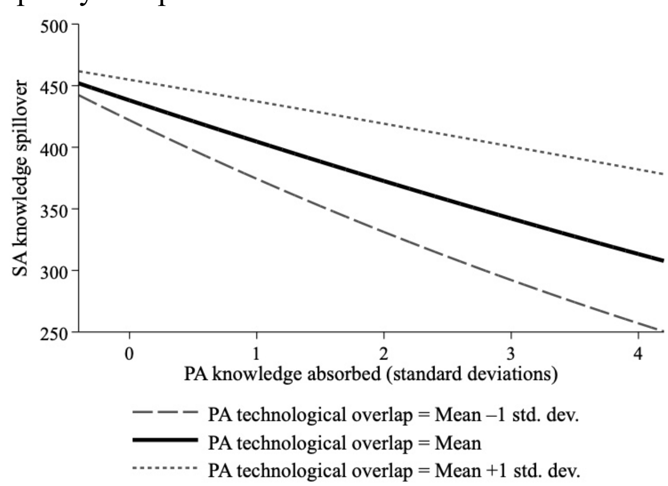

Table 2.5: Summary of robustness tests

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).
7.	Use non-discounted measures of knowledge spillover and knowledge absorption, to test the findings' sensitivity to discounting of patent citations.	Consistent findings.
8.	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.
9.	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.
10.	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.
11.	Exclude the subsequent partner's citations to those patents of the firm that cite the previous partner, to rule out the possibility that knowledge spillover in the subsequent alliance reflects the firm's "passing on" of knowledge absorbed in the previous alliance.	Consistent findings, except H5 (consistent sign).
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	Consistent findings.

	out the possibility that the findings are exaggerated by features of the distribution of countries along the index's scale.	
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	a) Weaker negative association in previous upstream alliances ($\beta=0.011$, $p<0.001$)

	subsequent alliance and knowledge absorbed in a previous alliance: a) Value chain function in previous alliance 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.	b) Insignificant interaction c) Insignificant interaction 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 by previous and subsequent alliances d) Cluster by firm and previous and subsequent alliances e) Cluster 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.

3. CHAPTER TWO:

NATIONAL INNOVATION SYSTEMS AND KNOWLEDGE ACQUISITION IN INTERNATIONAL ALLIANCES

(co-authored with Torben Pedersen)

ABSTRACT

Research on learning in alliances acknowledges that firms' learning outcomes often vary depending on their home-country contexts. However, little is known about the features of the national environment that explain such variability in firms' learning. This study contributes to this stream of research by focusing on national innovation systems and their corresponding innovation policies. It brings together theories on learning in alliances and theories on national innovation systems to examine how innovation policies in the respective home countries of firms and their partners can increase the effectiveness of knowledge acquisition. Our analyses of 1,578 international alliances formed by 461 firms from 38 countries between 2000 and 2015 indicate that supply-side innovation policies in firms' home countries and demand-side policies in their partners' home countries increase firms' knowledge acquisition from their partners in international alliances.

3.1. INTRODUCTION

Interfirm alliances enable firms to innovate by facilitating knowledge flows among them (Dyer & Singh, 1998; Mowery, Oxley, & Silverman, 1996). International alliances, in particular, are associated with learning motives because they provide access to complementary knowledge from different national contexts (Hagedoorn & Narula, 1996; Rothaermel & Boeker, 2008). Therefore, within knowledge-intensive industries, alliances are an important means for acquiring knowledge across national borders (Hagedoorn & Narula, 1996), especially as alternative channels, such as M&A or direct investments, can be more difficult to implement internationally and involve the acquisition of assets beyond the required knowledge. Accordingly, an extensive literature on learning in international alliances explains how firm-, knowledge-, and alliance-specific attributes influence firms' knowledge acquisition from their alliance partners (e.g., Hamel, 1991; Inkpen & Tsang, 2007; Lane, Salk, & Lyles, 2001; Simonin, 1999). Drawing on theories of national innovation systems (e.g., Lundvall, 1992; Nelson, 1993; Porter, 1990), we propose a contextual explanation, in which we consider the influence of firms' and their partners' home-country contexts on firms' learning in alliances. While recent research has studied how norms regarding firms' knowledge acquisition vary across countries (Vasudeva, Alexander, & Jones, 2015; Vasudeva, Spencer, & Teegen, 2013), little is known about how, in international alliances, the distinct national innovation systems of a firm's home country and of its partner's home country affect the learning of the focal firm in different ways. Therefore, we ask: How do the respective national innovation systems (in the focal firm's country and in the partner's country) contribute to the focal firms' knowledge acquisition from their partners in international alliances?

In responding to this question, we bring together theories on learning in alliances and theories on national innovation systems with a particular focus on innovation policies, which concern those aspects of national innovation systems that can be influenced by governmental actions (e.g., Aghion, David, & Foray, 2009; Edler & Fagerberg, 2017). In line with the typology of four innovation-policy dimensions proposed in the literature (e.g., Edler & Fagerberg, 2017; Edler & Georghiou, 2007), we differentiate between supply-side and demand-side innovation policies. Supply-side policies focus on innovation-process inputs and comprise: (a) the availability of R&D funding and (b) the availability of R&D personnel. Demand-side policies focus on innovation-process outputs and comprise: (c) public technology purchases and (d) public-private R&D collaboration. Our theory centers on these dimensions while invoking complementarities between internal knowledge development and knowledge acquisition from partners (e.g., Cassiman & Veugelers, 2006). It describes how each of the four innovation-policy dimensions affects the firm's *motivation*, *ability*, or *opportunities* to acquire its partner's complementary knowledge.

Our theory suggests that firms from countries with innovation policies that provide resources and incentives to engage in R&D are better able and more motivated to acquire knowledge from their partners. As international alliances link together separate firms embedded in different locations with their unique innovation systems, which bring complementary knowledge into the alliance, our study considers not only the impact of the innovation policy of the focal firm's (home) country but also the innovation policy of the partner's (home) country. We posit that the innovation policy in the partner's country provides knowledge-accumulation benefits to the partner, which increases the focal firm's opportunities to acquire knowledge from its partner. As such, we go beyond saying that the country context of the innovation policy matters for a firm's acquisition of knowledge from alliance partners by scrutinizing which distinct innovation policies exert significant effects on knowledge acquisition and by outlining the mechanisms behind these effects.

We test our predictions on a sample of 1,578 international alliances formed between 2000 and 2015 by 461 focal firms from 38 countries in technology-intensive industries. Alliances in which both the focal firm and the partner operate in the sampled industries form two dyads with the parties alternating between focal firm and partner roles (Gomes-Casseres, Hagedoorn, & Jaffe, 2006). We rely on patent-citation data to measure the acquisition of complementary knowledge and we use executive survey data to study national innovation policies. To isolate the effect of innovation policies from potentially confounding factors, we rely on an extensive set of control variables that describe the characteristics of the focal firm, its partner, the alliance, and the two companies' home countries. Moreover, as innovation policies may not only affect the focal firms' knowledge acquisition from partners but also their decisions to enter alliances, we control for this endogeneity using a two-stage model. Finally, in post-hoc analyses, we (a) explore the mediating mechanism of the focal firm's and its partner's R&D investments on the relationship between innovation policies and the focal firm's knowledge acquisition from the partner, and (b) compare the effects of innovation policy on learning in international alliances against the counterfactual case of alliances formed between firms originating in the same country.

Our findings suggest that supply-side innovation policies in the focal firm's country increase the focal firm's knowledge acquisition from its alliance partner, but demand-side innovation policies in the country of the focal firm do not have an effect. For the innovation policy of the partner's country we observe the opposite pattern: Demand-side policies in the partner's country positively affect the focal firms' knowledge acquisition from its alliance partner, but supply-side innovation policies of the partner's country have no effect. Hence, whereas the logic of national innovation systems suggests that both supply-side and demand-side innovation policies would be conducive to a focal firm's learning from its alliance partners, we instead find that different innovation policies have distinct effects depending on whether they are implemented in the focal firm's country or in a partner's country. We also find evidence that while in international alliances, innovation policies encourage firms' knowledge acquisition, this is not the case in same-country alliances. This finding indicates that national innovation policies are particularly important for knowledge acquisition in alliances where the partners are embedded in different national contexts.

The current study contributes to the literature on the impact of national institutions on firm-level outcomes (e.g., Peng, Sun, Pinkham, & Chen, 2009) by identifying innovation policy as an important factor affecting learning in alliances. Our study directs attention to the influence of the home-country context (Cuervo-Cazurra, 2011) of both alliance partners, thereby advancing alliance research, which has traditionally focused on the host-country context (e.g., Luo, 2005; Yu, Subramaniam, & Cannella, 2013) or on partners' cross-national distance (e.g., Barkema & Vermeulen, 1997; Lavie & Miller, 2008; Pothukuchi, Damanpour, Choi, Chen, & Park, 2002). In so doing, we unpack the "home-country effect" that is frequently invoked in studies on learning in alliances (e.g., Ahuja, 2000; Mowery et al., 1996; Rothaermel & Boeker, 2008) and elucidate the mechanisms underlying this heterogeneity between countries. We believe that our study can guide future research, which may extend our findings by exploring their boundary conditions at both the innovation-system level and the firm level. Overall, our study stresses the importance of the country context (of both the focal firm and the partner) in international alliances for firms' knowledge-acquisition strategies.

3.2. THEORETICAL BACKGROUND

3.2.1. National innovation systems and innovation policies

Theories of the national innovation system suggest that firms' learning activities are embedded in national contexts, with differences in national institutions and policies creating distinct learning conditions (e.g., Bartholomew, 1997; Lundvall, 1992; Nelson, 1993). In a broad sense, a national innovation system comprises the entirety of a country's institutions and policies that create the milieu within which learning occurs (Lundvall, 1992). In a narrower sense, it encompasses those formal institutions and policies that are directly concerned with firms' accumulation of knowledge (Freeman, 1992). Accordingly, the national innovation system can be defined as a set of interdependent actors (e.g., firms, government agencies, research centers, or universities), institutions, and policies that influence "the production, diffusion, and use of new and economically useful knowledge (…) inside the borders of a nation state" (Lundvall, 1992: 2).

Innovation policies aim to facilitate knowledge creation and diffusion within national innovation systems. The roots of national innovation policies were sown after the Second World War when national governments realized that large-scale public support of and investments in domestic R&D and knowledge development could simultaneously help establish military advantages and benefit the economy. This reflects the idea that higher rates of economic growth and productivity can be attributed to greater success in exploiting technological opportunities (e.g., Romer, 1990; Scherer, 1982). The contemporary understanding of innovation policy in terms of its scope and theoretical underpinnings stems from the notion of the national innovation system and its adoption by the Organization for Economic Cooperation and Development (OECD) as a policy advice framework (e.g., OECD, 1997). Notably, by the early 21st century, many national governments had adopted the concept as a basis for policy formulation (Edler & Fagerberg, 2017).

Innovation policies are implemented through a suite of institutions and policy instruments that provide resources and incentives for firms to engage in knowledge development. They also create interlinkages among foundational research, the public sector, and commercial enterprise (e.g., Aghion et al., 2009; Martin & Scott, 2000). Although there is no exhaustive taxonomy of the dimensions of a national innovation policy, we follow the literature and organize innovation policy into a supply-side component and a demand-side component (e.g., Edler & Fagerberg, 2017). This distinction reflects the dual role of the government in the innovation process: The government provides support for private-sector R&D and it is one of the most important users of innovations developed in the private sector (Lundvall, 1992). We also distinguish between innovation policies that provide financial capital and those that provide human capital (e.g., Edler & Georghiou, 2007).

Supply-side innovation policies provide firms with resources that enable them to innovate by engaging in knowledge development (Edler & Fagerberg, 2017). This entails making funding for R&D available through, for instance, direct subsidies, fiscal incentives, or national funds, all of which reflect the financial-capital dimension. The human-capital dimension of supply-side innovation policies helps ensure the availability of scientists and engineers through, for instance, education and training. Demand-side innovation policies incentivize firms' knowledge development by strengthening the role of government bodies as innovation drivers (Edler & Georghiou, 2007). In the financial-capital dimension, public technology purchasing can incentivize knowledge development and channel governmental funds to firms that are able to fulfil the government's demands for innovative solutions. In the human-capital dimension, R&D collaboration between public-sector organizations (e.g., research centers or universities) and private-sector firms can facilitate the diffusion of personnel, knowledge, and skills (e.g., Edler & Georghiou, 2007; Edquist, Hommen, & Tsipouri, 2000). Figure 3.1 shows the resulting typology of innovation-policy dimensions.

************* Insert Figure 3.1 here *************

3.2.2. Innovation policies and knowledge acquisition from partners in international alliances

Firms often rely on international alliances to acquire complementary knowledge from foreign partners and apply it in their own contexts (Rothaermel & Boeker, 2008). We consider acquired knowledge to be complementary if it has the potential to create synergistic value when combined with the firm's extant knowledge, and if it is non-redundant to the extent that the firm cannot produce it internally, at least not in the short run (e.g., because the required assets are not available in the firm's country) (Cassiman & Veugelers, 2006). We contend that a national innovation policy that strengthens firms' motivations and abilities to learn can increase the effectiveness with which domestic firms acquire complementary knowledge from foreign alliance partners. We also posit that the innovation policies in these partners' countries can create opportunities for firms to acquire complementary knowledge from their alliance partners.

The resources and incentives provided by a national innovation policy support the development and exchange of specialized knowledge among qualified domestic firms. By engaging in these activities, firms can discover knowledge gaps and identify the need for acquiring domestically unavailable knowledge (Arora & Gambardella, 1990; Cassiman & Veugelers, 2006). This may motivate them to search for complementary knowledge among foreign alliance partners (Phene, Fladmoe-Lindquist, & Marsh, 2006).[1] Moreover, a national innovation policy that supports domestic firms' knowledge development and that connects the knowledge bases of different actors within the innovation system can enable domestic firms to better identify and integrate complementary knowledge. This, in turn, can improve those firms' ability to learn from foreign partners.

Since liability of foreignness effects remain salient even for multinational enterprises (MNEs) that operate in multiple countries and institutional contexts (Noorderhaven & Harzing, 2003; Zaheer, 1995), domestic firms are naturally better positioned than foreign firms to benefit from national innovation policies in the domestic firms' home countries. Nevertheless, positive externalities across firms can cause a policy to produce advantages also for firms that are not the policy's main beneficiaries. Hence, even if domestic firms are better positioned to benefit from their home country's innovation policy, we propose that the positive externalities of such a policy (e.g., knowledge spillovers from R&D investments) can indirectly benefit foreign partners that have forged alliances with those domestic firms. More specifically, although foreign partners may not directly benefit from a domestic innovation policy, they can tap into the knowledge of domestic

[1] In fact, firms might be motivated to form new alliance relationships. While not the focus of our theory, our empirical design accounts for endogeneity in firms' decisions to form alliances with qualified partners.

firms that have benefitted from that policy. Indeed, the specialization and differentiation of knowledge embedded in distinct national contexts as a result of their different innovation policies creates potentials for knowledge complementarities between domestic firms and foreign partners, thereby providing learning opportunities (Bartholomew, 1997; Florida, 1997; Frost, 2001).

In the following, we expand on this reasoning by invoking the innovation-policy typology described in Figure 3.1. Based on its four dimensions, we develop hypotheses on how innovation policies in the home country of a focal firm and in the home country of its partner, respectively, influence the focal firm's motivation, ability, and opportunities to acquire complementary knowledge from the partner.

3.3. HYPOTHESES

3.3.1. The availability of R&D funding

As firms face limits in what they can feasibly and efficiently develop internally, they often rely on the acquisition of external knowledge from alliance partners to improve the outcomes of their internal R&D efforts (Rosenkopf & Almeida, 2003). Hence, internal R&D and external knowledge acquisition from alliance partners are considered to be complementary knowledge-development activities (Arora & Gambardella, 1990; Cassiman & Veugelers, 2006). In turn, to acquire and utilize complementary external knowledge, firms must build absorptive capacity by investing in internal R&D (Cohen & Levinthal, 1990). A firm's absorptive capacity reinforces its ability to identify, value, and assimilate its alliance partners' complementary knowledge. Therefore, by simultaneously engaging in internal R&D and external knowledge acquisition from partners, firms can improve their returns on both activities.

However, as R&D is a costly process that requires substantial financial commitments, firms often depend on external funding (Christensen, 1992). Thus, the greater the availability of R&D

funding in a country, the more R&D projects domestic firms can pursue (Monteiro, Mol, & Birkinshaw, 2017) and the greater their absorptive capacity should be. As a consequence, these firms would encounter more opportunities to realize synergies when they combine internal developments with complementary knowledge from partners. Indeed, as specialized knowledge tends to be dispersed globally, we expect a focal firm that benefits from the availability of R&D funding in its country to be motivated to seek complementary knowledge from foreign alliance partners.

We thus anticipate greater availability of R&D funding in a focal firm's country to improve that firm's ability and motivation to acquire complementary knowledge from a foreign partner.

Hypothesis 1a: *A focal firm acquires more complementary knowledge from a foreign partner in the course of their alliance as the availability of R&D funding in the focal firm's country increases.*

Next, we consider the effect of innovation policy in the partner's country: The greater the R&D funding that is available in the partner's country, the more R&D investments companies in that country can undertake. In so doing, these companies may establish internationally differentiated and specialized knowledge bases (e.g., Florida, 1997), which can provide their foreign alliance partners with opportunities to acquire complementary knowledge. Hence, we expect that a foreign focal firm which has formed an alliance with a local partner that benefits from R&D funding in its country faces greater opportunities to acquire complementary knowledge from that partner.

Moreover, as more public R&D funding becomes available in the partner's country and as the partner increases its R&D investments, that partner may increasingly find itself in need of complementary knowledge that is unavailable in its country. If the partner can obtain the required knowledge via international alliances, reciprocal knowledge-sharing opportunities may emerge between a focal firm and the partner. In fact, if firms seek to acquire complementary external knowledge, they must often simultanously reveal parts of their own knowledge (Alexy, George, & Salter, 2013; Arora, Belenzon, & Patacconi, 2021; Wadhwa, Bodas Freitas, & Sarkar, 2017).

Hence, a partner seeking to acquire a focal firm's knowledge may, in the process, reveal parts of its own knowledge that could be useful for the focal firm. Consequently, a foreign focal firm would face increased opportunities to learn from its partner. Therefore, we expect the focal firm to acquire more complementary knowledge from the partner if more public R&D funding becomes available in the partner' country.

Hypothesis 1b: *A focal firm acquires more complementary knowledge from a foreign partner in the course of their alliance as the availability of R&D funding in the partner's country increases.*

3.3.2. The availability of R&D personnel

Access to specialized personnel, such as scientists and engineers, is essential for enabling firms to sustain their R&D efforts (Lewin, Massini, & Peeters, 2011). While they face a liability of foreignness abroad (Zaheer, 1995), most firms, including MNEs, enjoy privileged access to their home country's talent pool and greater prestige among prospective employees in their home country (Nachum, 2011). Hence, firms' access to specialized R&D personnel is often influenced by the quality of their home country's talent pool. The higher the number of R&D personnel available in a country,[2] the greater is the capacity of domestic firms to pursue internal R&D and to develop proprietary knowledge. By engaging in internal R&D, these firms are also likely to identify needs for complementary knowledge that, in the short run, cannot be developed internally, yet which can potentially be acquired from foreign alliance partners.

Moreover, as firms rely on their employees for learning, critical knowledge-transfer tasks in alliances often depend on competent personnel who understand both the firm's knowledge and its partner's knowledge (Hamel et al., 1989; Oxley & Wada, 2009). Hence, when a firm wishes to

[2] Availability refers to the supply of qualified personnel in a country. This does not imply that these personnel are unemployed or ready for hire. However, the fewer personnel are available in a country, the greater would be the pressure on the domestic labor market, as firms are expected to hold on to scarce talent. As more personnel become available, more fluid labor market conditions are expected, and more hiring opportunities would emerge.

acquire complementary knowledge that requires expertise to internalize, it may seek to hire specialized personnel who can better understand that knowledge (Huber, 1991). Access to a large pool of scientists and engineers in the home country thus increases the probability that a firm can identify and hire qualified personnel, thereby enabling it to more effectively learn its partners' knowledge. Therefore, we expect a focal firm's ability to learn a partner's knowledge to increase with the availability of R&D personnel in the focal firm's country. If R&D personnel are widely available in the focal firm's country, that firm should be more effective at acquiring its partners' complementary knowledge.

Hypothesis 2a: *A focal firm acquires more complementary knowledge from a foreign partner in the course of their alliance as the availability of R&D personnel in the focal firm's country increases.*

As more R&D personnel become available in the partner's country, the probability that the partner will have specialist personnel and rely on those employees to develop specialized knowledge increases. This knowledge will most likely appear novel and complementary to a foreign focal firm, as talent pools differ across countries (e.g., Porter, 1990) and as the partner enjoys privileged access to the local talent pool in the partner's country. On the one hand, relying on specialized R&D personnel can enable the partner to learn a focal firm's knowledge. On the other hand, the partner's reliance on specialist personnel can increase the focal firm's exposure to that partner's knowledge. Indeed, prior research has stressed the significance of difficult-to-monitor informal interactions between partners' R&D personnel in alliances for inter-partner knowledge exchange (Hamel et al., 1989; Palomeras & Wehrheim, 2020). Thus, a partner's access to qualified R&D personnel in its home country can create opportunities for the focal firm to learn that partner's complementary knowledge. Due to the focal firm's increased opportunities to learn, we expect its acquisition of complementary partner knowledge to increase with the availability of R&D personnel in the partner's country.

Hypothesis 2b: *A focal firm acquires more complementary knowledge from a foreign partner in the course of their alliance as the availability of R&D personnel in the partner's country increases.*

3.3.3. Public technology purchasing

Public technology purchasing refers to the government's role as a commissioner, customer, and user of advanced technologies (Edler & Georghiou, 2007; Edquist et al., 2000). As governmental use of advanced technologies often centers on applications that are of strategic importance (e.g., intelligence and the military), essential for sustaining the country's economy (e.g., infrastructure and transportation), or important for public health (e.g., drugs and medical equipment), governments often prefer to purchase advanced technologies developed by domestic firms (Uyarra & Flanagan, 2010). Hence, public tenders for technology purchases can provide strong incentives for domestic firms to develop the requested knowledge (Edquist et al., 2000; Rothwell & Zegveld, 1981). Moreover, as influential lead users, governments can incentivize R&D focused on improving existing technologies (Edler & Georghiou, 2007).

If the knowledge needed to develop the requested technologies is not fully available in the domestic economy, public tenders can induce domestic firms to complement their own knowledge creation by acquiring the required knowledge from foreign partners in order to prepare themselves to independently supply the requested technologies in the future. Alternatively, domestic firms may attempt to increase their collective potential for developing the requested technologies by exchanging relevant knowledge and by consolidating their knowledge bases in the domain of the requested technologies. These activities can reduce the ambiguities associated with the required knowledge, enabling domestic firms to better integrate complementary knowledge from foreign partners.

For these reasons, public technology purchasing may bolster both the ability and motivation of a domestic focal firm to acquire complementary knowledge from a foreign partner.

Hypothesis 3a: *A focal firm acquires more complementary knowledge from a foreign partner in the course of their alliance as the prevalence of public technology purchasing in the focal firm's country increases.*

Public technology purchasing in a country can signal a high standard of quality of locally available knowledge given its typical applications in advanced-technology fields (Rothwell & Zegveld, 1981; Uyarra & Flanagan, 2010). Hence, if the government in the partner's country is a purchaser of advanced technologies, a foreign focal firm may attribute greater value to knowledge related to those technologies, which would motivate its knowledge acquisition from the partner.

Moreover, if the focal firm possesses specialized knowledge required for developing technologies requested by the government in the partner's country, but that required knowledge is not available locally in the partner's country, the partner has an incentive to enter into cross-licensing or cross-technology transfer agreements with the focal firm in order to acquire its knowledge. Although such arrangements are intended to make foreign technologies available in the partner's country, they can provide foreign firms with reciprocal learning opportunities (Laursen, Moreira, Reichstein, & Leone, 2017). Because of these learning opportunities, we anticipate a focal firm's acquisition of complementary knowledge from its partner to increase with public technology purchasing in the partner's country.

Hypothesis 3b: *A focal firm acquires more complementary knowledge from a foreign partner in the course of their alliance as the prevalence of public technology purchasing in the partner's country increases.*

3.3.4. Public-private R&D collaboration

R&D collaborations between firms and public-sector organizations such as research centers or universities can stimulate technological development by providing firms with access to scientific knowledge (Bartholomew, 1997). However, in order to innovate by applying and commercializing scientific knowledge, firms typically require complementary applied knowledge, which they can obtain either through R&D or from private-sector partners with knowledge bases distinct from those of the firms' public-sector partners (Arora & Gambardella, 1990). As incorporating knowledge from different national contexts can enhance firms' prospects for successful innovation (Phene et al., 2006), firms that benefit from public-private R&D collaboration in their home countries are likely to be more motivated to draw on their foreign partners' complementary knowledge.

Moreover, if a firm gains familiarity with scientific knowledge through public-private R&D collaborations, this can enable the firm to better understand and learn its partners' complementary knowledge. Indeed, the firm would become a nexus of rich combinatorial possibilities between its own knowledge, the scientific knowledge of public-sector partners, and the applied knowledge of private-sector alliance partners (Schilling & Phelps, 2007). Accordingly, firms that rely on extensive public-private R&D collaboration in their home countries should be better able to integrate complementary knowledge from foreign alliance partners.

In light of the above, a focal firm's motivation and ability to learn from foreign partners is expected to increase with the prevalence of public-private R&D partnerships in the focal firm's country, which should enhance its acquisition of complementary knowledge from partners.

Hypothesis 4a: *A focal firm acquires more complementary knowledge from a foreign partner in the course of their alliance as the prevalence of public-private R&D collaboration in the focal firm's country increases.*

By facilitating knowledge exchange, R&D collaborations between firms and public research centers or universities in the partner's country can contribute to the consolidation of that country's knowledge base and to its differentiation from other countries' knowledge bases (Furman, Porter, & Stern, 2002; Porter, 1990). Hence, by tapping into the knowledge bases of alliance partners that have benefitted from public-private R&D collaborations in their home countries, foreign firms may have better opportunities to acquire non-redundant and, thus, complementary knowledge.

In addition, the partner's engagement in public-private R&D collaboration in its country may induce the partner to search its alliance portfolio for complementary knowledge that can be used for combining and commercializing learned scientific knowledge. To the extent that a foreign focal firm possesses knowledge that the partner requires, and the focal firm agrees to share that knowledge with the partner (Arora et al., 2021), this firm may have reciprocal learning opportunities in which the partner grants the focal firm access to knowledge from the partner's country. If linkages between local companies and public research centers or universities are common in the partner's country, a well-connected partner may not only provide a foreign focal firm with access to its own knowledge but also serve as a conduit through which the focal firm can tap into complementary knowledge from the partner's broader network if that knowledge has been internalized by the partner (Vasudeva et al., 2013). This suggests that public-private R&D collaboration in a partner's country can create opportunities for a foreign focal firm to draw on the partner's knowledge.

Hypothesis 4b: *A focal firm acquires more complementary knowledge from a foreign partner in the course of their alliance as the prevalence of public-private R&D collaboration in the partner's country increases.*

3.4. METHODS

We tested our hypotheses on a sample of international alliances that were formed between 2000 to 2015 by firms operating in the global chemicals, machinery, and electronics industries. This empirical setting is characterized by frequent international alliance formation and patenting. We identified alliances using SDC Platinum and we obtained patent data from the Orbis Intellectual Property database. Survey data from the World Economic Forum (WEF) and the International Institute for Management Development (IMD) were used to assess innovation policies. For control variables, we gathered firms' financial data from Compustat and Orbis, and obtained additional country data from CEPII, the Hofstede Institute, and the World Bank.

We focused on industries with at least 50 listed firms globally in which at least 50 percent of all listed firms had been issued patents (SICs 283, 355, 357, 365, 366, 367, 372, 381, 382, 384, 873). We required that each sampled firm applied for, on average, at least four patents per year during the study's timeframe (Duysters, Lavie, Sabidussi, & Stettner, 2020) with the United States Patent and Trademark Office (USPTO), the European Patent Office (EPO), or the Japan Patent Office (JPO). The final sample comprised 1,578 alliances formed between 1,130 firms from 38 countries.[3] These included 461 focal firms operating in one of the sampled industries and 669 partners active in various industries. Alliances in which both parties operated in the sampled industries were disaggregated into two dyads with the parties alternating between "focal firm" and "partner" roles (Gomes-Casseres et al., 2006). The resulting 2,023 dyads serve as the unit of analysis. The alliances encompassed various value-chain activities: licensing, manufacturing, marketing, OEM, R&D, and supply. Research has shown that firms rely on different alliance types for knowledge acquisition and that the actual scope of an alliance is often greater than what is indicated in the alliance announcement (Alcacer & Oxley, 2014; Powell, Koput, & Smith-Doerr, 1996). We thus sampled alliances involved in various types of activities.[4] As firms typically do not announce alliance terminations (Schilling, 2009), we assumed a five-year alliance duration starting from the announcement date (e.g., Duysters et al., 2020).

We relied on patent-citation data to model knowledge flows between the focal firms and their partners (e.g., Gomes-Casseres et al., 2006; Mowery et al., 1996). Despite certain limitations, survey evidence suggests that patent citations can track interfirm knowledge flows quite reliably (Corsino, Mariani, & Torrisi, 2019; Duguet & MacGarvie, 2005). We relied on patent applications

[3] The distribution of sampled firms across countries was as follows: US 37.3%, Japan 10.3%, UK 6.1%, Canada 5.3%, China 5.0%, Taiwan 5.0%, India 4.2%, South Korea 3.4%, Germany 3.3%, Australia 2.6%, France 2.4%, Israel 2.2%, Switzerland 1.9%, Sweden 1.9%, Belgium 1.0%, Denmark 1.0%, Hong Kong 0.9%, Netherlands 0.9%, Singapore 0.9%, Italy 0.7%, Norway 0.7%, Finland 0.4%, and others 2.8%.

[4] In ancillary analyses, we excluded alliances less likely to involve knowledge transfer and obtained consistent results.

and assumed that the first date of filing (priority date) approximated the time of the invention. As firms can access knowledge held by their subsidiaries (e.g., Kogut & Zander, 1993), we also considered patent applications filed by the firms' subsidiaries.[5] We accounted for acquisitions and divestitures of subsidiaries, assuming that a subsidiary's knowledge is accessible to the new parent following its acquisition (Puranam & Srikanth, 2007).

We consolidated citing and cited patents at the patent-family level, which comprises all patents that cover the same invention (OECD, 2009). Subsequently, we identified unique citations in patent applications submitted by each sampled firm and collapsed them at the patent-family level to avoid double-counting of patents that covered the same invention.[6] Collapsing patent data at the family level purges the data of redundant information, which mitigates biases from inflationary citing behavior of applicant firms (Kuhn, Younge, & Marco, 2020) and helps to overcome selection issues that may arise if firms prefer filing patents at their domestic patent office (de Rassenfosse, Dernis, Guellec, Picci, & de la Potterie, 2013). Table 3.1 presents the total number of patent applications filed by the focal firms and their partners until the beginning of 2020.

************* Insert Table 3.1 here *************

3.4.1. Variables

We measure the extent of *complementary knowledge acquired* (dependent variable) by a focal firm from its partner using a count of the focal firm's backward citations to the partner's patents within the five years following the announcement of their alliance (Gomes-Casseres et al., 2006). A backward citation to the partner's patent in the focal firm's patent indicates that the partner's

[5] We obtained data on subsidiaries from Orbis and LexisNexis Corporate Affiliations, and data on acquisitions from Zephyr and SDC Platinum. We identified 8,760 acquisitions involving 761 acquirers and 470 divesting firms and their 8,348 target entities. The final dataset included the patents of the 1,130 firms and their 40,918 subsidiaries.

[6] The pool of citing patents includes patents filed with the USPTO, the JPO, and the EPO. As these patent offices follow similar standards (OECD, 2009) and given their global relevance, their patent citations are considered equally valuable. The pool of citable patents includes all patent offices worldwide (Gomes-Casseres et al., 2006).

patent contains some knowledge on which the focal firm's invention builds. To ensure that the acquired knowledge meets the criteria for complementarity (i.e., potential for synergistic value and non-redundancy) we considered citations between patents belonging to the same International Patent Classification (IPC) "class," while we excluded citations between patents within the same "group" or across classes.[7] The idea is that if the partner's knowledge is highly similar to the focal firm's extant knowledge, that knowledge may be redundant and less complementary (Rothaermel & Boeker, 2008). We also excluded citations to highly dissimilar patents because the acquired knowledge needs to be sufficiently related with the firm's extant knowledge to yield synergistic value (Dyer & Singh, 1998). As citations to older patents are less likely to reflect knowledge flows which occur in proximal relation to the alliance's activities than citations to recent patents, we apply an annual discount rate of r = 10%, weighting each citation by a discount factor of $(1-r)^t$, where t is the difference in years between the priority dates of the citing and cited patents.[8]

The independent variables evaluate the dimensions of innovation policy in the focal firm's and the partner's respective home countries at the time of their alliance. We define the home country as the country in which the headquarters is located, which proxies for the location in which most high-value-added activities are performed (Ghoshal, 1987).[9] We derived the independent variables from annual executive survey data published in the WEF's Global Competitiveness Report (GCR) and the IMD's World Competitiveness Yearbook (WCY). These reports cover many countries and have been used extensively in prior research to capture various aspects of the national

[7] Each IPC classification symbol has the form "A01B 100/00." The first letter represents the section, followed by a two-digit number representing the class. The final letter designates the subclass. The subclass is followed by a one-to-three-digit main group number, a slash, and a number of at least two digits representing the subgroup.
[8] Ancillary analyses confirmed that the findings were insensitive to different definitions of complementary knowledge and the discounting of citations.
[9] For 91.28% of the sampled firms, the country of headquarters was identical to the country of incorporation and the country of listing at the time of the alliance. Ancillary analyses confirmed that the findings were insensitive to defining the home country as the country of incorporation or the country of listing.

environment (see Kostova et al., 2020, for a recent review). The reports are based on representative surveys of local and foreign executives of domestic and international firms that have resided in the country under consideration for at least one year. Hence, the reports provide between-country comparability and are less likely than government-reported data to suffer from self-serving biases. In addition, meta-analyses have revealed high correlations between their common measures, suggesting reliability and comparability of their data items across reports (Berger & Bristow, 2009).

We assess the *availability of R&D funding* using the item "funding for technological development" in the WCY survey, which is derived from executives' responses to the statement "Public funding for technological development is readily available," with response options ranging from one to six (best). The *availability of R&D personnel* is measured using the GCR survey item "availability of scientists and engineers," which is based on responses to the statement "Scientists and engineers in your country are: (1 = nonexistent or rare, 7 = widely available)." *Public technology purchasing* relies on the GCR survey item "government procurement of advanced technology products," which evaluates responses to the statement "Government decisions on the procurement of advanced technology products are based on: (1 = price alone, 7 = technology and encouraging innovation)." Finally, *public-private R&D collaboration* is assessed using the WCY survey item "public-private partnerships for technological development," which records responses to the statement "Collaborations between public and private ventures are supporting technological development," with response options ranging from one to six (best). We averaged the independent variables over a five-year period beginning with the alliance's announcement year.[10] To ensure comparability of effect sizes, we standardized each variable to zero mean and unit variance.

[10] We did not lag the independent variables relative to the dependent variable given that the surveys recorded executives' responses in the year prior to the reports' publication. Moreover, executives' responses reflected the conditions present in their countries during a period preceding their survey participation. Nonetheless, we performed ancillary analyses with lagged versions of the independent variables, and we obtained consistent findings.

3.4.1.1. Control variables

The control variables describe characteristics of the partnering firms, their dyadic alliance relationship, and their home countries. Firm-level controls include the firms' age, size, solvency, and R&D intensity. Firms with greater *age* typically accumulate larger knowledge stocks (Cohen & Levinthal, 1990). *Siz*e, measured as total assets, indicates the resources available to support innovation (Hagedoorn & Schakenraad, 1994). Financial *solvency*, calculated as the natural logarithm of the ratio of cash to long-term total debt (Lavie & Miller, 2008), indicates slack resources that are available to sustain learning and R&D activities (Nohria & Gulati, 1996). *R&D intensity*, calculated as R&D expenses divided by revenue, measures investments in internal knowledge development (Cohen & Levinthal, 1990). Our measures of firm size, solvency, and R&D intensity are based on a moving average over the five years following the alliance announcement. In addition, we control for the partnering firms' general partnering experience (*GPE*), which relates to their alliance-management capabilities (Anand & Khanna, 2000). We measure GPE using a decay function over a decade prior to the alliance announcement date: $E_i = \sum_{t=0}^{S} x_t (1-r)^t$, with x_t indicating the number of alliances announced in year t, t = 0 marking the year preceding the alliance announcement, and r being an annual decay rate of 10% (Stettner & Lavie, 2014).

A firm's *patenting experience* indicates its overall absorptive capacity and relates to its ability to acquire knowledge from partners (Corredoira & Rosenkopf, 2010). We measure patenting experience using the number of patent applications in the decade prior to the alliance announcement and assume a 10% annual decay rate (Duysters et al., 2020). We also control for the focal firm's backward citations and patents purchased from its partner. The variable *total backward citations* counts the overall number of citations in the focal firm's patent applications during the five years following the alliance announcement, except for citations to the partner's patents. This accounts for the focal firm's overall propensity to make citations in its patents (Gomes-Casseres et al., 2006). We control for *patent purchasing* (another knowledge-acquisition channel) by counting the patents the focal firm purchased from the partner in the five years following the alliance's announcement. In addition, we control for *pre-alliance citations* in the five years prior to the alliance, which establishes a baseline for the knowledge the focal firm acquired from the partner before they had formed an alliance (Devarakonda & Reuer, 2018; Oxley & Wada, 2009). The partner's *scientific impact* measures the average forward citations in the partner's patent applications in the five years following the alliance announcement. It controls for how often the partner's patents are cited because of their quality, value, or foundational influence on subsequent innovations, irrespective of the alliance (e.g., Hall, Jaffe, & Trajtenberg, 2005).

Country-level controls account for attributes of the focal firm's and the partner's home countries at the time of their alliance. The level of economic development, measured as gross domestic product per capita (*GDPPC*), can affect domestic firms' propensity to learn from their foreign partners (Vasudeva et al., 2015). *Country patent applications* counts the annual number of patent applications in a country (Furman et al., 2002). This variable controls for the country-specific propensity of firms to engage in patenting, and for the fact that policymakers may adjust their innovation policies according to the innovation performance of domestic firms. A country's *intellectual property protection* can affect collaboration and learning in alliances (Oxley, 1999). It is assessed using the standardized GCR survey item "intellectual property protection," which records executives' responses to the statement "Intellectual property protection in your country is: (1 = weak or nonexistent, 7 = equal to the world's most stringent)."

Another set of controls accounts for attributes of the alliance relationship between the focal firm and its partner. We count their previous joint alliances to control for *joint partnering experience,* which may facilitate learning (Gulati, Lavie, & Singh, 2009). Next, we control for *patent co-*

applications by counting the patents for which the parties co-applied during the five years following their alliance announcement. Joint patents constitute an alternative learning path and capture the extent of common benefits derived from the alliance. In addition, we control for the *joint venture* status of the alliance, which may facilitate knowledge sharing (e.g., Oxley, 1999). We account for the alliance's *vertical scope* using a categorical variable that takes a value of 1 if the alliance covers upstream activities, -1 if it covers downstream activities, and 0 if it involves both types of activities (Lavie & Rosenkopf, 2006; Stettner & Lavie, 2014).

As similarities between the focal firm's and its partner's knowledge bases facilitate knowledge acquisition (Mowery et al., 1996), we control for their *technological overlap* using Jaffe's (1986) cosine index of the vectorized distributions of the focal firm's and its partner's patent applications across patent classes (e.g., Ahuja, 2000).[11] We also control for the *business overlap* between the focal firm and the partner by measuring the overlap in their four-digit primary SIC codes (Yang, Zheng, & Zaheer, 2015) because the focal firm's motivation to acquire its partner's knowledge can be influenced by their business similarity (Hamel, 1991). To account for the possibility that, in addition to the alliance, the focal firm relied on direct investments to tap into the knowledge base of the partner's home country (Almeida, Song, & Grant, 2002; Frost, 2001), we control for whether the focal firm owned or acquired *subsidiaries in the partner's country* in the five years following the alliance announcement.

We also consider other contextual differences and cross-national learning barriers by controlling for the cultural, administrative, geographical, and economic distances between the focal

[11] To compute this index, we define the patent class at the IPC subclass level and consider all patent applications starting ten years prior to the formation of the alliance (Devarakonda & Reuer, 2018) and ending five years after its formation. The extent of technological overlap is measured as $S_{ij} = (F_i F_j')/[(F_i F_i')(F_j F_j')]^{1/2}$, where the distribution of patent applications across patent subclasses is captured by the vector $F_i = (f_i^1 \dots f_i^k)$ for focal firm i and partner j in subclasses 1 to k, and F_i' is the transpose of F_i. Higher values indicate greater overlap (range from 0 to 1).

firm's and the partner's home countries. *Cultural distance* is measured as the absolute difference in Kogut and Singh's (1988) index of Hofstede's (1980) cultural dimensions in the parties' home countries. We measured *administrative distance* using the World Bank's governance indicators in the year of an alliance's announcement. Administrative distance between country i and country j is calculated using: $\sum_{d=1}^{6} |\mathrm{GI}_{di} - \mathrm{GI}_{dj}|/6$, where GI_{di} designates the value of governance indicator d of country i (Lavie & Miller, 2008). We calculated *geographical distance* as the geodesic distance in kilometers between the capital cities of the home countries of the focal firm and its partner (Lavie & Miller, 2008). *Economic distance* is calculated as the absolute difference between the natural logarithms of the GDPPC for countries i and j (Lavie & Miller, 2008). Finally, we include fixed effects for the focal firm's industry and the alliance announcement year.[12]

3.4.2. Analysis

We test our theory using a multi-stage analysis (Heckman, 1979). Specifically, we use two nested first-stage probit models to estimate a focal firm's selection to the sample and the selection of its alliance partner. In the sample-selection model, we consider all listed firms in the sampled industries that formed alliances from 2000 through 2015, and we estimate the probability of a firm being sampled in a given year. This model accounts for potential biases arising from the non-availability of data for certain years, countries, or firms. As predictors, we use a firm's age, size, R&D intensity, solvency, GPE, patenting experience, GDPPC, country patent applications, as well as year and industry fixed effects. Exclusion restrictions were the annual propensities of listed firms in a focal firm's industry to form alliances (*industry alliance formation*) and to own subsidiaries in countries in which the USPTO, the EPO, or the JPO operate (*industry US/EP/JP subsidiaries*).

[12] We do not include country fixed effects, as within-country variance is not observed for the home countries of each firm and partner. Focal firm fixed effects are excluded because of a lack of variance for firms with only one sampled alliance (39.05% of sampled firms).

Moreover, innovation policies in the focal firm's and the partner's home countries may affect not only the focal firm's learning from its partner but also its propensity to form an alliance with that partner. We control for this possibility by designing a first-stage partner-selection model that estimates the probability of an alliance being formed with a particular partner (e.g., Vasudeva et al., 2013). To construct a control group of unformed alliances, we identify up to four "counterfactual" partners operating in the same industry as the actual partner. We model partner selection as the focal firm's choice between the actual partner and the counterfactual partner closest in size to the actual partner (Mowery, Oxley, & Silverman, 1998; Yang et al., 2015). We predict alliance formation based on the focal firm's and the partner's size, age, R&D intensity, solvency, GPE, and patenting experience. At the dyad level, we account for technological overlap, prior joint alliances, the focal firm's subsidiaries in the partner's country, the dimensions of cross-national distance, and pre-alliance citations. Country-level measures include GDPPC, patent applications, and intellectual property protection. Moreover, we incorporate the innovation-policy variables at the year of alliance formation. Finally, we apply year and industry fixed effects. As exclusion restrictions, we used *partner relative size* and *partner relative GPE*, comparing the actual partner with the four identified counterfactual partners.

The second-stage model predicts the extent of complementary knowledge acquired by the focal firm from its partner using a Poisson pseudo-maximum likelihood (PPML) regression model. Unlike other count-data estimators, PPML does not require an integer dependent variable (Correia, Guimarães, & Zylkin, 2020). In addition, the data do not need to be Poisson distributed, as PPML estimates are robust to overdispersion (Blackburn, 2015) and zero inflation (Santos Silva, Tenreyro, & Windmeijer, 2015).[13] Moreover, PPML estimates can be corrected for sampling-induced

[13] To verify the appropriateness of PPML versus negative binomial and zero-inflated models, we performed the HPC test procedure by Santos Silva et al. (2015), which indicated a preference for PPML. We also verified that the

biases in a procedure analogous to that devised by Heckman (1979) for linear regressions (Terza, 1998). As the same focal firm or partner can participate in multiple alliances, and because multiple firms can be based in the same countries, we apply four-way clustered standard errors by the focal firm, the partner, the focal firm's country, and the partner's country. This clustering approach accounts for the multi-level character of our data (firms within countries), with some variables captured at the firm level and others at the country level (Cameron, Gelbach, & Miller, 2011).

3.5. RESULTS

Table 3.2 provides summary statistics and pairwise correlations. With a few exceptions, the correlations among the control variables are low and the variance inflation factors (VIFs) are all below the threshold of 10.[14] More problematically, high correlations are observed among some of the independent variables with their VIFs exceeding the threshold when specified together in the same model. For this reason, we used partial models for hypothesis testing (Cohen, Cohen, West, & Aiken, 2003), although we present a full model for reference without interpreting its results.

************* Insert Table 3.2 here *************

The results of the first-stage models, including the sample-selection model and the partner-selection models for all eight model specifications, are provided in Table 3.3. The estimates show that sample selection relates to the firms' age, solvency, R&D intensity, GPE, patenting experience, country patent applications, and industry-alliance formation. The partner-selection models suggest that the focal firms tend to form alliances with partners that are younger, that have more patenting experience, and with whom they have technological overlap, but whose patents they cite less frequently prior to alliance formation. The focal firms also prefer partners from geographically

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dependent variable's conditional variance was proportional to its conditional mean (Santos Silva & Tenreyro, 2006).

[14] A few control variables are highly correlated (e.g., economic distance and geographical distance). However, we do not interpret the coefficients of these variables, and their correlation does not bias the coefficients of interest.

distant countries in which they do not have subsidiaries. These countries have a lower GDPPC and fewer patent applications, but stronger intellectual property rights. Finally, the focal firms opt for larger partners with greater partnering experience relative to the identified counterfactual partners. Of the innovation-policy variables, the availability of R&D funding in the focal firm's and the partner's countries has a negative effect on international alliance formation as does the extent of public-private R&D collaboration in the focal firm's and the partner's countries. These negative coefficients may be explained by a substitution effect: firms in countries which feature a high availability of R&D funding and public-private R&D collaborations face limited needs for forming international alliances as sufficient knowledge acquisition opportunities are available domestically. Similarly, the negative coefficients of the partner-country variables could indicate that partners from countries with munificent innovation policies are reluctant to form alliances with foreign firms for fear of incurring greater knowledge outflows in their alliances.

************* Insert Table 3.3–3.4 and Figures 3.2–3.5 here *************

Table 3.4 reports the second-stage estimates. Model 1 is the baseline model, which includes the control variables. It reveals that a focal firm's acquisition of complementary knowledge from its partner declines with the focal firm's home-country GDPPC, with the partner's patenting experience, with geographical and economic distance between both parties, and when the focal firm has subsidiaries in the partner's country. In turn, complementary knowledge acquisition increases with the focal firm's patent citations, the partner's size, GPE, scientific impact, and home-country GDPPC as well as with the parties' technological and business overlap, their cultural distance, their patent co-applications, and the extent of the focal firm's pre-alliance citations of the partner. These effects persist in all models with only a few exceptions.

Models 2 to 5 test the hypotheses, which is also illustrated in Figures 3.2 to 3.5. Model 2 (Table 3.4; Figure 3.2) reveals that the extent of complementary knowledge the focal firm acquires from its partner increases with the availability of R&D funding in the focal firm's country (β = 0.393, $p < 0.001$), but does not increase with the availability of R&D funding in the partner's country (β = 0.227, p = 0.143), lending support to Hypothesis 1a but not to Hypothesis 1b. In line with Hypothesis 2a, Model 3 (Table 3.4; Figure 3.3) shows that the focal firm's acquisition of complementary partner knowledge increases with the availability of R&D personnel in the focal firm's country (β = 0.251, p = 0.012), but it offers no support for Hypothesis 2b (β = -0.012, p = 0.943). Model 4 (Table 3.4; Figure 3.4) provides no support for Hypothesis 3a (β = 0.221, p = 0.165), but it does support Hypothesis 3b, which associates an increased amount of complementary knowledge acquisition with the extent of public technology purchasing in the partner's country (β = 0.428, p = 0.002). Model 5 (Table 3.4; Figure 3.5) offers no support for Hypothesis 4a (β = 0.081, p = 0.419), but it does support Hypothesis 4b (β = 0.389, p = 0.009), suggesting that the focal firm's acquisition of complementary knowledge increases with the prevalence of public-private R&D collaboration in the partner's country.

Due to multicollinearity issues, we do not interpret the full model (Model 6). Instead, Model 7 presents the joint effects of the independent variables by summarizing them into two indices that describe the innovation policy in the focal firm's country and in the partner's country.[15] The significant, positive coefficients of these indices for the countries of the focal firm (β = 0.237, p = 0.039) and the partner (β = 0.316, p = 0.034) indicate a positive joint effect of the innovation-policy variables in both the focal firm's country and the partner's country on the focal firm's acquisition of complementary knowledge from the partner. We also tested a model with separate indices for supply-, and demand-side policies in the focal firm's country and partner's country. In line with

[15] We relied on principal component analysis to generate the indices for the firm's country and the partner's country innovation policies. The index for the firm's country had an eigenvalue of 2.44 and a standardized Cronbach's alpha of 0.78. The index for the partner's country had an eigenvalue of 2.60 and a standardized Cronbach's alpha of 0.82. Missing values for public-private R&D collaboration were replaced with the variable's sample mean.

our findings, we obtained significant, positive coefficients of the supply-side policy index in the focal firm's country ($\beta = 0.460$, $p < 0.001$) and of the demand-side policy index in the partner's country ($\beta = 0.441$, $p = 0.014$). The indices for demand-side policy in the focal firm's country ($\beta = -0.125$, $p = 0.350$) and supply-side policy in the partner's country ($\beta = -0.138$, $p = 0.464$) were not significantly different from zero.

3.6. ROBUSTNESS TESTS

We tested the robustness of our findings in several ways. First, we tested three- and seven-year windows for patent citations. All findings remained intact, with additional support found for Hypotheses 1b and 3a. Second, we assumed alliance durations of three and seven years, with consistent findings except for Hypothesis 4b under the seven-year assumption. Third, we recalculated all patent-based variables using only USPTO patents and found consistent results. In fact, the results improved, with seven out of eight hypotheses supported (the exception was Hypothesis 2b).

Fourth, we considered alternative measures for the dependent variable: We replaced the decay function with a non-discounted measure and we considered citations of all patents without the complementarity restriction, and found no changes to our results. Moreover, we captured complementarity in different ways (e.g., by considering citations within the same IPC section or subclass) and derived consistent results.

Fifth, we expressed the independent variables as reversed ordinal rankings and obtained consistent findings. We also varied the definition of the home country by using the country of incorporation or the country of listing instead of the country of headquarters. This produced similar findings, and we gained additional support for Hypotheses 3a when we considered the country of listing. Relatedly, we lagged the independent variables by one year relative to the dependent variable. The results were consistent, and we gained additional support for Hypotheses 3a and 4a.

Sixth, we tested alternative measures of various controls (e.g., size, R&D intensity, GPE, patenting experience, cross-national distance, business overlap, and technological overlap) and found mostly consistent results. Moreover, we specified additional controls (e.g., the number of value-chain activities covered by the alliance, the focal firm's and the partner's business diversification, their patent filings during the alliance, GDP in their respective home countries, an index of the World Bank's governance measures in both countries, an indicator of whether the alliance took place in the focal firm's or the partner's country, and dummy variables indicating the focal firm's and the partner's origins by region). These controls were either insignificant or yielded inflated VIFs, but our findings remained intact. We also ran models with focal firm fixed effects. Despite diminished degrees of freedom and the loss of observations, we found support for Hypotheses 1a, 2b, and 3b, and a consistent sign for Hypothesis 4b.

Seventh, we tested models without controls or with a simplified list of controls. While we did not find support for our hypotheses in models without controls, we obtained consistent findings when relying on models with a simplified list of controls. These included the focal firm's and partner's age, size, and patenting experience, the focal firm's total backward citations, as well as the economic distance between their home countries. As the number of patent citations between two firms depends on their maturity, size, and patenting, these variables represent important baselines that should be held fixed. Likewise, the economic distance between the focal firm's and partner's countries is an important contextual variable in international settings. This suggests that our findings are not artifacts of overfitting or specification errors.

Eighth, we removed alliances that were less likely to involve knowledge exchange. More specifically, we removed alliances from our sample that focused on marketing or sales activities. Alternatively, we excluded alliances that were licensing agreements but did not cover other activities. In either of these tests, our results held. We also tried excluding alliances that involved US firms to see whether our findings remained relevant in a non-US context. We found support for Hypotheses 1a, 3b, and 4b, and a consistent sign for Hypotheses 2a.

Ninth, in order to test whether a focal firm may benefit directly from the innovation policy in the partner's country through its local subsidiaries, we incorporated interactions between subsidiaries in the partner's country and the independent variables. The interactions were insignificant, but we found consistent main effects, which precludes the possibility that the focal firm benefits from the innovation policy in the partner's country only if it has local subsidiaries.

Tenth, we ran different versions of the first-stage models in which we, for instance, relied on four counterfactual partners or generated one "composite" counterfactual partner per formed alliance, and found consistent results. Eleventh, we tested alternative estimators (e.g., log-linear OLS, negative binomial, and zero-inflated Poisson), and found support for our hypotheses. Twelfth, we tested for misspecification by controlling for the squared terms of the independent variables. Their coefficients were insignificant, which suggests that the models are correctly specified. Thirteenth, we separately tested the effects of the independent variables for the focal firm's and partner's home countries, with consistent results. Finally, our findings were insensitive to removing potential outliers. Overall, these analyses reaffirmed the robustness of our findings.

3.7. POST-HOC ANALYSES

In additional analyses we (a) explored the mediating mechanism of the focal firm's and its partner's R&D investments on the relationship between innovation policies and the focal firm's knowledge acquisition from the partner, and (b) compared the effects of innovation policy on learning in international alliances against the counterfactual case of alliances formed between firms from the same country. Overall, the findings from these additional analyses reinforce the logic of the mechanisms underlying the observed effects, as predicted in this study.

3.7.1. Mediation analyses

Consistent with our hypotheses, our analyses provide evidence that innovation policies in the focal firm's and the partner's home countries affect the focal firm's acquisition of complementary knowledge from its partner. As our predictions rest, in part, on the assumption that the focal firm and its partner benefit from their home countries' innovation policies, we tested whether this condition applies. We reason that if the focal firm and its partner have benefitted from their home countries' innovation policies, this would be reflected in the R&D investments of the focal firm and the partner. Hence, we investigate how the association of innovation policies in the focal firm's and the partner's home countries with the focal firm's knowledge acquisition is mediated by the two companies' R&D investments.

************* Insert Table 3.5 and Figure 3.6 here *************

To test this, we used a generalized structural equation model, which is visualized in Figure 3.6. We estimated the structural equation which predicts the focal firm's complementary knowledge acquisition with a Poisson model. In turn, we estimated the intermediate equations predicting the focal firm's and its partner's R&D investments with OLS. R&D investments were captured as the average annual R&D expenditure in the five years following the alliance announcement. Because R&D investments were heavily skewed and serve as the dependent variable in the intermediate equations, we utilized the natural logarithm. We include the same covariates as reported in the main analysis with the exception of *R&D intensity*, as our mediator is R&D investments.[16]

The results, which are shown in Table 3.5, indicate that the effects of the availability of R&D funding in the focal firm's and the partner's countries on the focal firm's knowledge acquisition

[16] We also ran analyses using the firm's and its partner's patent applications as mediators, and obtained similar findings.

from the partner are partially mediated by the two companies' R&D investments. Likewise, the effect of the availability of R&D personnel in the focal firm's country on that firm's knowledge acquisition is partially mediated by its R&D investments. Moreover, the effects of the availability of R&D personnel and public technology purchasing in the partner's country are fully mediated by the partner's R&D investments. The results of public-private R&D collaboration in the partner's country were inconclusive: Although the direct and mediated effects of public-private R&D collaborations in the partner's country are insignificant, we find a significant total effect. We find no significant mediation effects of public-private R&D collaboration in the focal firm's country and of public technology purchasing in the focal firm's country, which instead exerts a direct effect on the focal firm's knowledge acquisition. Overall, we find that the effects of most innovation-policy variables are either partially or fully mediated by the parties' R&D investments, with total effects similar to those estimated in our main analysis.[17] As R&D investments proxy for firms' own learning and their capability to learn from others, this evidence is consistent with the claim that home-country innovation policies increase a firm's ability to acquire complementary knowledge from its partners.

3.7.2. Comparison between international alliances and same-country alliances

To study the significance of the international alliance context for our findings, we explored how the effects of national innovation policies on firms' knowledge acquisition in international alliances compare against the effect of national innovation policies on firms' knowledge acquisition in alliances with partners from the same country. To this end, we collected additional data on alliances that the 461 focal firms had formed with listed partners from their "own" country during

[17] Different from our main analysis, however, we find that supply-side policies also in the partner's country contribute to the focal firm's knowledge acquisition from the partner. An interpretation is that the focal firm benefits from these policies indirectly via the partner's greater ability to develop valuable knowledge by investing into R&D. Hence, this effect may become evident only when the mediating role of the partner's R&D investment is taken into account.

the observation period 2000–2015. We identified 1,242 such alliances that were formed by 311 focal firms[18] from 20 countries with 483 additional same-country partners.[19] These same-country alliances constitute our control group. The 2,023 international alliances from the main analysis serve as the treatment group.

************* Insert Tables 3.6–3.7 here*************

We relied on split-sample analyses to compare the effects of national innovation policies on the focal firms' knowledge acquisition from their partners in the treatment and control groups. The models for both treatment and control groups were estimated using PPML, and they incorporate a similar set of variables as the second-stage models in the main analysis. To ensure consistency across treatment and control group estimates, we omitted control variables describing the partner's country and the parties' cross-national distance, as these variables lack counterfactuals in the control group. Descriptive statistics for the control-group alliances are reported in Table 3.6 (treatment-group descriptive statistics are identical with those reported in Table 3.2).

The results of our analyses are shown in Table 3.7. Models 1–5 show the treatment group estimates, which are consistent with Models 2–5, and 7 from Table 3.4. Control group estimates are shown by Models 6–10 (Table 3.7). These estimates reveal negative and significant effects of the innovation policy variables on the focal firms' knowledge acquisition from same-country partners.[20] We formally tested the difference in coefficients between the treatment- and control-group models using seemingly unrelated regression (SUR) estimation. We then applied Wald tests with the null hypothesis of equal coefficients in the treatment-group model and in the control-group

[18] The remaining 150 focal firms did not form alliances with listed same-country partners during 2000–2015.
[19] Consistent with our method in the main analysis, we collected data on 1,074,161 patent families filed at the USPTO, EPO, and JPO by the 483 same-country partners with their 12,335 subsidiaries.
[20] These effects were robust to removing potential outliers. Consistent findings were also obtained when restricting the treatment group to alliances of those firms that were also represented in the control group (i.e., when excluding those 150 firms from the treatment group that did not form same-country alliances).

model. For the partner's country's innovation policy, we compared the coefficients of the partner-country innovation policy variables in the treatment-group model against the coefficients of the firm-country variables in the control-group model (because the focal firm's and partner's country are the same in the control-group). The results of these Wald tests are shown in the rightmost column of Table 3.7. They are consistent with our findings from the partial models.

There are several potential explanations for these findings. In the case of supply-side innovation policies, a positive effect of the focal firm's country's policies is observed in international alliances with a negative effect in same-country alliances. An interpretation of this pattern is that within the same country, all qualified firms benefit from the same national resource endowments, and thus are less likely to hold knowledge which a focal firm would consider complementary to its own. Hence, if many resources are available in a country to support R&D activities, domestic firms may prefer developing knowledge in-house over acquiring it from partners that have benefitted from the same resource inputs. By contrast, foreign partners rely on different resource conditions in their respective countries, which is why they may hold valuable knowledge that the focal firms cannot feasibly produce in-house despite the availability of resources in their home country.

As it pertains to demand-side policies, no effect of the focal firm's country's policies is observed in international alliances, and a negative effect is seen in same-country alliances. Regarding public-private R&D collaborations, it is possible that if such collaborations are common in a country, then public-sector partners in that country may hold better accessible knowledge than private-sector partners. Hence, public-private partnerships may become the preferred channel for knowledge acquisition, crowding out firms' learning from private-sector partners (to a lesser extent internationally and to a greater extent domestically). In the case of public technology purchases, the requested knowledge may be highly specialized, making it difficult for the focal firms to obtain that knowledge from international partners. Indeed, it might be even more unlikely that the focal firms could obtain such knowledge from domestic partners. Hence, firms would reduce their knowledge acquisition efforts from domestic partners, although they still may not be able to obtain the required knowledge from international partners.

3.8. DISCUSSION

In this paper, we study the effect of innovation policies in the focal firms' and their partners' home countries on the focal firms' knowledge acquisition from partners in international alliances. Our findings indicate that differences in national innovation policies help explain why firms from certain countries are more effective at learning from foreign partners' knowledge than firms from other countries. Our findings also suggest that differences in national innovation policies may contribute to partners' accumulation of specialized and differentiated knowledge, thereby offering opportunities to acquire complementary knowledge from their foreign partners. When controlling for various confounding factors, we find that the innovation policies of the home countries of both the focal firm and the partner significantly influence the focal firm's knowledge acquisition from partners. This has implications for firms engaging in international alliances, which need to understand and take advantage of these opportunities, and for policymakers, who can alter alliance partners' learning through the design of national innovation policies.

More specifically, we find that a country's supply-side innovation policies (i.e., the availability of R&D funding and R&D personnel) can enhance the effectiveness with which firms based in that country acquire complementary knowledge from their foreign alliance partners. The availability of R&D inputs in the form of funding and talent affects the knowledge base and absorptive capacity of firms in that country, thereby enabling them to assimilate complementary knowledge. In contrast, demand-side innovation policies (i.e., public technology purchasing and public-private R&D partnerships) do not appear to influence the extent to which domestic firms acquire knowledge from their foreign partners. There are several potential explanations for this non-finding. One might be that the required innovations are idiosyncratic, making the generated knowledge more specialized and less useful in other contexts, so that demand-side innovation policies do not expand broader knowledge acquisition in the same way as supply-side innovation policies. Alternatively, governments may be less discriminating between domestic and foreign firms when they demand innovations, as they have to team up with any firm that possesses the sought-after knowledge. A case in point is the public purchasing of some military technologies or information and communication technologies that are only available from a few producers. While we were unable to uncover the exact reasons for the non-finding, future research should explore why home-country supply-side and demand-side innovation policies have these distinctly different effects on the focal firms' learning from their international partners.

Taken together, these results indicate that supply-side innovation policies in the home country upgrade the knowledge and absorptive capacity of domestic firms, which forms a platform for acquiring complementary knowledge from alliance partners. Demand-side innovation policies in the home country promote development of specialized knowledge among domestic firms, but do not engender the same motivation and ability for acquiring knowledge from alliance partners.

Moreover, our findings suggest that demand-side innovation policies in the partner's country tend to increase the focal firm's knowledge acquisition from its partner. This is in line with our conjecture that an innovation policy designed to promote innovation in the partner's country can stimulate and expand the partner's knowledge base, thereby providing the focal firm with learning opportunities. However, our findings do not support the claim that supply-side innovation policies in a partner's country increase the focal firm's knowledge acquisition from that partner. This could be because countries that invest in supply-side innovation policy may seek to curtail knowledge outflows by restricting technology transfers to foreign firms (Huang, Geng, & Wang, 2017).

Alternatively, partners may implement stronger knowledge protections if they obtain R&D funding from national governments or if they rely on more qualified personnel (Palomeras & Wehrheim, 2020).

While previous research has considered international alliances and national innovation systems separately, this study merges the two streams of literature to contribute to the literature on learning in alliances as well as the literature on the effects of innovation policy on learning in firms. In particular, it contributes to the emerging stream of alliance literature that focuses on the impact of institutional factors on knowledge acquisition from partners. While prior studies have regarded such factors as boundary conditions (Vasudeva et al., 2013; 2015) or inferred their effects on knowledge flows by focusing on governance mechanisms (Oxley, 1999), our study suggests that home-country institutions can more directly influence firms' opportunities, motivations, and abilities to acquire their partners' knowledge. Although scholars have shown that home-country institutions can affect managers' perceptions of partners' opportunism (Dickson, Weaver, & Hoy, 2006), this study relies on patent citations and, thus, offers more direct evidence of the impact of home-country institutions on knowledge flows between firms and their partners.

In addition, by identifying home-country innovation policies as a factor affecting firms' knowledge acquisition in international alliances, this study responds to calls for an improved understanding of the influence of the home-country context on firm-level outcomes (Cuervo-Cazurra, 2011; Peng et al., 2009). Indeed, in contrast to prior studies that separately consider national policies and alliances, our study juxtaposes them. It shows that even though governments are unlikely to develop innovation policies with interfirm alliances in mind, those policies can affect firms' learning in alliances. Whereas earlier research has emphasized the significance of the national innovation system for knowledge transfers at the country level (Mowery & Oxley, 1995), this study, which focuses on interfirm alliances, sheds light on a meso-level mechanism through which innovation policies effectuate knowledge flows between countries. This implies that when designing national innovation policies, governments can regulate knowledge inflows and outflows to their economy by influencing firms' learning from their foreign alliance partners.

Similarly, our study has implications for managers of firms that engage in international alliances. Managers can expect more learning opportunities when allying with partners from countries with innovation policies that stimulate public technology purchasing or encourage public-private R&D collaboration. In turn, managers can anticipate knowledge outflows when allying with partners from countries whose innovation policies provide access to R&D funding and personnel.

This study suffers from some limitations, and, as such, offers several directions for future research. Given its reliance on archival data sources, the study does not capture the effects of innovation policy at the firm level but infers those effects from country-level indicators. Future research may use surveys to observe these inferred mechanisms (e.g., R&D grants awarded, government purchase orders signed) at the firm level. Alternatively, future research may corroborate this study's correlational findings by relying on natural experiments to examine the impact of a policy's implementation on firms' knowledge acquisition. Moreover, patent data suffer from known limitations (e.g., Corsino et al., 2019; Kuhn et al., 2020). For instance, patents may be cited for reasons that may not indicate knowledge flows. Moreover, patent citations only indicate those knowledge flows that generate innovations. Although we account for various potential confounding factors and alternative explanations, we cannot completely rule out such caveats. Finally, we believe that future research may extend our findings by exploring their boundary conditions or by considering aspects of national innovation systems other than those associated with innovation policy.

3.9. FIGURES AND TABLES

Figure 3.1: Typology of innovation-policy dimensions

	Provides financial capital	**Provides human capital**
Supply-side innovation policy	Availability of R&D funding	Availability of R&D personnel
Demand-side innovation policy	Public technology purchasing	Public-private R&D collaboration

Table 3.1: Patent applications filed by the focal firms and their partners until the beginning of 2020

Patent applications	Focal firms (N = 461)	Partners (N = 669)
Patent applications worldwide	15,918,124 (n = 461)	8,169,163 (n = 621)
USPTO patent applications	2,609,770 (n = 461)	1,120,886 (n = 548)
EPO patent applications	633,943 (n = 458)	372,117 (n = 520)
JPO patent applications	5,068,761 (n = 448)	2,365,323 (n = 401)
Patent families (USPTO/EPO/JPO)	5,185,197 (n = 461)	3,298,039 (n = 570)

Table 3.2: Descriptive statistics and pairwise correlations for second-stage model

Variables	Mean	Std. Dev.	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.
1. Complementary knowledge acquired	180.73	445.13												
2. Firm availability of R&D funding	0.00	1.00	0.03											
3. Partner availability of R&D funding	0.00	1.00	0.12	0.22										
4. Firm availability of R&D personnel	0.00	1.00	-0.06	0.35	-0.07									
5. Partner availability of R&D personnel	0.00	1.00	0.01	-0.11	0.51	-0.27								
6. Firm public technology purchasing	0.00	1.00	0.10	0.48	0.18	0.49	-0.17							
7. Partner public technology purchasing	0.00	1.00	0.12	0.18	0.45	-0.18	0.54	0.11						
8. Firm public-private R&D collaboration	0.00	1.00	0.03	0.26	0.06	0.65	-0.18	0.64	-0.04					
9. Partner public-private R&D collab.	0.00	1.00	0.02	0.07	0.39	-0.18	0.65	-0.03	0.63	-0.13				
10. Firm innovation-policy index	0.00	1.00	0.03	0.62	0.12	0.81	-0.24	0.85	0.01	0.84	-0.09			
11. Partner innovation-policy index	0.00	1.00	0.08	0.10	0.71	-0.22	0.85	0.02	0.82	-0.09	0.84	-0.07		
12. Firm age	45.85	42.07	0.03	0.19	-0.05	-0.08	0.02	-0.09	-0.02	-0.15	0.00	-0.06	-0.01	
13. Firm size	30698.55	39755.43	0.14	-0.06	-0.10	-0.05	-0.04	-0.02	-0.12	-0.05	-0.11	-0.05	-0.11	0.33
14. Firm R&D intensity	0.41	2.16	-0.03	0.00	0.03	0.05	0.02	-0.00	0.01	0.04	0.00	0.03	0.02	-0.12
15. Firm solvency	1.92	2.98	-0.04	0.03	0.02	0.14	-0.03	0.03	-0.04	0.07	-0.01	0.09	-0.02	-0.17
16. Firm GPE	44.17	72.26	0.22	0.29	0.11	0.12	-0.11	0.24	0.06	0.09	0.00	0.23	0.01	0.29
17. Firm patenting experience	13107.04	26112.94	0.17	0.22	0.04	-0.22	0.08	-0.02	0.07	-0.17	0.00	-0.08	0.06	0.36
18. Firm total backward citations	74116.93	135987.70	0.32	0.08	0.03	-0.04	-0.02	0.14	0.04	0.04	-0.01	0.07	0.01	0.26
19. Firm patent purchasing	31.78	423.77	0.02	0.01	-0.01	0.01	0.01	-0.03	-0.02	-0.03	-0.03	-0.01	-0.01	0.05
20. Firm GDPPC	35125.07	10656.86	-0.07	0.00	-0.25	0.62	-0.21	0.11	-0.34	0.41	-0.28	0.38	-0.34	-0.02
21. Firm country patent applications	160094.45	126418.79	0.03	0.43	-0.05	0.12	-0.07	0.23	-0.10	0.03	-0.11	0.23	-0.11	0.12
22. Firm intellectual property rights	0.00	1.00	-0.06	0.34	0.08	0.56	-0.16	0.19	0.01	0.17	-0.02	0.39	-0.03	0.09
23. Partner age	35.63	38.92	0.16	-0.03	0.17	0.04	-0.02	-0.01	-0.08	0.03	-0.11	0.01	-0.02	-0.03
24. Partner size	24414.61	56081.72	0.13	-0.02	0.02	-0.05	0.05	-0.09	0.03	-0.06	0.00	-0.07	0.03	0.08
25. Partner R&D intensity	1.25	17.60	-0.01	0.00	-0.01	0.03	-0.01	0.01	-0.02	0.03	0.01	0.02	-0.01	-0.01
26. Partner solvency	2.53	3.58	-0.06	0.02	0.04	-0.02	0.11	0.03	0.04	0.00	0.10	0.01	0.09	-0.00
27. Partner GPE	27.26	59.20	0.39	0.12	0.22	-0.09	0.14	0.08	0.19	-0.01	0.08	0.03	0.19	0.08
28. Partner patenting experience	6307.51	18065.67	0.39	0.04	0.22	0.05	-0.05	0.08	0.06	0.04	-0.07	0.07	0.04	-0.00
29. Partner scientific impact	9.28	11.81	0.16	0.20	0.31	-0.12	0.23	0.18	0.34	0.05	0.21	0.09	0.34	0.05
30. Partner GDPPC	33975.41	12452.96	-0.03	-0.28	0.18	-0.20	0.70	-0.32	0.23	-0.22	0.45	-0.32	0.49	0.00
31. Partner country patent applications	135672.51	134270.42	0.09	-0.13	0.33	-0.11	0.23	-0.15	0.34	-0.15	0.06	-0.17	0.29	-0.01
32. Partner intellectual property rights	0.00	1.00	0.01	0.08	0.41	-0.09	0.64	0.05	0.28	0.03	0.33	0.02	0.52	-0.04
33. Joint venture	0.18	0.38	0.01	-0.09	-0.17	-0.12	-0.18	-0.10	-0.11	-0.15	-0.20	-0.15	-0.20	0.13
34. Vertical scope	-0.10	0.73	-0.04	-0.04	0.03	0.06	0.06	-0.06	-0.03	0.04	0.04	0.00	0.03	-0.05
35. Joint partnering experience	1.41	1.31	0.39	0.08	0.10	-0.06	0.02	0.02	0.08	-0.05	-0.01	-0.01	0.06	0.14
36. Technological overlap	0.49	0.32	0.15	0.03	0.20	0.01	0.16	-0.01	0.11	0.08	0.12	0.04	0.18	-0.08
37. Business overlap	0.48	0.39	-0.03	-0.12	-0.04	-0.03	0.05	-0.12	0.03	-0.03	0.03	-0.09	0.02	-0.12
38. Cultural distance	1.92	1.24	0.08	0.02	-0.00	-0.16	-0.04	0.07	0.17	-0.12	-0.03	-0.07	0.03	0.02
39. Administrative distance	0.50	0.51	-0.01	-0.10	-0.31	-0.13	-0.41	-0.03	-0.15	-0.04	-0.19	-0.09	-0.33	0.05
40. Geographical distance	7906.06	3823.10	-0.02	0.12	0.10	0.05	0.09	0.16	0.14	0.03	0.08	0.11	0.13	-0.05
41. Economic distance	0.53	0.64	-0.06	-0.09	-0.21	-0.11	-0.34	-0.04	-0.15	-0.05	-0.12	-0.09	-0.25	-0.07
42. Subsidiaries in the partner's country	0.56	0.50	0.05	-0.10	0.07	-0.28	0.22	-0.22	0.13	-0.23	0.12	-0.27	0.17	0.31
43. Patent co-applications	2.77	18.19	0.13	0.02	0.06	-0.04	0.01	0.04	0.08	-0.01	0.01	0.01	0.05	0.00
44. Pre-alliance citations	97.72	421.21	0.69	0.04	0.13	-0.04	0.02	0.07	0.10	0.03	0.02	0.03	0.08	0.06

N = 2,023 dyads, except for variables 8. and 9., where N = 1,463 dyads.

Table 3.2: Descriptive statistics and pairwise correlations for second-stage model (continued)

	13.	14.	15.	16.	17.	18.	19.	20.	21.	22.	23.	24.	25.	26.	27.	28.	29.	30.	31.	32.	33.	34.	35.	36.	37.	38.	39.	40.	41.	42.	43.
14.	-0.11																														
15.	-0.24	0.08																													
16.	0.50	-0.08	-0.17																												
17.	0.47	-0.08	-0.20	0.47																											
18.	0.59	-0.08	-0.14	0.57	0.58																										
19.	-0.00	-0.01	-0.03	-0.00	0.01	-0.00																									
20.	0.15	0.03	0.10	0.02	-0.08	0.00	0.02																								
21.	0.11	-0.07	0.06	0.17	0.45	0.20	0.00	0.23																							
22.	0.01	0.05	0.05	0.18	-0.11	-0.06	0.03	0.51	-0.10																						
23.	0.01	0.03	0.02	-0.00	0.01	0.01	0.06	0.08	0.03	0.01																					
24.	0.00	0.01	-0.03	0.01	0.11	0.02	0.04	0.01	0.02	-0.02	0.30																				
25.	-0.01	0.01	-0.01	-0.03	-0.03	-0.03	-0.00	0.01	-0.01	0.02	-0.05	-0.03																			
26.	-0.00	-0.03	0.05	0.01	-0.00	-0.00	-0.03	-0.00	0.04	-0.03	-0.23	-0.19	-0.01																		
27.	0.04	-0.02	-0.07	0.13	0.15	0.10	0.02	-0.11	0.04	0.00	0.21	0.30	-0.02	-0.01																	
28.	0.04	-0.03	-0.04	0.09	0.04	0.12	0.03	-0.01	-0.02	0.05	0.35	0.27	-0.02	-0.16	0.47																
29.	-0.03	-0.01	-0.04	0.13	0.14	0.11	-0.01	-0.22	-0.01	-0.01	-0.04	0.04	-0.03	0.11	0.33	0.05															
30.	-0.03	0.03	0.01	-0.19	-0.02	-0.08	0.00	-0.07	-0.11	-0.17	0.05	0.13	0.01	0.04	0.06	-0.02	0.01														
31.	-0.01	0.02	-0.01	-0.07	-0.01	-0.01	0.00	-0.09	-0.13	-0.02	0.13	0.07	-0.03	0.04	0.17	0.35	0.04	0.18													
32.	-0.07	0.06	-0.00	-0.04	0.03	-0.02	0.02	-0.14	0.01	-0.06	0.08	0.07	0.03	0.03	0.13	-0.02	0.19	0.65	-0.05												
33.	0.10	-0.04	-0.12	0.00	0.13	0.02	0.06	-0.10	0.00	-0.09	0.10	0.09	-0.03	-0.14	-0.01	0.09	-0.06	-0.18	0.03	-0.23											
34.	-0.02	0.08	0.07	-0.06	-0.08	-0.09	-0.03	0.16	0.01	0.07	-0.02	-0.03	0.07	0.04	-0.00	-0.03	-0.07	0.14	0.04	0.10	-0.23										
35.	0.16	-0.03	-0.07	0.24	0.30	0.19	0.02	-0.03	0.10	0.02	0.18	0.33	-0.02	-0.08	0.32	0.38	0.10	0.02	0.14	0.02	0.15	-0.03									
36.	-0.07	0.09	0.04	-0.05	-0.09	-0.08	0.06	-0.00	-0.05	-0.00	0.03	0.04	-0.02	-0.00	0.09	0.08	0.13	0.14	0.08	0.18	-0.14	0.10	0.12								
37.	-0.16	0.09	0.02	-0.25	-0.21	-0.23	0.05	-0.01	-0.07	-0.05	-0.04	-0.05	0.05	-0.02	-0.15	-0.06	-0.13	0.08	-0.00	0.05	-0.03	0.08	-0.03	0.33							
38.	0.05	-0.08	0.02	0.03	0.20	0.18	-0.01	-0.16	0.26	-0.27	0.01	-0.02	-0.05	0.03	0.07	0.11	0.06	-0.15	0.29	-0.26	0.10	-0.10	0.07	-0.09	-0.08						
39.	0.03	-0.05	-0.08	0.04	-0.00	0.04	-0.03	-0.24	-0.11	-0.27	-0.10	-0.11	-0.03	-0.03	-0.08	-0.10	-0.04	-0.54	-0.10	-0.61	0.15	-0.14	-0.07	-0.16	-0.02	0.26					
40.	-0.00	-0.07	0.06	0.03	0.08	0.06	-0.04	-0.02	0.28	-0.11	-0.01	-0.01	-0.02	0.09	0.05	0.05	0.03	-0.03	0.25	-0.07	-0.08	-0.01	0.04	-0.02	-0.04	0.53	0.10				
41.	-0.04	-0.05	-0.03	0.01	-0.06	-0.02	-0.03	-0.26	-0.05	-0.32	-0.14	-0.10	-0.02	0.01	-0.10	-0.11	-0.08	-0.53	-0.07	-0.60	0.13	-0.14	-0.08	-0.12	-0.00	0.25	0.81	0.21			
42.	0.35	-0.10	-0.18	0.21	0.26	0.25	0.03	-0.17	-0.10	-0.06	-0.06	0.05	-0.00	0.05	0.09	0.01	0.05	0.18	0.17	0.07	0.06	-0.05	0.10	-0.03	-0.13	-0.02	-0.00	-0.06	-0.01		
43.	0.03	-0.00	-0.04	0.11	0.08	0.09	0.04	-0.03	-0.00	0.04	0.06	0.04	-0.01	-0.05	0.18	0.15	0.07	-0.01	0.03	0.05	-0.00	0.02	0.15	0.07	0.02	-0.03	-0.06	-0.01	-0.07	0.03	
44.	0.15	-0.03	-0.05	0.20	0.19	0.30	0.06	-0.03	0.04	-0.03	0.20	0.18	-0.01	-0.09	0.38	0.45	0.11	-0.00	0.13	0.01	0.04	-0.04	0.44	0.15	-0.02	0.08	-0.04	0.00	-0.08	0.08	0.11

Table 3.3: First-stage probit regressions for sample selection (Model 1) and partner selection (Models 2–8)

Variables	Model (1)		Model (2)		Model (3)		Model (4)		Model (5)		Model (6)		Model (7)		Model (8)	
Firm age	0.060***	(0.016)	0.002	(0.028)	0.008	(0.029)	0.008	(0.029)	0.002	(0.028)	0.000	(0.034)	0.003	(0.034)	0.008	(0.029)
Firm size	-0.010	(0.076)	0.003	(0.034)	-0.006	(0.034)	0.002	(0.034)	0.005	(0.034)	-0.005	(0.037)	-0.013	(0.037)	-0.000	(0.034)
Firm R&D intensity	-2.924***	(0.846)	-0.001	(0.021)	-0.000	(0.021)	0.001	(0.021)	-0.001	(0.021)	0.014	(0.042)	0.013	(0.043)	-0.000	(0.021)
Firm solvency	-0.055**	(0.017)	0.002	(0.024)	0.004	(0.024)	0.003	(0.024)	0.001	(0.024)	0.000	(0.027)	-0.001	(0.027)	0.004	(0.024)
Firm GPE	0.992***	(0.048)	0.005	(0.033)	0.008	(0.034)	0.005	(0.033)	0.006	(0.033)	-0.007	(0.060)	-0.008	(0.061)	0.006	(0.033)
Firm patenting experience	0.174***	(0.012)	-0.004	(0.045)	-0.006	(0.045)	-0.018	(0.046)	-0.002	(0.045)	0.017	(0.053)	0.011	(0.057)	-0.008	(0.045)
Firm GDPPC	-0.042+	(0.022)	-0.007	(0.038)	0.026	(0.042)	-0.013	(0.038)	0.007	(0.040)	0.058	(0.052)	0.052	(0.055)	0.033	(0.043)
Firm country patent applications	-0.048*	(0.021)	-0.057+	(0.031)	-0.054+	(0.031)	-0.028	(0.037)	-0.051	(0.031)	-0.075*	(0.037)	-0.066	(0.051)	-0.047	(0.031)
Firm intellectual property rights			0.043	(0.036)	0.062	(0.037)	0.060	(0.038)	0.037	(0.036)	0.035	(0.046)	0.043	(0.055)	0.044	(0.036)
Partner age			-0.190***	(0.030)	-0.202***	(0.031)	-0.189***	(0.031)	-0.185***	(0.031)	-0.204***	(0.036)	-0.195***	(0.036)	-0.194***	(0.031)
Partner size			0.005	(0.024)	-0.007	(0.024)	0.005	(0.024)	0.003	(0.024)	-0.004	(0.026)	-0.010	(0.026)	0.001	(0.024)
Partner R&D intensity			-0.046	(0.040)	-0.046	(0.040)	-0.047	(0.041)	-0.044	(0.039)	-0.044	(0.037)	-0.042	(0.036)	-0.045	(0.039)
Partner solvency			0.034	(0.022)	0.041+	(0.022)	0.034	(0.022)	0.033	(0.022)	0.034	(0.026)	0.039	(0.026)	0.035	(0.022)
Partner GPE			-0.037+	(0.021)	-0.032	(0.021)	-0.038+	(0.021)	-0.039+	(0.021)	-0.045	(0.037)	-0.045	(0.037)	-0.039+	(0.021)
Partner patenting experience			0.059**	(0.020)	0.053**	(0.020)	0.059**	(0.020)	0.058**	(0.020)	0.041+	(0.023)	0.023	(0.023)	0.062**	(0.020)
Partner GDPPC			-0.215***	(0.041)	-0.133**	(0.044)	-0.216***	(0.041)	-0.232***	(0.043)	-0.175***	(0.049)	-0.167***	(0.050)	-0.183***	(0.045)
Partner country patent applications			-0.146***	(0.024)	-0.115***	(0.025)	-0.139***	(0.027)	-0.158***	(0.027)	-0.138***	(0.028)	-0.150***	(0.036)	-0.130***	(0.026)
Partner intellectual property rights			0.095*	(0.041)	0.175***	(0.045)	0.102*	(0.043)	0.095*	(0.042)	0.215***	(0.050)	0.276***	(0.055)	0.113**	(0.042)
Joint partnering experience			0.022	(0.022)	0.020	(0.022)	0.021	(0.022)	0.022	(0.022)	0.063+	(0.035)	0.066+	(0.035)	0.021	(0.022)
Technological overlap			0.149***	(0.023)	0.159***	(0.023)	0.152***	(0.023)	0.147***	(0.023)	0.161***	(0.027)	0.166***	(0.027)	0.154***	(0.023)
Cultural distance			0.034	(0.032)	0.026	(0.033)	0.032	(0.033)	0.032	(0.033)	0.031	(0.037)	0.013	(0.038)	0.031	(0.033)
Administrative distance			0.070	(0.045)	0.046	(0.046)	0.060	(0.047)	0.070	(0.045)	0.088+	(0.052)	0.041	(0.057)	0.064	(0.046)
Geographical distance			0.215***	(0.031)	0.218***	(0.031)	0.216***	(0.031)	0.218***	(0.031)	0.225***	(0.036)	0.236***	(0.037)	0.217***	(0.031)
Economic distance			-0.046	(0.046)	-0.001	(0.047)	-0.036	(0.047)	-0.050	(0.046)	-0.031	(0.055)	0.007	(0.058)	-0.027	(0.047)
Subsidiaries in the partner's country			-0.153**	(0.052)	-0.127*	(0.053)	-0.157**	(0.052)	-0.160**	(0.052)	-0.080	(0.061)	-0.063	(0.062)	-0.154**	(0.053)
Pre-alliance citations			-0.039*	(0.018)	-0.035+	(0.018)	-0.038*	(0.018)	-0.039*	(0.018)	-0.031	(0.021)	-0.031	(0.021)	-0.037*	(0.018)
Industry alliance formation	0.175***	(0.017)														
Industry US/EP/JP subsidiaries	0.025+	(0.014)														
Partner relative size			0.402***	(0.024)	0.407***	(0.024)	0.403***	(0.024)	0.404***	(0.024)	0.391***	(0.031)	0.403***	(0.031)	0.403***	(0.024)
Partner relative GPE			0.196***	(0.027)	0.202***	(0.027)	0.197***	(0.027)	0.196***	(0.027)	0.200***	(0.033)	0.207***	(0.033)	0.198***	(0.027)
Firm availability of R&D funding					-0.068*	(0.035)							-0.031	(0.087)		
Partner availability of R&D funding					-0.192***	(0.040)							-0.347**	(0.106)		
Firm availability of R&D personnel							-0.052	(0.036)					-0.013	(0.049)		
Partner availability of R&D personnel							-0.021	(0.033)					0.048	(0.050)		
Firm public technology purchasing									-0.035	(0.032)			0.011	(0.046)		
Partner public technology purchasing									0.032	(0.031)			0.112*	(0.045)		
Firm public-private R&D collaboration											-0.084*	(0.041)	-0.064	(0.082)		
Partner public-private R&D collaboration											-0.110**	(0.037)	0.036	(0.076)		
Firm innovation-policy index															-0.069*	(0.034)
Partner innovation-policy index															-0.064+	(0.036)
λ sample selection			-0.022	(0.046)	-0.014	(0.047)	-0.031	(0.047)	-0.020	(0.047)	0.031	(0.086)	0.008	(0.087)	-0.019	(0.047)
Year and industry fixed effects	Included		Included		Included		Included		Included		Included		Included		Included	
Constant	-2.170	(0.135)	0.258	(0.221)	0.140	(0.223)	0.200	(0.225)	0.273	(0.231)	-0.181	(0.297)	0.131	(0.317)	0.095	(0.231)
N selected	1,280		2,023		2,023		2,023		2,023		1,463		1,463		2,023	
N population	17,842		4,046		4,046		4,046		4,046		2,926		2,926		4,046	
Pseudo R-squared	0.2117		0.1569		0.1614		0.1573		0.1573		0.1465		0.1503		0.1581	
Log likelihood	-3630.4		-2364.4		-2351.8		-2363.2		-2363.2		-1727.4		-1719.7		-2361.1	

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

Table 3.4: Second-stage PPML regressions for complementary knowledge acquired by the focal firm from the partner

Variables	Model (1)		Model (2)		Model (3)		Model (4)		Model (5)		Model (6)		Model (7)	
Firm age	-0.206	(0.143)	-0.289*	(0.138)	-0.243+	(0.129)	-0.168	(0.160)	-0.318**	(0.121)	-0.507*	(0.210)	-0.208	(0.153)
Firm size	-0.038	(0.072)	-0.014	(0.063)	0.000	(0.074)	0.009	(0.058)	0.102	(0.085)	0.041	(0.066)	0.014	(0.058)
Firm R&D intensity	-0.798+	(0.423)	-0.784*	(0.342)	-0.670*	(0.340)	-0.813+	(0.447)	-0.938	(0.592)	-0.912*	(0.460)	-0.815+	(0.432)
Firm solvency	0.108	(0.073)	0.066	(0.072)	0.096	(0.080)	0.078	(0.064)	0.069	(0.075)	0.017	(0.071)	0.078	(0.077)
Firm GPE	-0.004	(0.051)	-0.057	(0.053)	0.004	(0.045)	-0.017	(0.046)	0.054	(0.116)	0.025	(0.120)	-0.035	(0.047)
Firm patenting experience	0.018	(0.056)	0.016	(0.057)	-0.043	(0.052)	0.008	(0.067)	0.067	(0.168)	-0.043	(0.138)	-0.004	(0.068)
Firm total backward citations	0.626***	(0.082)	0.638***	(0.093)	0.653***	(0.075)	0.621***	(0.080)	0.475**	(0.166)	0.530***	(0.137)	0.643***	(0.080)
Firm patent purchasing	0.017	(0.058)	0.021	(0.054)	0.013	(0.058)	0.015	(0.056)	0.042	(0.037)	0.027	(0.039)	0.020	(0.055)
Firm GDPPC	-0.168*	(0.067)	-0.348***	(0.097)	-0.146*	(0.072)	-0.255**	(0.081)	-0.000	(0.102)	-0.034	(0.090)	-0.290**	(0.097)
Firm country patent applications	0.060	(0.098)	0.031	(0.102)	-0.051	(0.114)	0.033	(0.095)	0.044	(0.159)	-0.006	(0.161)	0.035	(0.097)
Firm intellectual property rights	0.278	(0.176)	0.110	(0.180)	0.135	(0.169)	0.296+	(0.170)	0.144	(0.182)	-0.173	(0.191)	0.250	(0.180)
Partner age	0.137	(0.091)	0.133+	(0.080)	0.153	(0.095)	0.159	(0.097)	-0.016	(0.084)	0.089	(0.093)	0.116	(0.088)
Partner size	0.150**	(0.048)	0.156**	(0.051)	0.154**	(0.051)	0.143**	(0.045)	0.217***	(0.048)	0.210***	(0.052)	0.157***	(0.047)
Partner R&D intensity	-0.008	(0.147)	-0.021	(0.173)	-0.005	(0.156)	-0.054	(0.235)	-0.270	(0.455)	-0.303	(0.404)	-0.040	(0.216)
Partner solvency	-0.185+	(0.112)	-0.180	(0.115)	-0.173+	(0.104)	-0.171+	(0.095)	-0.416***	(0.118)	-0.383***	(0.098)	-0.191+	(0.107)
Partner GPE	0.268***	(0.031)	0.268***	(0.033)	0.272***	(0.034)	0.260***	(0.032)	0.298***	(0.045)	0.326***	(0.044)	0.272***	(0.033)
Partner patenting experience	0.043	(0.058)	0.051	(0.052)	0.040	(0.056)	0.046	(0.063)	0.140	(0.101)	0.152	(0.105)	0.042	(0.058)
Partner scientific impact	0.215***	(0.053)	0.213***	(0.052)	0.213***	(0.057)	0.205***	(0.053)	0.487***	(0.070)	0.488***	(0.069)	0.206***	(0.057)
Partner GDPPC	0.302	(0.322)	0.165	(0.341)	0.304	(0.323)	0.107	(0.310)	-0.115	(0.205)	-0.148	(0.187)	0.099	(0.330)
Partner country patent applications	-0.079	(0.162)	-0.124	(0.162)	-0.069	(0.190)	-0.090	(0.177)	0.181	(0.125)	0.358**	(0.135)	-0.114	(0.173)
Partner intellectual property rights	0.007	(0.208)	-0.129	(0.218)	0.001	(0.245)	0.089	(0.203)	0.354*	(0.162)	0.654***	(0.195)	-0.033	(0.231)
Joint venture	-0.180+	(0.105)	-0.195+	(0.103)	-0.180+	(0.101)	-0.187+	(0.098)	-0.173	(0.120)	-0.198	(0.152)	-0.180+	(0.101)
Vertical scope	-0.027	(0.043)	-0.030	(0.040)	-0.031	(0.046)	-0.034	(0.040)	-0.102	(0.083)	-0.087	(0.090)	-0.036	(0.040)
Joint partnering experience	0.011	(0.041)	0.027	(0.046)	0.011	(0.043)	0.006	(0.042)	0.042	(0.050)	0.038	(0.056)	0.015	(0.043)
Technological overlap	0.903***	(0.144)	0.914***	(0.141)	0.899***	(0.136)	0.921***	(0.138)	1.041***	(0.190)	1.030***	(0.185)	0.912***	(0.141)
Business overlap	0.171*	(0.082)	0.176+	(0.093)	0.176*	(0.084)	0.109	(0.101)	0.092	(0.108)	0.149	(0.102)	0.144	(0.095)
Cultural distance	0.356***	(0.089)	0.375***	(0.098)	0.370***	(0.077)	0.361***	(0.084)	0.493**	(0.151)	0.446*	(0.174)	0.382***	(0.082)
Administrative distance	0.376+	(0.215)	0.335	(0.204)	0.377+	(0.216)	0.352+	(0.206)	0.250*	(0.125)	0.224	(0.184)	0.344+	(0.206)
Geographical distance	-0.293**	(0.091)	-0.296**	(0.102)	-0.308**	(0.094)	-0.330**	(0.104)	-0.416**	(0.147)	-0.368*	(0.159)	-0.319**	(0.103)
Economic distance	-0.536**	(0.187)	-0.622**	(0.209)	-0.533**	(0.190)	-0.613**	(0.225)	-0.175	(0.209)	-0.284	(0.199)	-0.569**	(0.221)
Subsidiaries in the partner's country	-0.516***	(0.141)	-0.469**	(0.171)	-0.487**	(0.157)	-0.422***	(0.110)	-0.239	(0.214)	-0.064	(0.302)	-0.476**	(0.148)
Patent co-applications	0.095***	(0.018)	0.100***	(0.023)	0.101***	(0.018)	0.087***	(0.018)	0.169***	(0.042)	0.135*	(0.061)	0.095***	(0.019)
Pre-alliance citations	0.136***	(0.014)	0.130***	(0.015)	0.132***	(0.015)	0.128***	(0.014)	0.138***	(0.023)	0.116***	(0.024)	0.130***	(0.015)
Firm availability of R&D funding			0.393***	(0.083)							0.740*	(0.325)		
Partner availability of R&D funding			0.227	(0.149)							-0.422+	(0.247)		
Firm availability of R&D personnel					0.251**	(0.094)					-0.033	(0.138)		
Partner availability of R&D personnel					-0.012	(0.167)					-0.226+	(0.130)		
Firm public technology purchasing							0.221	(0.135)			-0.009	(0.216)		
Partner public technology purchasing							0.428**	(0.138)			0.277	(0.170)		
Firm public-private R&D collaboration									0.081	(0.092)	-0.360*	(0.149)		
Partner public-private R&D collaboration									0.389*	(0.158)	0.561+	(0.321)		
Firm innovation-policy index													0.237*	(0.105)
Partner innovation-policy index													0.316*	(0.151)
λ sample selection	-0.180	(0.148)	-0.242+	(0.127)	-0.187	(0.133)	-0.095	(0.145)	-0.793	(0.555)	-3.350**	(1.033)	-0.147	(0.138)
λ partner selection	-0.188+	(0.110)	-0.190	(0.116)	-0.194+	(0.117)	-0.200*	(0.098)	-0.012	(0.120)	-0.018	(0.096)	-0.578+	(0.317)
Year and industry fixed effects	Included		Included		Included		Included		Included		Included		Included	
Constant	2.950***	(0.158)	2.844***	(0.191)	2.865***	(0.131)	2.562***	(0.099)	1.920***	(0.490)	0.219	(0.883)	3.099***	(0.195)
Maximum VIF	4.15		4.37		4.26		4.18		4.06		11.97		4.26	
Log pseudo-likelihood	-51226		-50198		-50804		-49384		-26948		-25493		-50328	

N = 2,023 dyads, except for models (5) and (6), where N = 1,463 dyads. Standardized coefficients. Clustered standard errors in parentheses.
Significance: *** p < 0.001, ** p < 0.01, * p < 0.05, + p < 0.10.

Figure 3.2: Complementary knowledge acquired by availability of R&D funding with 95% confidence intervals (Model 2)

Figure 3.3: Complementary knowledge acquired by availability of R&D personnel with 95% confidence intervals (Model 3)

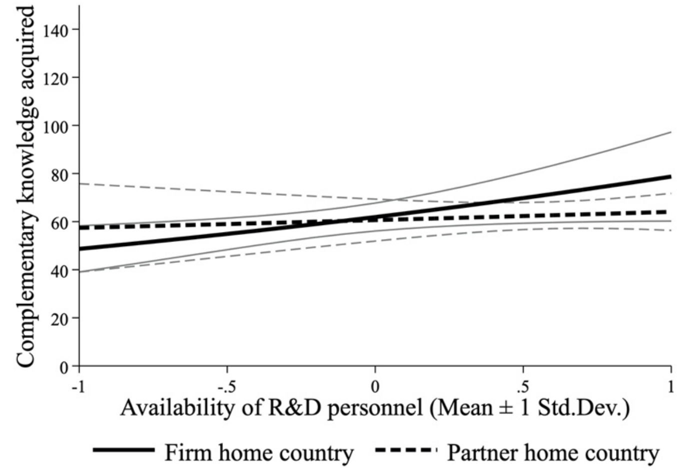

Figure 3.4: Complementary knowledge acquired by public technology purchasing with 95% confidence intervals (Model 4)

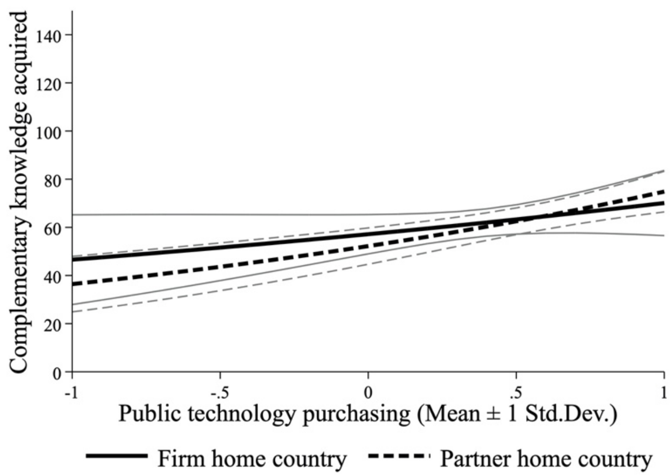

Figure 3.5: Complementary knowledge acquired by public-private R&D collaboration with 95% confidence intervals (Model 5)

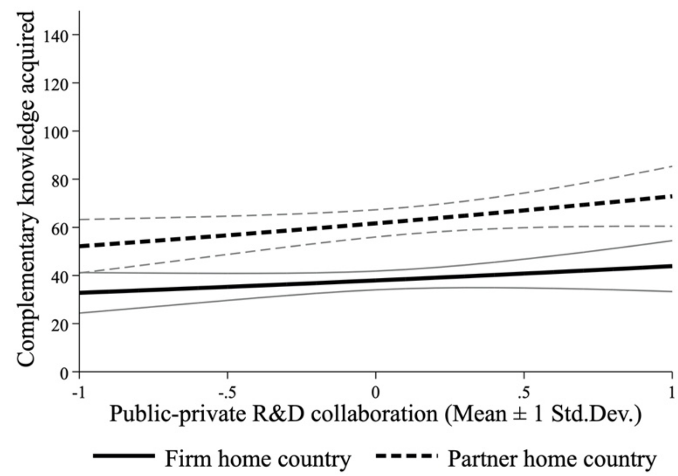

Figure 3.6: Path diagram of mediation model

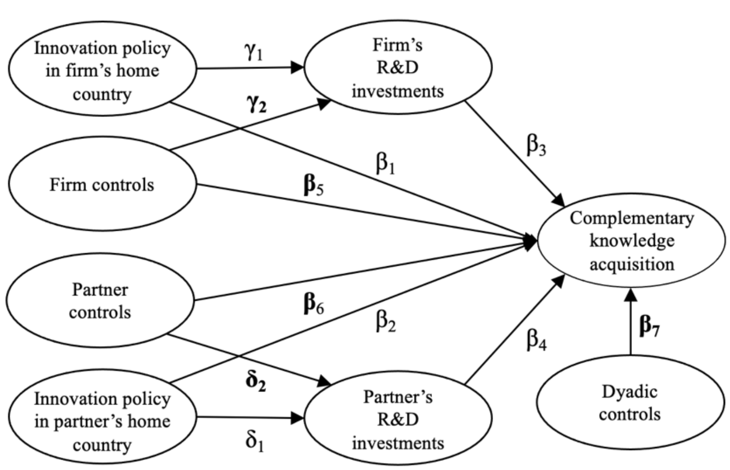

Table 3.5: Mediation model (GSEM) for complementary knowledge acquired by the focal firm from the partner

Variables	Model (1)		Model (2)		Model (3)		Model (4)		Model (5)	
Direct effect on knowledge acquisition										
Firm availability of R&D funding	0.436***	(0.071)							0.601**	(0.179)
Partner availability of R&D funding	0.354***	(0.088)							0.329	(0.219)
Firm availability of R&D personnel			0.167*	(0.074)					-0.004	(0.116)
Partner availability of R&D personnel			0.105	(0.111)					-0.109	(0.167)
Firm public technology purchasing					0.217*	(0.035)			0.020	(0.119)
Partner public technology purchasing					0.078	(0.133)			-0.098	(0.133)
Firm public-private R&D collaboration							0.152	(0.144)	-0.268	(0.167)
Partner public-private R&D collaboration							0.161	(0.103)	0.087	(0.177)
Direct effect on firm R&D investments										
Firm availability of R&D funding	0.216***	(0.043)							-0.454***	(0.110)
Firm availability of R&D personnel			0.095*	(0.048)					0.185**	(0.063)
Firm public technology purchasing					-0.048	(0.039)			0.063	(0.058)
Firm public-private R&D collaboration							-0.049	(0.308)	0.224*	(0.093)
Direct effect on partner R&D investments										
Partner availability of R&D funding	0.155*	(0.079)							-0.177	(0.212)
Partner availability of R&D personnel			0.373***	(0.073)					0.549***	(0.104)
Partner public technology purchasing					0.464***	(0.068)			0.572***	(0.106)
Partner public-private R&D collaboration							0.096	(0.073)	-0.308*	(0.154)
Indirect effect on knowledge acquisition										
Firm availability of R&D funding	0.117***	(0.025)							-0.304***	(0.077)
Partner availability of R&D funding	0.101*	(0.051)							-0.118	(0.142)
Firm availability of R&D personnel			0.048+	(0.025)					0.124**	(0.043)
Partner availability of R&D personnel			0.241***	(0.048)					0.366***	(0.073)
Firm public technology purchasing					-0.025	(0.020)			0.042	(0.039)
Partner public technology purchasing					0.299***	(0.046)			0.382***	(0.074)
Firm public-private R&D collaboration							-0.031	(0.030)	0.150*	(0.063)
Partner public-private R&D collaboration							0.065	(0.049)	-0.206*	(0.103)
Total effect on knowledge acquisition										
Firm availability of R&D funding	0.542***	(0.076)							0.297	(0.194)
Partner availability of R&D funding	0.455***	(0.102)							0.210	(0.262)
Firm availability of R&D personnel			0.215**	(0.080)					0.120	(0.125)
Partner availability of R&D personnel			0.346**	(0.122)					0.257	(0.182)
Firm public technology purchasing					0.191+	(0.107)			0.062	(0.127)
Partner public technology purchasing					0.378**	(0.134)			0.283+	(0.147)
Firm public-private R&D collaboration							0.120	(0.109)	-0.118	(0.177)
Partner public-private R&D collaboration							0.226*	(0.045)	-0.118	(0.207)
Control variables	Included		Included		Included		Included		Included	
Year and industry fixed effects	Included		Included		Included		Included		Included	
Observations	2,023		2,023		2,023		1,463		1,463	
Log pseudo-likelihood	-31284		-32537		-32380		-17991		-17496	

Standardized coefficients. Robust standard errors in parenthesis. Significance: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, + $p < 0.10$.

Table 3.6: Descriptive statistics and pairwise correlations for the control group of same-country alliances

Variables	Mean	Std.Dev.	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.
1. Complementary knowledge acquired	132.83	495.25											
2. Availability of R&D funding	0.00	1.00	0.16										
3. Availability of R&D personnel	0.00	1.00	-0.20	-0.07									
4. Public technology purchasing	0.00	1.00	-0.05	0.30	0.59								
5. Public-private R&D collaboration	0.00	1.00	-0.09	0.11	0.58	0.81							
6. Firm innovation-policy index	0.00	1.00	-0.10	0.24	0.78	0.93	0.91						
7. Firm age	45.42	36.35	0.18	0.16	-0.36	-0.24	-0.31	-0.32					
8. Firm size	35079.98	39347.41	0.17	-0.03	-0.07	-0.06	-0.08	-0.08	0.44				
9. Firm R&D intensity	0.34	1.08	-0.07	-0.04	0.13	0.04	0.05	0.07	-0.22	-0.21			
10. Firm solvency	1.61	2.86	-0.06	0.04	0.06	0.03	0.04	0.05	-0.21	-0.24	0.09		
11. Firm GPE	73.65	100.15	0.18	0.27	0.09	0.19	0.10	0.17	0.34	0.62	-0.16	-0.18	
12. Firm patenting experience	19283.30	32661.28	0.39	0.33	-0.50	-0.16	-0.26	-0.30	0.48	0.50	-0.15	-0.19	0.42
13. Firm total backward citations	102690.30	173166.00	0.25	0.11	-0.05	0.05	-0.00	0.02	0.47	0.66	-0.14	-0.13	0.75
14. Firm patent purchasing	16.10	86.70	0.23	0.03	-0.20	-0.14	-0.19	-0.19	0.05	0.07	-0.04	-0.04	-0.01
15. Partner age	34.27	34.49	0.23	0.18	-0.48	-0.31	-0.37	-0.41	0.21	0.04	-0.07	0.00	-0.08
16. Partner size	20663.89	41253.61	0.23	-0.01	-0.14	-0.16	-0.18	-0.18	0.11	0.09	-0.00	-0.01	-0.03
17. Partner R&D intensity	0.75	4.61	-0.04	-0.03	0.07	0.02	0.02	0.03	-0.09	-0.03	0.17	-0.02	-0.04
18. Partner solvency	2.54	3.64	-0.06	-0.02	0.15	0.08	0.07	0.11	-0.03	-0.00	-0.04	0.02	0.12
19. Partner GPE	9.86	4.01	-0.01	0.02	-0.03	-0.01	-0.03	-0.02	0.00	-0.02	0.01	0.04	-0.02
20. Partner patenting experience	10371.72	25982.94	0.54	0.28	-0.43	-0.17	-0.24	-0.28	0.25	0.09	-0.09	-0.09	0.05
21. Partner scientific impact	11.95	16.21	0.05	0.20	0.19	0.22	0.17	0.24	-0.06	0.02	-0.03	0.06	0.25
22. GDPPC	38864.02	8744.27	-0.17	-0.38	0.68	0.27	0.37	0.44	-0.22	0.05	0.08	0.03	-0.10
23. Country patent applications	231035.50	90781.85	0.22	0.44	-0.39	-0.07	-0.21	-0.19	0.34	0.11	-0.12	-0.02	0.00
24. Intellectual property rights	0.00	1.00	-0.14	0.21	0.68	0.33	0.20	0.46	-0.18	-0.05	0.15	0.07	0.20
25. Joint venture	0.17	0.37	0.12	0.06	-0.40	-0.25	-0.39	-0.38	0.22	0.08	-0.10	-0.03	-0.03
26. Vertical scope	-0.07	0.71	-0.08	-0.07	0.08	0.05	0.11	0.08	-0.11	-0.10	0.19	0.02	-0.19
27. Joint partnering experience	2.78	4.97	0.66	0.24	-0.29	-0.12	-0.18	-0.19	0.24	0.21	-0.09	-0.09	0.20
28. Technological overlap	0.55	0.32	0.22	0.12	0.10	0.12	0.14	0.15	-0.01	0.07	0.03	-0.03	0.13
29. Business overlap	0.41	0.40	0.05	-0.13	-0.07	-0.13	-0.05	-0.11	-0.05	-0.15	0.08	0.04	-0.29
30. Patent co-applications	9.87	40.96	0.30	0.20	-0.26	-0.01	-0.04	-0.08	0.12	0.03	-0.04	-0.07	0.03
31. Pre-alliance citations	108.10	415.16	0.67	0.12	-0.22	-0.13	-0.18	-0.18	0.17	0.18	-0.07	-0.08	0.12

	12.	13.	14.	15.	16.	17.	18.	19.	20.	21.	22.	23.	24.	25.	26.	27.	28.	29.	30.
13.	0.56																		
14.	0.21	0.06																	
15.	0.37	0.02	0.25																
16.	0.20	0.06	0.14	0.36															
17.	-0.08	-0.07	-0.02	-0.09	-0.07														
18.	-0.12	0.03	-0.07	-0.27	-0.18	0.06													
19.	-0.01	-0.01	-0.00	0.02	0.05	-0.01	-0.04												
20.	0.48	0.08	0.34	0.48	0.38	-0.06	-0.18	-0.01											
21.	-0.05	0.12	-0.05	-0.16	-0.03	0.07	0.14	-0.01	-0.04										
22.	-0.36	-0.06	-0.12	-0.29	0.00	0.06	0.08	-0.02	-0.31	-0.03									
23.	0.53	0.10	0.14	0.45	0.16	-0.06	-0.15	0.04	0.45	-0.17	-0.09								
24.	-0.31	-0.02	-0.10	-0.33	-0.09	0.08	0.17	-0.02	-0.28	0.28	0.30	-0.41							
25.	0.30	0.03	0.12	0.30	0.16	-0.03	-0.11	0.06	0.24	-0.10	-0.36	0.22	-0.25						
26.	-0.15	-0.17	-0.06	-0.10	-0.08	0.11	-0.01	0.05	-0.11	-0.09	0.18	0.01	0.02	-0.28					
27.	0.54	0.20	0.30	0.35	0.29	-0.05	-0.10	-0.01	0.71	0.03	-0.24	0.32	-0.17	0.20	-0.14				
28.	0.04	0.09	0.07	-0.04	0.04	0.04	0.06	-0.02	0.16	0.15	0.04	0.06	0.03	-0.11	0.07	0.27			
29.	-0.10	-0.22	0.07	0.08	-0.04	0.05	-0.09	-0.04	0.10	-0.20	0.01	0.02	-0.15	-0.00	0.13	0.09	0.29		
30.	0.29	0.05	0.39	0.25	0.19	-0.03	-0.11	-0.01	0.43	-0.03	-0.21	0.28	-0.20	0.13	0.02	0.36	0.11	0.06	
31.	0.41	0.23	0.37	0.27	0.29	-0.04	-0.11	-0.01	0.60	0.01	-0.14	0.23	-0.14	0.13	-0.11	0.69	0.22	0.11	0.26

N=1,163 dyads, except for variable 5., where N = 762.

Table 3.7: PPML regressions for complementary knowledge acquired by the focal firm from the partner. Comparison of effects in international alliances versus same-country alliances.

Variables	International alliances (treatment group)					Same-country alliances (control group)					Wald tests of difference in coefficients
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)	Model (7)	Model (8)	Model (9)	Model (10)	
Firm availability of R&D funding	0.316***					-1.174***					χ^2 = 45.87 (intl. > dom.)
	(0.089)					(0.241)					($p < 0.001$)
Partner availability of R&D funding	0.182					(omitted)					χ^2 = 37.63 (dom. < intl.)
	(0.137)										($p < 0.001$)
Firm availability of R&D personnel		0.230*					-0.772***				χ^2 = 25.12 (intl. > dom.)
		(0.090)					(0.172)				($p < 0.001$)
Partner availability of R&D personnel		0.028					(omitted)				χ^2 = 18.18 (dom. < intl.)
		(0.151)									($p < 0.001$)
Firm public technology purchasing			0.210					-0.327*			χ^2 = 8.97 (dom. < intl.)
			(0.128)					(0.145)			($p = 0.003$)
Partner public technology purchasing			0.441***					(omitted)			χ^2 = 19.04 (intl. > dom.)
			(0.132)								($p < 0.001$)
Firm public-private R&D collaboration				0.081					-0.701*		χ^2 = 9.18 (dom. < intl.)
				(0.106)					(0.328)		($p = 0.003$)
Partner public-private R&D collaboration				0.393**					(omitted)		χ^2 = 17.04 (intl. > dom.)
				(0.145)							($p < 0.001$)
Firm innovation-policy index					0.209*					-0.946***	χ^2 = 33.11 (intl. > dom.)
					(0.107)					(0.143)	($p < 0.001$)
Partner innovation-policy index					0.319*					(omitted)	χ^2 = 39.65 (intl. > dom.)
					(0.146)						($p < 0.001$)
Control variables	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	
Year and industry fixed effects	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	
Constant	2.954***	2.950***	2.626***	2.377***	2.797***	3.198***	3.483***	3.424***	3.090***	3.513***	
	(0.187)	(0.134)	(0.103)	(0.311)	(0.145)	(0.167)	(0.213)	(0.173)	(0.362)	(0.145)	
Observations	2,023	2,023	2,023	1,463	2,023	1,163	1,163	1,163	762	1,163	
Log pseudo-likelihood	-51254	-51742	-50160	-26970	-51142	-44682	-44619	-46504	-24754	-44889	

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

4. CHAPTER THREE:

KNOWLEDGE SPILLOVER AND KNOWLEDGE "SPILLBACK" IN ALLIANCES

ABSTRACT

Research on alliances suggests that exposing knowledge to partners diminishes firms' value appropriation in alliances. This study examines the possibility that knowledge spillover to partners instead provides opportunities for firms to learn from partners' use of the spilled knowledge, thereby enabling firms to regain value that would otherwise be lost. This is termed knowledge "spillback." Analyses of 1,089 alliances formed in technology-intensive industries between 2000 and 2015 show that knowledge spillover to a partner induces subsequent knowledge spillback, yet knowledge spillback diminishes as knowledge spillover intensifies. Knowledge spillovers encourage knowledge spillback especially if partners combine firms' spilled knowledge in novel and non-redundant ways. Moreover, knowledge spillback from partners increases the technological value of the firm's inventions, and thus can contribute to the firm's value gain from its alliances.

4.1. INTRODUCTION

Interfirm alliances enable firms to improve their inventions by absorbing knowledge from partners (Ahuja, 2000; Gomes-Casseres, Hagedoorn, & Jaffe, 2006; Mowery, Oxley, & Silverman, 1996). While firms that enter alliances often seek to facilitate knowledge inflows from their partners, outbound knowledge spillovers to partners are typically considered to be undesirable (Kale, Singh, & Perlmutter, 2000; Khanna, Gulati, & Nohria, 1998). Indeed, it is conventionally assumed that exposing knowledge to partners restricts firms' prospects for appropriating the gains of their knowledge (e.g., Hamel, 1991; Lavie, 2006). Accordingly, firms face disincentives to continue developing knowledge that was exposed to partners, and they may consider prior investments into the spilled knowledge a sunk cost (Teece, 1986). In turn, they would rather invest in developing other knowledge that has not spilled over to a partner. This claim is widely adopted in the literature on learning and protecting knowledge in alliances (e.g., Diestre & Rajagopalan, 2012; Hamel, 1991; Khanna et al., 1998; Lavie, 2006; 2007; Oxley & Wada, 2009).

Another possibility, however, is that spilling knowledge to an alliance partner could actually benefit the firm, if the firm could learn from the partner's inventions that build upon the firm's spilled knowledge. This can be referred to as knowledge "spillback." [1] Recognizing this possibility implies that by considering knowledge spilled to a partner a sunk cost, many firms constrain their potential for generating value from their alliances. If instead, these firms could learn from a partner's recombinations of their spilled knowledge, they might regain some value which otherwise

[1] Related phenomena wherein a firm absorbs external knowledge whose roots are internal to the firm have been studied in the cumulative innovation literature (Alnuaimi & George, 2016; Belenzon, 2012; Yang, Phelps, & Steensma, 2010). Alliances present a distinct context in that alliances are not intended to facilitate firms' appropriation of their partners' knowledge outside of the alliance, and thus are unlikely to be designed with a knowledge "spillback" rationale in mind. Another related context is employee mobility, whereby an employee may disclose a previous employer's knowledge to a new employer. In turn, the previous employer may leverage its employees' social ties to enable knowledge inflows from the new employer (Corredoira & Rosenkopf, 2010). A crucial difference in alliances is that the firm can be more proactive in absorbing the partner's knowledge. By contrast, the firm cannot influence its employees' social ties.

would have been considered lost. This suggests that protecting knowledge from spilling to partners is not only a costly activity (Inkpen, Minbaeva, & Tsang, 2019), but may, under certain conditions, impose opportunity costs for the firm, precluding valuable knowledge development opportunities. Indeed, while prior research implies that firms may refrain from forming alliances in fear of knowledge spillovers (e.g., Balachandran & Hernandez, 2019; Li, Eden, Hitt, & Ireland, 2008), this study suggests that such concerns may be unfounded in light of knowledge spillback.

Against this backdrop, the current study asks: how can outbound knowledge spillover from a firm to an alliance partner enable the firm to learn from the partner's inventions that are based on the firm's spilled knowledge? And, by extension: what conditions may increase inbound knowledge spillback from the partner to the firm relative to the extent of outbound knowledge spillover from the firm to the partner? Answering these questions can provide insights into how firms should balance protecting knowledge from partners with exploring opportunities for absorbing spillback of knowledge that has spilled over to these partners.

Extending research on learning in alliances, I first explain why firms in alliances would attempt to internalize recombinations of their own knowledge that has spilled to a partner. To this purpose, I focus on the firm's *awareness*, *motivation*, and *ability* to learn from the partner. My theory suggests that a firm's familiarity with its own spilled knowledge that is adopted by the partner would increase the firm's *awareness* of the partner's recombinations of that knowledge and its *ability* to absorb these inventions. Moreover, the complementary value of those recombinations may *motivate* the firm to learn from the partner's inventions. However, beyond a certain threshold of knowledge spillover, absorbing the partner's recombinations becomes more challenging to the firm, as the firm can attend only to a limited number of recombinations at a time, and because the partner may cease cooperating once it has absorbed extensive knowledge spillover from the firm. Thus, I predict that inbound knowledge spillback to the firm from its partner increases at a diminishing rate with preceding outbound knowledge spillover from the firm to its partner.

Next, I study contingencies that explain why firms benefit to varying degrees from knowledge spillovers to partners. To this end, I identify conditions that increase or decrease knowledge spillback relative to the extent of preceding knowledge spillover, thereby strengthening or weakening the positive, linear portion of the association between spillback and spillover. I focus on three distinct dimensions of knowledge relatedness common to the search and recombination literature (see Savino, Petruzzelli, & Albino, 2017, for a review) that collectively shape the firm's awareness, motivation, and ability to absorb the partner's recombinations: the relatedness of the firm's current knowledge with prior knowledge of (a) the partner, (b) the firm itself, and (c) the firm's industry peers. I predict that greater knowledge base relatedness of the firm and its partner reinforces the positive association between knowledge spillback and spillover at low levels of knowledge base relatedness. In turn, greater knowledge base relatedness weakens that association at high levels of knowledge base relatedness. I also expect the positive association between knowledge spillback and spillover to be reinforced by the cumulativeness of the firm's knowledge, and to be weakened by the firm's reliance on prior knowledge of its industry peers.

I test my theory with a sample of alliances formed during 2000–2015 by 323 technology-intensive firms in the global electronics and machinery industries, relying on patent citation data as proxies for broader knowledge flows of firms and their partners. I observe that knowledge spillback increases not only at a diminishing rate with preceding knowledge spillover, but, counter expectations, begins to decrease at very high levels of spillover. My analyses of contingencies further reveal that knowledge spillovers encourage the firm's continued development of its spilled knowledge especially if partners combine the spilled knowledge in ways that appear novel and non-redundant to the firm. Finally, in post-hoc analyses, I compare the dynamics of knowledge spillback and spillover for allied firms against a sample of non-allied firms, showing how knowledge spillovers to alliance partners benefit the firm in ways distinct from spillovers to non-partners. I also show that knowledge spillback from partners increases the technological value of the firm's inventions, suggesting that spillback not only limits value loss from knowledge spillovers, but may contribute to the firm's value gain from its alliances.

This study shows how outbound knowledge spillovers to alliance partners can benefit the firm as it learns from its partners' recombinations of the spilled knowledge. In particular, the study shifts focus from the benefits of intentional knowledge disclosure (Arora, Belenzon, & Patacconi, 2021), to suggest that even if a partner internalizes the firm's knowledge opportunistically, the firm can still benefit from that knowledge by absorbing knowledge spillback. These important insights can help executives decide how to balance protecting knowledge from spilling to partners with exploring opportunities for absorbing spillback of knowledge that has spilled over to these partners.

4.2. THEORY AND HYPOTHESES

Knowledge spillover refers to the case in which a firm (recipient) internalizes some proprietary knowledge originating from another firm (source) and absorbs it by using the knowledge in its inventions (e.g., Griliches, 1992; Jaffe, 1986). Whereas absorbing the source's knowledge requires some deliberate effort by the recipient, from the source firm's perspective, the knowledge spillover can either be involuntary or voluntary.[2] Traditionally, scholars have focused on the positive effects of knowledge spillovers for recipient firms (e.g., Cohen & Levinthal, 1990; Griliches, 1992) while underscoring its negative implications for the source firm (e.g., Jaffe, 1986; Kogut & Zander, 1992). Recent research, however, suggests that under certain conditions, knowledge spillover can benefit the source firm. Some of these studies argue that knowledge

[2] Involuntary knowledge spillover occurs when proprietary knowledge leaks from the source to the recipient in a way that was not intended by the source. Voluntary knowledge spillover occurs when the source proactively "teaches" the recipient some of its knowledge, e.g., via licensing a technology.

spillover can initiate reciprocation, whereby recipients behave more collaboratively or provide the source with access to their own resources (Alexy, George, & Salter, 2013; Arora et al., 2021).

Another claim in the literature on cumulative innovation is that firms can benefit from external recombinations of their own inventions (Alnuaimi & George, 2016; Belenzon, 2012; Yang et al., 2010). Accordingly, knowledge spillback refers to the case in which a source firm internalizes inventions of a particular recipient firm, which had previously internalized related knowledge elements from the source and recombined them in its own inventions. In this case, the source firm makes a deliberate effort to absorb the recipient's inventions, which the recipient involuntarily or voluntarily discloses to the source. Although some initial knowledge spillover is necessary for enabling subsequent knowledge spillback, it is unlikely to be a sufficient condition. Rather, the extent to which knowledge spillover induces spillback would probably depend on the source firm's awareness of the recipient's recombinations of the spilled knowledge, and on the source's motivation and ability to learn from these recombinations.

However, it is doubtful to what extent these conditions apply to the alliance context. Given the extraordinary breadth and multiplicity of channels for knowledge flows that are available in many alliance relationships, firms often wish to limit knowledge spillovers to alliance partners, for fear that these partners would exploit that knowledge for private gains (Devarakonda & Reuer, 2018). Indeed, alliances have various objectives and, due to their quasi-formal nature, often suffer from the incompleteness of contracts. Therefore, alliances frequently encounter misalignment of the partners' objectives with respect to value appropriation (Lavie, 2006; Panico, 2017), whereby the firm and its partner may engage in learning races and opportunistically appropriate each other's knowledge (Hamel, 1991; Khanna et al., 1998). Hence, the alliance literature has devoted much attention to knowledge spillover and its prevention without considering the possibility of knowledge spillback. This research has found that an alliance can restrict the firm's appropriation of value from its proprietary knowledge, leading to discontinued investments in developing knowledge that has been exposed to partners. This suggests that the source firm may invest more in protecting proprietary knowledge than in exploring knowledge spillback opportunities. Even once a knowledge spillover has occurred, the source firm would seek opportunities to internalize the partner's original knowledge, instead of attempting to absorb knowledge spillback.[3]

Another strand of research, namely the relational view (Dyer & Singh, 1998), has considered the possibility that a firm may voluntarily share some of its knowledge with its alliance partner. Such research acknowledges that the transfer of knowledge may help align the parties' knowledge bases, which is necessary for realizing synergies, and may motivate an otherwise unwilling partner to collaborate (Arora et al., 2021; Phene & Tallman, 2014). Yet even if the firm discovers that the partner has absorbed its disclosed knowledge elements, it may pay less attention to the partner's inventions because such voluntarily shared knowledge would not be central to the firm's own inventions and therefore less valuable (Norman, 2002). Thus, whereas the alliance literature has identified scenarios in which the firm spills knowledge to a partner, these studies do not explain why the firm would proceed to absorb the partner's recombinations of the firm's spilled knowledge.

In the following, I introduce an alternative narrative that could explain why firms in alliances may indeed attempt to absorb spillback of their knowledge that has spilled over to a partner.

4.2.1. Knowledge spillover and knowledge spillback in alliances

Consider the case where a firm spills some of its knowledge to a partner in the course of their alliance: The firm is likely to continuously monitor the partner's use of that knowledge to prevent

[3] The economic rationale for this claim is that the expected returns from an invention diminish once the firm's ability to capitalize on it is constrained. The firm can only accrue rents before imitators enter its technology domain and the market reaches equilibrium (Arrow, 1962; Schumpeter, 1934). Once imitation occurs, the prospects for appropriating the gains of the invention diminish, reducing the firm's incentives to continue to develop its invention (Teece, 1986). In alliances, this tendency is ascribed to a lessened motivation of the firm to invest in developing knowledge that has been exposed to frequent spillover and imitation by partners (Zeng & Hennart, 2002).

misuse of its knowledge and restrict its appropriation by the partner beyond the scope of the alliance agreement (Devarakonda & Reuer, 2018).[4] As a consequence, the source firm is likely to be aware of the recipient partner's use of its spilled knowledge beyond the scope of their alliance.

Given that the knowledge development routines and complementary knowledge available to the partner differ from those available to the firm, the partner's use and development of the spilled knowledge is likely to differ from that of the firm. The partner would not be bound by the firm's constraints and path dependencies (Leonard-Barton, 1992; Tripsas & Gavetti, 2000), and thus can be more flexible in recombining the spilled knowledge. Hence, the partner may develop inventions based on the knowledge absorbed from the firm, which can be complementary to those developed by the firm using the same knowledge. This would make the partner's recombinations valuable to the firm, especially as the firm already possesses the complementary assets needed to leverage the recombined knowledge in its established customer markets. Therefore, the source firm is likely to be motivated to absorb the partner's recombinations that are based on the firm's spilled knowledge.

Eventually, when the firm has identified new knowledge combinations that the partner has generated based on the firm's spilled knowledge, and to the extent that such follow-up inventions are valuable as they entail a skillset distinct from that of the firm, the firm may attempt to learn the partner's recombinations of the spilled knowledge by observing and imitating the partner's use of that knowledge (Yang et al., 2010). Indeed, the source firm's intimate familiarity with the specific knowledge elements adopted by the recipient partner would enable it to efficiently and effectively absorb the partner's recombinations and to deploy them in its own subsequent inventions (Fleming, 2001; Ter Wal, Criscuolo, & Salter, 2017). While the superior access and frequent and meaningful

[4] If the spillover was intentional, the purpose of this monitoring may be to provide the partner with further guidance or to track its progress toward the alliance's objectives. If the knowledge spillover was unintentional, the purpose of monitoring may be to ensure that the partner does not violate the knowledge's terms of use per the alliance agreement.

interactions between the firm and the partner in their alliance support knowledge spillover from the firm to the partner (Mowery et al., 1996), once the firm's knowledge has spilled over to the partner, the alliance ceases to be necessary for knowledge spillback, given that the firm is already familiar with the relevant knowledge that has served as the basis for the partner's recombinations.

Overall, given the firm's awareness of the partner's recombinations and its motivation and ability to internalize them, greater knowledge spillover from the firm to the partner during their alliance suggests an increased absorption of knowledge spillback by the firm from that partner.

This baseline prediction speaks to the existence of knowledge spillback in alliances. Should firms indeed experience knowledge spillback from partners, it may not be surprising that the extent of knowledge spillback would increase with the extent of knowledge spillover, as some knowledge spillover is necessary for enabling knowledge spillback, and a greater risk set of spillovers is likely to increase the probability of spillback. However, as argued next, the firm's absorption of knowledge spillback from its partner may not increase linearly with the amount of preceding knowledge spillover to the partner. Rather, it is expected that with increasing knowledge spillover, the firm's absorption of the partner's recombinations diminishes.

In fact, the greater the amount of knowledge that spills to the partner, the more the firm needs to divide its limited attention (Ocasio, 1997) between tracing and internalizing an increasing number of the partner's knowledge recombinations. This suggests that with increasing spillover, the firm would focus on absorbing those knowledge recombinations it deems more valuable and that are more relevant to the firm's knowledge development objectives. However, the firm would increasingly forgo spillback opportunities for knowledge recombinations that appear less relevant. As the firm begins to accomplish its current knowledge development goals, further spillover to the partner may serve the firm to a lesser extent, as, to achieve its next goals, the firm may require different kinds of complementary knowledge than that held by the partner. Indeed, the firm may seek to form new alliances with different partners as it attends to its next learning goals. In turn, the firm's attention to the current partner's recombinations would diminish further (Uzzi, 1997).

Finally, if the partner has absorbed knowledge spillover sufficiently extensive to conclude that it cannot learn further from the firm, this partner may cease cooperating with the firm (Khanna et al., 1998). At that point, the partner may discontinue the alliance and/or invest more in knowledge protection to fend off attempts by the firm to access the partner's recombinations. Hence, accessing the partner's knowledge would become more difficult for the firm, which restricts the firm's absorption of knowledge spillback. Once this point is reached, the firm's absorption of knowledge spillback would be unlikely to further increase with preceding knowledge spillover.

In sum, as outbound knowledge spillover from the source firm to the recipient partner increases, so does the firm's awareness of inbound knowledge spillback from the partner and motivation and ability to absorb it. With increasing knowledge spillover, however, the firm's absorption of knowledge spillback is likely to taper off. Overall, this suggests that the extent of knowledge spillback increases at a diminishing rate with the extent of preceding knowledge spillover. Thus, knowledge spillback from a partner exhibits an r-shaped (half inverted U-shape within the data range) association with the extent of knowledge spillover to that partner.

Hypothesis 1: *The extent of inbound knowledge spillback to the firm from its partner increases at a diminishing rate with the extent of preceding outbound knowledge spillover from the firm to its partner in the course of their alliance.*

Firms in alliances are likely to vary with respect to the rate at which spilling knowledge to partners generates knowledge spillback. The greater this rate, the more the firm would benefit from exploring spillback opportunities instead of investing in knowledge protection. As argued next, that rate is contingent on the extent to which the partner can recombine the firm's knowledge to develop inventions that appear valuable and worthwhile learning to the firm. This in turn may depend on how related the firm's knowledge is with prior knowledge of (a) the partner, (b) the firm itself, and (c) the firm's industry peers. These dimensions of knowledge relatedness are commonly studied in the search and recombination literature (e.g., Belenzon, 2012; Rosenkopf & Nerkar, 2001; Savino et al., 2017), and they may influence the firm's *awareness* of the partner's recombinations, and its *motivation* and *ability* to absorb them. At the same time, they can influence the partner's *motivation* and *ability* to absorb the firm's knowledge spillover. By increasing or decreasing the extent of knowledge spillback relative to that of spillover, these conditions can strengthen or weaken the positive, linear portion of the association between spillback and spillover. Thus, they may influence the rate by which spilled knowledge induces knowledge spillback.

4.2.2. The relatedness of the knowledge bases of the firm and its partner

If the knowledge bases of the firm and its partner are related, the partner is likely to be familiar with the content and utility of the firm's knowledge. Therefore, the partner would enjoy an enhanced relative absorptive capacity (Lane & Lubatkin, 1998), which enables it to assess, understand, and apply the firm's spilled knowledge in its own inventions. In consequence, as the relatedness between the parties' knowledge bases increases, it would become easier for the partner to absorb the firm's knowledge spillovers (Mowery et al., 1996). With increasing knowledge base relatedness, the firm's knowledge would also become more relevant to the partner. In turn, the partner may face greater incentives to apply the firm's spilled knowledge independently for a private benefit without requiring the firm's advice and guidance (Diestre & Rajagopalan, 2012; Oxley & Sampson, 2004). For these reasons, it is unlikely that knowledge spillover from the firm to the partner would decrease with increasing knowledge base relatedness.

To the extent that the partner has absorbed the firm's knowledge spillover, greater knowledge base relatedness can make it easier for the firm to become aware of the partner's recombinations of the firm's spilled knowledge, given the firm's familiarity with developments in related knowledge domains. Moreover, as the knowledge base relatedness between the firm and its partner increases, the partner's recombinations of the spilled knowledge would become more relevant to the firm's parallel development efforts (Yang et al., 2010). As a consequence, the firm is likely to face an increased motivation to absorb the partner's knowledge recombinations. In fact, the firm's motivation to absorb knowledge spillback would probably be greater than the partner's motivation to absorb the firm's knowledge spillover, because the firm faces fewer uncertainties about the usefulness of its own recombined knowledge than the partner faces about the usefulness of the firm's spilled knowledge, and because, unlike the partner, the firm may already own the complementary assets necessary for leveraging this knowledge in its established customer markets.

However, as the knowledge base relatedness between the firm and the partner exceeds a certain threshold, the firm and the partner tend to face increasingly similar constraints in the development trajectory of the spilled knowledge (Dosi, 1982). As a consequence, the partner's knowledge recombinations would appear less novel to the firm (Nooteboom, Van Haverbeke, Duysters, Gilsing, & van den Oord, 2007) and increasingly resemble the firm's own recombinations. Therefore, if knowledge base relatedness approaches higher levels, the firm may consider the partner's recombinations of its spilled knowledge redundant, because the firm could have developed similar recombinations using its own related knowledge. Fearing that the partner's recombinations would compete against or substitute for the firm's own recombinations and thus diminish the firm's prospects for capitalizing on them, the firm would rather focus on developing knowledge that has not been exposed to the partner (Teece, 1986), or attempt to internalize the partner's original knowledge, rather than internalize recombinations of the spilled knowledge. It is thus expected that the firm's motivation to absorb the partner's recombinations would increase at lower levels of knowledge base relatedness and decrease at higher levels of that relatedness.

While the firm's awareness of the partner's recombinations would continue to increase with knowledge base relatedness, this greater awareness would induce the firm to increasingly notice certain redundancies between the firm's and the partner's recombinations, and thus contribute to the firm's decreasing motivation to absorb knowledge spillback from the partner.

Finally, the marginal improvement of the firm's ability to absorb the partner's recombinations of its spilled knowledge elements due to greater knowledge base relatedness would not be greater than the marginal improvement of the partner's ability to absorb the firm's initial knowledge spillover due to the same relatedness: At any level of knowledge base relatedness, the firm probably enjoys a certain understanding of inventions whose roots are internal to the firm, so an incremental increase in overall relatedness would facilitate the firm's absorption of spillback to a lesser extent than it would facilitate the partner's absorption of spillover. Thus, the firm's greater ability to absorb knowledge spillback would be unlikely to increase the spillback-to-spillover ratio.

Overall, these arguments suggest an increase in the extent of knowledge spillback relative to the extent of knowledge spillover at lower levels of knowledge base relatedness, and a decrease in the extent of knowledge spillback relative to the extent of knowledge spillover at higher levels of that relatedness. Hence, with increasing knowledge base relatedness between the firm and the partner, the positive association between knowledge spillback and knowledge spillover would be reinforced at low levels of relatedness and attenuated at high levels of knowledge base relatedness.

Hypothesis 2: *The positive association between inbound knowledge spillback to the firm from its partner and the extent of preceding outbound knowledge spillover from the firm to its partner in the course of their alliance increases at low levels of the relatedness of the firm's and the partner's knowledge bases and decreases at high levels of that relatedness.*

4.2.3. The cumulativeness of the firm's knowledge

The cumulativeness of a firm's knowledge refers to the extent to which a firm's current knowledge builds on its own prior knowledge (Breschi, Cassi, & Malerba, 2009; Hall, Jaffe, & Trajtenberg, 2001). Cumulative knowledge relies to a greater extent on knowledge which is idiosyncratic to the firm. Hence, if the partner seeks to internalize part of the firm's cumulative knowledge, the partner may also need to understand the other related knowledge of the firm. This limits the partner's ability to understand the firm's knowledge and makes it more challenging to absorb the firm's knowledge spillovers (Kok, Faems, & de Faria, 2020). Moreover, if the firm's knowledge development is highly cumulative, this may indicate that the firm's knowledge is specific to some particular applications. Thus, the partner faces fewer incentives to absorb the firm's knowledge spillovers, given that this knowledge may be less useful in other applications (Diestre & Rajagopalan, 2012). Therefore, it is unlikely that knowledge spillover from the firm to the partner would increase with the firm's knowledge cumulativeness.

If, nevertheless, the partner absorbs some knowledge spillover from a firm whose knowledge substantially relies on knowledge that it has developed in-house, the firm should find it straightforward to discern the partner's recombinations of its spilled knowledge from the partner's recombinations of other knowledge. Doing so enhances the firm's awareness of the partner's recombinations of its spilled knowledge. Such recombinations are likely to differ from those of the firm, as the partner's knowledge development is less bound by the same firm-specific path dependencies and rigidities that characterize the firm's cumulative knowledge development process (Tripsas & Gavetti, 2000). Yet, to the extent that the partner's recombinations are still cumulative, they would probably remain relevant to the firm and could be complementary to the firm's own recombinations. Hence, absorbing knowledge spillback from the partner may enable the firm to overcome certain rigidities in its internal knowledge development process, thus reinforcing its motivation to absorb the partner's knowledge recombinations.

As the firm is familiar with, and hence has an understanding of, its own knowledge elements, the firm would probably still find it straightforward to absorb the partner's recombinations of those elements, even if they diverge in parts from the firm's current knowledge development trajectory.

Consequently, the amount of knowledge spillback that the firm absorbs from its partner is expected to increase vis-à-vis the amount of knowledge spillover that the partner absorbs from the firm. This suggests a stronger positive association between the amount of knowledge spillback and preceding knowledge spillover as the firm's knowledge becomes more cumulative.

Hypothesis 3: *The positive association between inbound knowledge spillback to the firm from its partner and the extent of preceding outbound knowledge spillover from the firm to its partner in the course of their alliance increases with the extent to which the firm's knowledge is cumulative.*

4.2.4. The firm's reliance on prior industry knowledge

If the firm's current knowledge relies to a substantial extent on prior knowledge from other firms operating in its industry (as opposed to the firm's own prior knowledge, or that of other firms operating in unrelated industries), the firm's knowledge development is likely to be aligned with its industry's knowledge development trajectory (e.g., Henderson & Clark, 1990; Tushman & Anderson, 1986). This can facilitate the partner's understanding and application of the firm's knowledge, while the firm may be less protective of its knowledge, which is considered less proprietary or novel (Lanjouw & Schankerman, 2001). The result would be an increased ability of the partner to absorb the firm's knowledge spillovers. Moreover, the firm's reliance on prior industry knowledge can reduce uncertainties about the usefulness and recombinant potential of the firm's knowledge (Fleming, 2001), given that related knowledge has been tried in use by other firms operating in the industry. This may motivate the partner to absorb the firm's knowledge spillovers. For these reasons, knowledge spillover from the firm to the partner is unlikely to decrease with the extent to which the firm's extant knowledge relies on prior industry knowledge.

When the partner has absorbed knowledge spillover from the firm, it is likely that many of the partner's recombinations of the firm's spilled knowledge would remain aligned with the development trajectory of that industry knowledge, considering that prior knowledge guides and confines the development of new knowledge (Cohen & Levinthal, 1990; Utterback, 1994). Thus, it may be less obvious to the firm whether the partner has relied on the firm's spilled knowledge, or rather combined related knowledge from other firms in the firm's industry. This may diminish the firm's awareness of the partner's recombinations. Moreover, a firm whose knowledge relies substantially on prior industry knowledge may depend to a lesser extent on the partner for related combinations, given that other firms in its industry engage in combinations of similar knowledge. Hence, a partner's recombinations of such knowledge would probably appear less distinctive and novel to the firm. As a consequence, the firm may consider a partner's recombinations of its spilled knowledge less valuable, reducing its motivation to absorb knowledge spillback from the partner.

The firm's ability to absorb the partner's recombinations is unlikely to be affected by the firm's reliance on prior industry knowledge, considering that the firm would probably enjoy a certain understanding of any knowledge that recombines its own knowledge elements, irrespective of the extent to which the firm has drawn on prior knowledge available in its industry.

In sum, these arguments suggest a decrease of the extent of knowledge spillback relative to that of knowledge spillover. The consequence is an attenuation in the positive association between the amount of preceding knowledge spillover to the partner and subsequent knowledge spillback to the firm as the firm's knowledge becomes more reliant on prior knowledge from its industry.

Hypothesis 4: *The positive association between inbound knowledge spillback to the firm from its partner and the extent of preceding outbound knowledge spillover from the firm to its partner in the course of their alliance decreases with the firm's reliance on prior industry knowledge.*

4.3. METHODS

The theory is tested with a sample of dyadic alliances formed during the period 2000–2015. Unlike multiparty consortia, dyadic alliances often feature competitive learning dynamics rather than an "open innovation" rationale (Yang, Zheng, & Zaheer, 2015). Hence, they are unlikely to be formed with the explicit purpose to facilitate knowledge spillback. The sample includes both domestic and international alliances formed by listed firms from 23 countries that are active in sectors of the global machinery and electronics industries. Firms in these industries exhibit comparable patterns of innovation, with similar patenting and citing behaviors (Belenzon, 2012; Hall et al., 2001). Moreover, in those industries, firms frequently rely on partners to absorb knowledge spillovers (Dussauge, Garrette, & Mitchell, 2000; Duysters, Lavie, Sabidussi, & Stettner, 2020). I focus on sectors with at least 50 listed firms globally in which at least 50 percent of listed firms had been issued patents (SICs 354, 355, 357, 365, 366, 367, 372, 381, 382, 384, 873). I required that each sampled firm had applied for a minimum of four patents per year on average during the study's timeframe with the USPTO (Duysters et al., 2020). Firms and alliances were selected via the SDC Platinum database, with patent data gathered via the Orbis Intellectual Property database. I collected firm data from Compustat, LexisNexis Corporate Affiliations, Orbis, and Zephyr, and retrieved country data from the CEPII, the Hofstede Institute, and the World Bank.

The sample comprises a set of 1,089 alliances formed between 552 firms. These include 323 firms operating in one of the eleven focal industries and 229 partners active in various industries. In 450 alliances, both parties operate in the focal industries. These alliances were sampled twice, generating two dyads with alternating "firm" and "partner" roles (Gomes-Casseres et al., 2006). The resulting 1,539 dyads serve as the unit of analysis. The sampled alliances encompass various value-chain activities: licensing, manufacturing, marketing, OEM, R&D, and supply.[5] As firms typically do not report alliance termination dates, I follow the convention in the literature and

[5] Research has shown that various alliance types can facilitate knowledge spillovers (e.g., Gomes-Casseres et al., 2006; Mowery et al., 1996). Moreover, the scope of an alliance is often greater than what the alliance agreement explicates as the purpose for collaboration (e.g., Alcacer & Oxley, 2014; Balachandran & Hernandez, 2019). Accordingly, I sampled alliances with all activity types. In ancillary analyses, I obtain consistent findings when excluding alliances that focus on sales and marketing activities and thus are less likely to involve a technology component.

impute a five-year alliance duration starting from the announcement date (e.g., Duysters et al., 2020; Zaheer & Hernandez, 2011). I rely on patent citation data to model flows of proprietary knowledge between the parties in an alliance (e.g., Devarakonda & Reuer, 2018; Gomes-Casseres et al., 2006; Kok et al., 2020; Mowery et al., 1996). Despite certain limitations, survey evidence suggests that patent citations can track inter-firm knowledge flows quite reliably (Corsino, Mariani, & Torisi, 2019; Duguet & MacGarvie, 2005; Jaffe, Trajtenberg, & Fogarty, 2000). Although patents are publicly available, patent citations can proxy for a broad range of knowledge flows, even if these flows are non-public or unintended (Corsino et al., 2019). Indeed, whereas forward citations are generally associated with more valuable patents (Hall, Jaffe, & Trajtenberg, 2005), citations by alliance partners can indicate spillovers the firm seeks to avoid, given that an alliance can furnish detailed insights into the underlying knowledge and thereby enable the partner to exploit the firm's knowledge for private gains (Devarakonda & Reuer, 2018).

Because differences in citation requirements across patent offices may confound measurements of the association between knowledge spillback and spillover, I rely on USPTO patents.[6] I use patent applications, assuming that the date of first filing (priority date) represents the date of invention (Jaffe & de Rassenfosse, 2017). Since the same invention can comprise more than one patent document at the USPTO, all patent data was consolidated at the invention level, to avoid double counting patents that refer to the same invention. As firms rely on the knowledge of their subsidiaries (Zaheer & Hernandez, 2011), I consolidate the firms' patent portfolios by considering applications filed by each firm along with those filed by its subsidiaries (Mowery et al., 1996). I account for acquisitions and divestitures of subsidiaries, assuming that a subsidiary's

[6] The USPTO requires applicants to disclose all relevant prior art in a patent application (the "duty of candor"). Hence, US patents are well suited for studying inter-firm knowledge flows (Jaffe & de Rassenfosse, 2017). Moreover, firms rely on US patents to appropriate important inventions even when they are based outside of the US (Ahuja, 2000).

knowledge is accessible to the new parent following its acquisition (Puranam & Srikanth, 2007).[7] The 552 firms and partners have accumulated a total of 3,781,470 USPTO patent applications (including patents of subsidiaries), with filing dates ranging from 1877 to 2020. Out of these, 2,462,663 patents were applied for by the firms, and 1,318,807 by the partners.

4.3.1. Variables

The extent of *knowledge spillback* (dependent variable) to the firm from the partner is captured by a count of backward citations in the firm's patent applications to the partner's patents within seven years following the announcement of their alliance.[8] A backward citation in the firm's patent to the partner patent indicates that the partner's patent contains some knowledge on which the firm's invention builds. Thus, if the firm cites the partner, the firm's inventors would have—explicitly or implicitly—known some information embodied in a partner's patent and utilized it to generate a new combination of their own knowledge with the partner's knowledge. Hence, the firm's backward citations to its partner are a proxy for the extent to which the firm recombines the partner's knowledge in its own inventions (Belenzon, 2012). Because a knowledge spillback occurs only if the firm absorbs knowledge of the partner that has recombined the firm's prior knowledge, the measure only considers backward citations to those partner patents that have cited at least one prior patent of the firm and that were applied for within five years following the alliance announcement. As knowledge diffuses with time, the number of firms that potentially cite a given patent increases exponentially with time (Jaffe & de Rassenfosse, 2017; Jaffe & Trajtenberg, 1999).

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[7] I obtained data on subsidiaries from Orbis and LexisNexis Corporate Affiliations, and data on acquisitions from Zephyr and SDC Platinum. I identified 6,617 acquisitions involving 437 acquirers and 250 divesting firms and their 6,467 target entities. The dataset includes all patent applications of 552 firms and partners and their 23,648 subsidiaries.

[8] Firms and their partners most frequently cite each other within a five-year period following the announcement of their alliance (Gomes-Casseres et al., 2006). Considering the longer time required for the firm to absorb a knowledge spillback from the partner (the partner needs to internalize the firm's knowledge and develop recombinations, which, in turn, the firm must identify and absorb), knowledge spillback is captured within a seven-year period following the alliance announcement. This period exceeds the assumed alliance duration, but, for absorbing knowledge spillback, the alliance does not need to be active anymore. In ancillary analyses, I consider alternative timeframes.

Hence, firms are more likely to cite older partner patents by chance, or for reasons other than knowledge flows occurring in proximal connection with the alliance's activities. To reduce this bias, an annual discount rate r = 10% is applied, weighting each citation by a factor of $(1-r)^t$, with t being the difference in years between the priority date of the citing patent and the priority date of the cited patent. To preclude the possibility that knowledge spillback reflects the firm's recombination of knowledge it had jointly developed with the partner during their alliance, I exclude the parties' patent co-applications when computing the measure.

The extent of *knowledge spillover* (independent variable) from the firm to the partner is captured by a count of backward citations in the partner's patent applications to the firm's patents within five years following their alliance's announcement (Gomes-Casseres et al., 2006). As with the dependent variable, I apply a ten-percent annual discount rate and exclude co-applications.

Knowledge base relatedness (moderator) is captured using Jaffe's (1986) cosine index of the extent to which the firm and the partner patent in similar classes (e.g., Ahuja, 2000; Oxley & Sampson, 2004). The index captures knowledge base relatedness as the angular separation between the vectorized distributions of the firm's and the partner's patent applications across patent classes. The distribution is represented by a vector $F_i = \left(f_i^1 \ldots f_i^k\right)$ for firm i in patent classes 1 to k. The index can be presented as: $S_{ij} = (F_i F_j')/[(F_i F_i')\left(F_j F_j'\right)]^{1/2}$, where F_i' designates the transpose of vector F_i. The resulting measure varies from 0 to 1. A value of 0 indicates no overlap in the parties' knowledge bases, while a value of 1 indicates complete overlap. I 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 during a period starting ten years prior to the formation of the alliance and ending five years after that (Devarakonda & Reuer, 2018).

The firm's *knowledge cumulativeness* (moderator) is captured by the number of the firm's self-citations in patents applied for within five years following the alliance announcement (Hohberger, Kruger, & Almeida, 2020; Rosenkopf & Nerkar, 2001), standardized by the number of the firm's patent applications during that five-year period.

The firm's *reliance on industry knowledge* (moderator) is captured by the number of backward citations in the firm's patents applied for within five years following the alliance's announcement, to patents whose applicants are active in the firm's three-digit SIC industry.[9] The measure is standardized by the number of the firm's patent applications during that five-year period. As the measure captures the firm's reliance on external knowledge, I exclude the firm's self-citations.

4.3.1.1. Control variables

The moderators also serve as control variables. I furthermore control for the partner's knowledge cumulativeness and reliance on industry knowledge. In addition, I control for several characteristics of the firm, the partner, and their dyadic alliance relationship. Firm and partner controls include their age, size, solvency, and R&D intensity. Firms with greater *age* typically accumulate more knowledge upon which partners may draw (Cohen & Levinthal, 1990). *Size*, measured as total assets, indicates the resources available to generate inventions (Hagedoorn & Schakenraad, 1994). *Solvency*, calculated as the natural logarithm of the ratio of cash to long-term total debt (Lavie & Miller, 2008), indicates the financial resources available to sustain search and R&D activities (Nohria & Gulati, 1996). *R&D intensity*, calculated as R&D expenses divided by revenue, measures a firm's investments into knowledge development and relates to its absorptive capacity (Cohen & Levinthal, 1990). The measures of firm size, solvency, and R&D intensity are averaged over a five-year period following the alliance announcement.

[9] 62.4% of the sampled firms were active in two or more four-digit SIC industries that were part of a single three-digit industry. Hence, I capture the industry at the three-digit SIC level. In ancillary analyses I consider different industry definitions.

Moreover, I control for the firms' and partners' *general partnering experience* (GPE), which relates to their alliance-management capabilities that support the absorption of knowledge and help preventing unintended spillovers (Gulati, Lavie, & Singh, 2009). I measure GPE using a decay function over a decade prior to the alliance announcement date: $E_i = \sum_{t=0}^{S} x_t(1-r)^t$, where x_t is the number of alliances announced in year t, t = 0 the year preceding the alliance's formation, and r a decay rate of ten percent (Duysters et al., 2020). Next, *patenting experience* controls for the firm's and partner's accumulated knowledge, indicating each party's overall absorptive capacity (Corredoira & Rosenkopf, 2010). This accounts for the extent to which knowledge spillback is driven by the sizes of the parties' knowledge bases. I measure patenting experience using the number of patent applications in the decade prior to the alliance announcement, assuming a ten percent annual decay rate (Duysters et al., 2020). The firm's and partner's *scientific impact* measures the average forward citations in either party's patent applications during the five years following the alliance's formation, which controls for how commonly the parties' patents are cited because of their quality, value, or foundational influence on subsequent innovations, irrespective of the alliance (e.g., Hall et al., 2005; Harhoff, Narin, Scherer, & Vopel, 1999). *Patent purchasing* controls for the number of patents the firm purchased from the partner (and vice versa) within five years after their alliance's announcement. These patent purchases may constitute an alternate channel for knowledge flows. As employee transfers can serve as another channel for knowledge flows between the parties (Corredoira & Rosenkopf, 2010; Fosfuri & Rønde, 2004), *inventor mobility* controls for the number of inventors that transferred from the firm to the partner (and vice versa) during the five years following their alliance's formation.[10] Next, the firm's *rate of*

[10] A case of mobility from the firm to the partner was identified if an inventor listed in the firm's patent applications is listed in a subsequent patent application of the partner. It was required that an inventor be listed in the firm's patents for the last time after the alliance announcement, and an inventor with an identical name appear listed for the first time on a later patent of the partner that was filed during the alliance (Corredoira & Rosenkopf, 2010).

knowledge integration controls for the firm's tendency to build on others' recombinations of its own knowledge (Yang et al., 2010), irrespective of whether these other parties had formed alliances with the firm. This is measured by the number of the firm's backward citations to third-party patents that have cited the firm's prior patents, standardized by the total number of forward citations received by the firm's patents. The measure is captured during the seven-year spillback interval following the alliance's formation.

Another set of controls accounts for attributes of the alliance relationship between the firm and its partner. I count their previous joint alliances to control for *joint partnering experience*, which can instigate trust and facilitate knowledge sharing while preventing unintended spillover (Gulati et al., 2009). Moreover, I control for *patent co-applications* by counting the patents for which the parties co-applied during the five years following their alliance announcement. Joint patents capture the extent of common benefits derived from the alliance, which may facilitate voluntary knowledge sharing. In addition, I control for *joint venture* governance of the alliance, which may facilitate knowledge flows and mitigate partner opportunism (e.g., Oxley & Sampson, 2004). Because upstream and downstream alliances entail distinct motives for absorbing knowledge spillovers from partners (Lavie & Rosenkopf, 2006), I account for the alliance's *value chain function* using a categorical variable with a value of 1 if the alliance covers upstream activities, -1 if it covers downstream activities, and 0 if it covers both activity types. In addition, a greater *alliance scope* implies that more channels are available to support knowledge flows (Oxley & Sampson, 2004). I thus control for the number of alliance activities, standardized by the number of possible activities listed in SDC (Lavie, 2007). Because the parties' motivation to absorb each other's knowledge can be influenced by their business similarity (Hamel, 1991), I control for the parties' *business overlap* by measuring the overlap in their four-digit primary SIC codes (Yang et al., 2015). If a *technology transfer* was contractually specified in the alliance agreement, the firm may anticipate potential knowledge spillback as an opportunity to "outsource" part of its knowledge development. To account for this possibility, I control for whether the alliance agreement foresees transfer of technology. Because of cross-national barriers to knowledge flows, I control for *cross-national distance* between the firm's and partner's countries, using a composite index of cultural, administrative, geographical, and economic distances (Lavie & Miller, 2008).

Next, I include several control variables that serve as baselines for the extent of knowledge flows between the parties. The firm's *non-spillback partner citations* is a count of the firm's backward citations to the partner's patents within seven years following the alliance announcement, excluding citations that constitute knowledge spillback. This accounts for the extent to which the firm draws from the partner's knowledge besides absorbing knowledge spillback. *Pre-alliance knowledge spillover* controls for the baseline level of knowledge spillover from the firm to the partner, irrespective of their alliance. This is measured by a count of the partner's backward citations to the firm's patents within a ten-year interval preceding the alliance's formation. *Pre-alliance knowledge spillback* establishes the baseline level of knowledge spillback to the firm from the partner. This is captured by counting the firm's backward citations to those partner patents that have cited the firm's prior patents, within a ten-year interval preceding the alliance's formation. Finally, industry, country, and year fixed effects account for unobserved heterogeneity.[11]

4.3.2. Analysis

The hypotheses are tested with a two-stage analysis (Heckman, 1979) in order to account for potential self-selection biases in firms' decision to form alliances with partners from whom they may expect to absorb knowledge spillback. The second-stage model estimates the extent of knowledge spillback absorbed by the firms from their partners. It applies the control function

[11] Firm fixed effects are excluded, as not each firm experiences within-firm variation in knowledge spillback. In ancillary analyses, I included firm fixed effects and obtained consistent findings, despite a loss of observations.

method (Terza, 2017; Wooldridge, 2015) to account for endogeneity in knowledge spillover.

The first-stage probit model estimates the probability of the focal firm to form an alliance with a particular partner. To construct a control group of unformed alliances, I identify up to four "counterfactual" partners operating in the same industry as the actual partner in the year of alliance formation (Robinson & Stuart, 2007). I predict partner selection using a set of variables that predate the alliance's formation. Such variables would influence the firm's partner-selection decision but are exogenous to the alliance's post-formation dynamics (Arend & Amit, 2005). The measures include the firm's and partners' size, age, R&D intensity, solvency, GPE, and patenting experience in the year of alliance formation. At the dyad level, I include the degree of knowledge base relatedness prior to alliance formation, joint partnering experience, and cross-national distance. In addition, I control for pre-alliance knowledge spillover and spillback. Finally, I include year, industry, and country fixed effects. The variable *partner relative size* serves as exclusion restriction. It compares the partner's total assets with those of the four counterfactual partners. The larger a prospective partner is vis-à-vis potential alternatives, the more visible it is to the firm. Greater visibility increases the chance that the firm forms an alliance with that partner, without affecting the firm's absorption of knowledge spillback once the alliance is formed. This reasoning is supported by the variable's insignificant coefficient when included in the second-stage model.

The second-stage model tests the hypotheses, relying on the Poisson pseudo-maximum likelihood (PPML) estimator.[12] As many variables that affect knowledge spillover also influence knowledge spillback, knowledge spillback is likely to correlate with numerous unobservables that

[12] Unlike other count data estimators, PPML does not require an integer dependent variable (Correia, Guimarães, & Zylkin, 2020; Santos Silva & Tenreyro, 2006). Simulation evidence also shows that PPML is consistent in the presence of overdispersion (Blackburn, 2015; Santos Silva & Tenreyro, 2006) and zero-inflation (Santos Silva, Tenreyro, & Windmeijer, 2015). To compare the validity of PPML against alternate estimators (e.g., negative binomial or zero-inflated models), I applied the HPC test procedure (Santos Silva et al., 2015), which indicated a preference for PPML.

also correlate with knowledge spillover. This implies that the exogeneity assumption is likely to be violated. Whereas methods such as two-stage least squares or the generalized method of moments (GMM) are conventionally applied to correct for endogeneity in regressors, these methods are difficult to implement reliably for nonlinear models that include quadratic and moderated effects of the endogenous variable (Rutz & Watson, 2019). An additional challenge is that the endogenous variable, knowledge spillover, has a distribution similar to that of the dependent variable, and thus requires estimating a nonlinear first stage. Fortunately, the control function method is well suited for such contexts (Rutz & Watson, 2019; Wooldridge, 2015) and generalizes to nonlinear first-stage models (Terza, 2017).[13] I apply this correction following the procedure outlined by Terza (2017). Because the control function method relies on instrumental variables, I identify the following measures as exogenous predictors of knowledge spillover:

The extent of *industry inter-partner knowledge flows* accounts for the extent to which alliances in the firm's three-digit SIC industry facilitate knowledge flows, which relates to the probability that the firm spills knowledge to its partner in the course of their alliance. This is captured by the average cross-citation rate (Mowery et al., 1996) in alliances formed by the firm's industry peers (excluding the focal firm) in the observation year. The industry cross-citation rate is expressed as $\frac{1}{N_i} \times \sum_i (C_{ij}/C_i + C_{ji}/C_j)$, where C_{ij} indicates the number of backward citations in firm i's patent applications to firm j's patents within five years following the announcement of their alliance, C_i is the total number of backward citations in firm i's patent applications within that period, and N_i is the number of alliances formed in firm i's industry in the observation year.

[13] The control function method derives a proxy variable that conditions on the part of the endogenous regressor that correlates with the unobserved error. It relies on instrumental variables and requires estimating two regression equations: an auxiliary model that estimates the control function of the endogenous variable, and a structural model that regresses the dependent variable on the endogenous variable and its control function. Once implemented, the remaining variation in the endogenous variable remains independent of the unobserved error, rendering it exogenous.

The firm's *diversity of alliance experience* serves as an additional instrument. Experience with diverse alliance types relates to the extent to which the firm could establish alliance management routines that may limit knowledge spillover to a current partner (Castellaneta & Zollo, 2015), but would be unlikely to affect the partner's propensity to recombine the firm's spillover knowledge, nor the firm's propensity to subsequently internalize those recombinations. It is measured by an inverse standardized Herfindahl index $H_i = \left[1 - \sum_j (\frac{N_{ij}}{N_i})^2\right] \times \frac{N_i}{N_i - 1}$, where N_{ij} is the share of the firm's alliances with value chain activity j announced within a ten-year period prior to the announcement of the alliance under consideration, and N_i is the total number of distinct value chain activities included in the firm's alliances. The measure equals the probability that two alliances selected at random from the firm's past alliances include a different value chain activity.

The instruments were both individually and jointly significant predictors of knowledge spillover from the firm to the partner in the auxiliary model ($\chi^2 = 21.13$, $p < 0.001$).[14] An insignificant Hansen-Sargan statistic suggests instrument validity ($p = 0.903$). This conclusion was further supported by the instruments' insignificance in the structural model ($\chi^2 = 1.45$, $p = 0.485$).[15]

************* Insert Tables 4.1–4.3b and Figures 4.1–4.4 here *************

4.4. RESULTS

Table 4.1 reports descriptive statistics and pairwise correlations. To preclude multicollinearity concerns, I standardized all variables and verified that their variance inflation factors (VIFs) remain below the threshold of 10. Estimates of the first-stage models are reported

[14] As a rule, in linear regression, the F-statistic for the instruments' joint significance should be greater than 10 to ensure instrument relevance (Staiger & Stock, 1997). In PPML regression, the test statistic has a chi-square distribution, which is why I rely on the corresponding chi-square values for testing instrument relevance.
[15] Similar conclusions were reached when relying on different sets of instruments (e.g., the extent of industry knowledge spillover, or the industry average scientific impact), with consistent findings.

in Table 4.2.[16] Table 4.3a reports the second-stage estimates. Model 1 regresses knowledge spillback on the control variables. It finds that the firm absorbs more knowledge spillback from the partner if the partner has hired the firm's inventors (Corredoira & Rosenkopf, 2010). Moreover, the firm absorbs more knowledge spillback when it has cited the partner's patents both before and during their alliance, and when the firm frequently relies on others' recombinations of its knowledge. The firm also absorbs more knowledge spillback from larger partners with greater R&D intensity and solvency, whose knowledge is cumulative and scientifically impactful. Likewise, greater business overlap, alliance scope, knowledge base relatedness, and patent co-applications increase the firm's absorption of knowledge spillback from the partner. Knowledge spillback also increases with the parties' cross-national distance, underlining the benefits of drawing upon knowledge from distant national contexts (Zaheer & Hernandez, 2011). In turn, knowledge spillback declines with the partner's GPE and reliance on industry knowledge. The firm also absorbs less spillback when it had formed prior alliances with the partner and absorbed pre-alliance knowledge spillback from the partner. Finally, spillback declines in upstream alliances and joint ventures. The effects of these control variables persist in all models, with only few exceptions.

Model 2 introduces the main effect of knowledge spillover, finding a positive association with knowledge spillback ($\beta = 0.298$, $p < 0.001$). When the quadratic term of knowledge spillover is included in Model 3, a significant positive main effect ($\beta = 1.083$, $p < 0.001$) and a negative quadratic effect ($\beta = -0.102$, $p < 0.001$) are observed. Model 4 introduces the control function.[17] A significant control function ($\rho = 0.146$, $p < 0.001$) implies the control function should be retained

[16] The sample selection model relates selection to firms' solvency, GPE, patenting experience, and industry alliance formation. The partner selection model suggests that firms preferred forming alliances with partners that were younger, with greater GPE and patenting experience, with whom they had joint partnering experience and a related knowledge base. The firms also opted for cross-nationally proximate partners that were relatively larger than alternative partners.
[17] As control-function estimates may suffer from generated regressor bias, I applied the bootstrap procedure suggested by Terza (2017) to derive asymptotically correct standard errors. Although I do not find indications of such bias, I report bootstrap standard errors along with Huber-White robust standard errors for control-function estimates.

to obtain unbiased estimates. In Model 4, both the main effect of knowledge spillover ($\beta = 0.535$, $p < 0.001$), and its quadratic effect ($\beta = -0.060$, $p < 0.001$) remain significant. As predicted by Hypothesis 1, these findings suggest that the extent of knowledge spillback to the firm from its partner increases at a diminishing rate with the extent of knowledge spillover from the firm to the partner. Lind and Mehlum's (2010) test for curvilinear relationships indicates a positive slope on the left of the inflection point (slope = 0.581, $p < 0.001$) and a negative slope on its right (slope = -0.430, $p < 0.001$). This suggests that knowledge spillback not only increases at a diminishing rate with knowledge spillover but exhibits an inverted U-shaped relationship, as shown in Figure 4.1, with the inflection point occurring at the 98th percentile of knowledge spillover. In relative terms, these predictions indicate that, on average, 4.48 percent of a firm's knowledge spillovers produce knowledge spillback, with that ratio increasing to 5.14 percent at the inflection point. At the maximum extent of knowledge spillover, only 1.49 percent of spillovers produce spillback.

Table 4.3b reports results for the moderation hypotheses. Models 5–8 introduce interactions between the linear term of knowledge spillover and the moderators, with Model 9 presenting the full model.[18] To test Hypothesis 2, which predicts a positive interaction effect of knowledge base relatedness with knowledge spillover at lower values of the moderator and a negative interaction effect at higher values of the moderator, I used a spline function. The spline function splits knowledge base relatedness into two separate variables that capture knowledge base relatedness above its mean versus below its mean. Contrary to my prediction, I find negative signs on the interaction between knowledge spillover and knowledge base relatedness both below the mean ($\beta = -1.803$, $p < 0.001$) and above the mean ($\beta = -0.112$, $p = 0.001$) of knowledge base relatedness

[18] Per my hypotheses, the moderators affect only the linear part of the association. In ancillary models I moderate the entire curve (Haans, Pieters, & He, 2016). However, due to multicollinearity, these results were difficult to interpret.

(Model 9).[19] Based on these results, I reject Hypothesis 2, concluding instead that increasing knowledge base relatedness attenuates the positive association between knowledge spillback and spillover at any level of relatedness. This finding suggests that knowledge spillback opportunities emerge due to the nonoverlapping nature of the parties' knowledge bases. This conclusion is accommodated in Model 10, which presents the full model without the spline function of knowledge base relatedness. It reveals that the positive association between knowledge spillback and knowledge spillover is attenuated by the firm's and the partner's knowledge base relatedness ($\beta = -0.200$, $p < 0.001$) (Figure 4.2). It further reveals that the positive association between knowledge spillback and knowledge spillover is reinforced by the cumulativeness of the firm's knowledge ($\beta = 0.178$, $p = 0.004$), in line with Hypothesis 3 (Figure 4.3). Finally, it finds that the positive association between knowledge spillback and knowledge spillover is attenuated by the firm's reliance on prior industry knowledge ($\beta = -0.250$, $p = 0.006$), lending support to Hypothesis 4 (Figure 4.4). VIFs of all moderated effects remained below the threshold level, precluding multicollinearity concerns. To further rule out specification errors or overfitting concerns, Model 11 presents the full model without the control function, while Model 12 excludes all control variables. The corresponding results are consistent with Model 10.

Finally, I examined whether the moderators influence not only the linear term but the entire curve (Haans et al., 2016). As the corresponding models suffer from multicollinearity, I instead explored how the moderators affect the positive and negative slopes of the spline function relating to the inverted U-shaped effect of knowledge spillover. The interaction effects of the positive slope were consistent with Models 10–12. The negative slope exhibits an insignificant interaction with

[19] Splining knowledge base relatedness at different points along its distribution, e.g., quartiles or deciles, produced findings with consistent signs. I also tested models in which I interacted knowledge spillover with both the linear and quadratic effects of knowledge base relatedness, but I could not interpret their results due to multicollinearity.

knowledge base relatedness, a positive interaction with the firm's knowledge cumulativeness (β = 0.922, p = 0.001), and a negative interaction with the firm's reliance on prior industry knowledge (β = -1.292, p = 0.002). These findings suggest that a firm experiences fewer negative returns on spilled knowledge at high levels of knowledge spillover if its knowledge is cumulative, but experiences more negative returns if it relies on knowledge of other firms in its industry.

4.5. ROBUSTNESS TESTS

I tested my findings' robustness in several ways. First, I varied the length of the time intervals for capturing knowledge spillover and knowledge spillback. I tested a three-year (and seven-year) spillover interval with a five-year (and ten-year) spillback interval, and my results remain intact, except for Hypothesis 3 with the longer intervals. I also varied the alliance duration, assuming a three-, or seven-year duration, and find consistent results. Second, to preclude reverse causality, I captured knowledge spillover and spillback in subsequent, non-overlapping five-year intervals, with consistent results for Hypotheses 1 and 2, and consistent signs for Hypotheses 3 and 4. Third, because 202 alliances (13.13% of the sample) that were announced in 2012 or later had a right-censored seven-year spillback interval, I excluded their observations, and my results remain intact.

Fourth, I computed all patent-based measures by including EPO and JPO patents in addition to USPTO patents. To avoid duplicate data, I collapse citing and cited patents at the patent-family level, which comprises all patents that cover the same invention. This generates consistent findings, except for Hypothesis 3, whose effect remained insignificant with a consistent sign.

Fifth, I excluded citations that were introduced by the USPTO's patent examiners from the measures for knowledge spillback and knowledge spillover. I relied on Sampat's (2012) examiner citation dataset for granted USPTO patents issued during 2001–2010 and restricted my sample to alliances formed during 2001–2005. Despite losing 881 observations (57.44% of the sample), I obtain a consistent effect for Hypothesis 1 and consistent signs for the moderators.

Sixth, I tested the results' sensitivity to varying the annual discount rate for patent citations in the measures for knowledge spillback and knowledge spillover, by replacing the 10% discount rate with a 5% or 20% rate, and all findings hold. The findings also hold when not discounting citations and instead considering only those cited patents whose application dates precede the alliance announcement by no more than ten years. Seventh, I considered alternative measures for knowledge base relatedness (e.g., Jaccard index, Euclidean distance, and the common citation rate). My findings remain intact, with a few exceptions for Hypotheses 3 and 4, which retain consistent signs. Seventh, I computed reliance on prior industry knowledge by defining the industry at the four-digit SIC level as well as on the four- and six-digit NAICS levels, with consistent findings.

Eighth, I explored ancillary models which illustrate the effects of the mechanisms driving the association between knowledge spillback and spillover. For example, I find evidence consistent with the claim that the value of the partner's recombinations drives the firm's motivation to absorb knowledge spillback, by showing that the relationship between spillback and spillover is partially mediated by the average number of forward citations received by the partner's patents that draw from the firm's spilled knowledge. A patent's forward citations indicate its technological value, which is likely to relate to the firm's motivation to learn from these inventions. I also find evidence consistent with the ability argument, by showing that the relationship between knowledge spillback and spillover is partially mediated by the technological similarity of the partner's recombinations with the firm's previous knowledge. That similarity proxies for the firm's ability to absorb those recombinations. The claim that, beyond a certain level of spillover, the firm foregoes spillback opportunities as it begins searching for knowledge other than that held by the partner, gains support from showing that the curvilinear portion of the relationship between spillback and spillover is partially mediated by the firm's formation of new alliances during the spillback interval. Ancillary moderation models also furnish evidence consistent with the claim that the absorption of knowledge spillback is driven by the firm's monitoring of the partner's inventions. I find that the positive association between spillback and spillover becomes weaker with greater joint partnering experience, which proxies for trust among the parties and reduces the need for monitoring. Finally, I find that the negative slope of the curvilinear function is attenuated in alliances that are joint ventures. Because joint venture governance mitigates partner opportunism, this finding provides evidence consistent with the claim that the diminishing rate at which knowledge spillovers produce spillback may be attributed to partner uncooperativeness.[20]

Ninth, I tried different second-stage estimators (e.g., log-linear OLS and negative binomial), and I found consistent results except for Hypothesis 4 in the negative binomial model. I also modeled knowledge spillback conditional on non-zero spillover, using zero-inflated Poisson and Poisson-logit hurdle models, and all findings hold.

Tenth, to rule out the possibility that the positive, linear portion of the relationship between knowledge spillback and knowledge spillover is solely driven by a greater volume of spillovers, I fitted models with percentile fixed effects for knowledge spillover. My findings hold, indicating that knowledge spillover exerts an effect on knowledge spillback beyond the effect of a greater risk set of spillovers. My findings also hold with firm fixed effects, despite incurring a loss of 329 observations (21.38% of the sample). Finally, my findings were insensitive to replacing potential outliers with their variables' means. Overall, these analyses reaffirm my findings' robustness.

4.6. POST-HOC ANALYSES

[20] I explore the mechanisms proxied by joint partnering experience and joint venture governance via moderation rather than mediation analyses, given that these proxy variables temporally precede knowledge spillover. Hence, these variables are unlikely to mediate between knowledge spillover and subsequent knowledge spillback.

My findings provide evidence consistent with the claim that firms can leverage knowledge spillovers to alliance partners in order to learn from the partners' recombinations of their spilled knowledge. In additional analyses I explore how (a) the dynamics between knowledge spillback and spillover differ between allied firms and non-allied firms, and how (b) absorbing knowledge spillback from alliance partners influences the technological value of the firm's inventions.

4.6.1. Comparing knowledge spillback in alliances versus non-alliance dyads

To better understand the implications of the alliance context for my findings, I examined differences in the association between knowledge spillback and spillover for firms in alliances versus a matched sample of firms that have not formed alliances. Such differences may indicate whether knowledge spillovers to partners benefit the source firm in ways distinct from spillovers to non-partner recipients. The sample for this analysis consists of a treatment group comprising the 1,539 alliance dyads and a control group comprising 1,539 non-alliance dyads. To construct a control group, I relied on the sample of counterfactual partners from the partner selection model. If more than one counterfactual partner was available for a given alliance, the one most similar to the actual partner in terms of size and industry was selected into the control group. This allows for a more conservative test of an alliance's effect than comparing the actual partners against a set of randomly selected non-partners, given that knowledge recombinations developed by similar recipients may provide similar learning opportunities for the source firm.

*************Insert Tables 4.4–4.5 and Figure 4.5 here *************

I rely on comparative split-sample analyses to juxtapose the effects for the treatment and control groups. The models are estimated using PPML and incorporate the same set of variables for both treatment and control groups as the second-stage models in the main analysis. Exceptions are the variables *joint venture*, *technology transfer*, *alliance scope*, and *value chain function*, which lack counterfactuals for the non-alliance dyads. Descriptive statistics and pairwise correlations for the control group of non-alliance dyads are reported in Table 4.4 (treatment-group descriptive statistics and correlations are reported in Table 4.1). The results of the analyses are shown in Table 4.5. Models 1 and 2 show the treatment group estimates and find results consistent with Models 4 and 10 from Tables 4.3a and 4.3b. Models 3 and 4 (Table 4.5) present the corresponding control group estimates. A comparison between Models 2 and 4 reveals a smaller main effect of knowledge spillover in the control group ($\beta = 0.448$, $p = 0.031$) than in the treatment group ($\beta = 0.604$, $p < 0.001$). Also the quadratic effect of knowledge spillover was smaller in the control group ($\beta = -0.024$, $p = 0.008$) than in the treatment group ($\beta = -0.057$, $p < 0.001$). The test for curvilinear relationships (Lind & Mehlum, 2010) finds an inverted U-shaped association for the treatment group (positive slope = 0.612, $p < 0.001$; negative slope = -0.410, $p < 0.001$), but fails to detect an inverted U-shape for the control group. Figure 4.5. displays the predicted curvilinear functions for treatment and control groups, revealing a flattened curve with a right-shifted inflection point for the control group: Whereas the association between knowledge spillback and spillover is inverted U-shaped for allied firms, it is r-shaped for non-allied firms. All moderated effects were insignificant in the control group, which reinforces the logic of the mechanisms underlying the moderators' effects as predicted by this study.

To formally test whether effects differ between control and treatment groups, I also performed nested sample analyses of alliances and non-alliance dyads, which is shown in Models 5 and 6. The dummy variable *alliance* indicates whether a dyad is an alliance, taking the value 1 for alliances and 0 for non-alliance dyads. The treatment effect of forming an alliance was obtained by testing the joint significance of the alliance dummy and its interactions with the independent variable and its moderated functions (due to multicollinearity, I could not interpret the coefficients of the alliance dummy and its interactions individually). The resulting significant χ^2 statistics reject the null hypothesis of equal effects across treatment and control groups, providing evidence consistent with the presence of contextual differences in the dynamics of knowledge spillback and spillover between allied firms and non-allied firms.

These findings suggest that increasing knowledge spillovers to alliance partners induce greater amounts of knowledge spillback than knowledge spillovers to non-partners. However, whereas the association between spillback and spillover in alliances is inverted U-shaped, spillback from non-partners increases monotonically with spillover. An explanation for this finding is that learning in alliances is more competitive, so partners absorb the firm's knowledge more effectively, but once they achieve their learning goals, they may increase their asset protection (Khanna et al., 1998), restricting knowledge spillback at high spillover levels. Unrelated firms, by contrast, are less effective at absorbing and recombining each other's knowledge (Gomes-Casseres et al., 2006; Mowery et al., 1996), which limits spillover and spillback. Indeed, due to lesser misappropriation risks in non-alliance settings, spillover recipients may also make fewer efforts to suppress spillback.

4.6.2. The technological value of knowledge spillback in alliances

To substantiate the claim that knowledge spillback generates valuable benefits for the firm, I explored how absorbing knowledge spillback from partners influences the technological value of the firm's inventions, as indicated by their scientific impact (e.g., Capaldo, Lavie, & Petruzzelli, 2017). Prior research has shown that a patent's scientific impact serves as a key an indicator of its technological importance and market value (e.g., Hall et al., 2005; Harhoff et al., 1999). Accordingly, using patent-level analyses, I investigated how a patent's scientific impact increases or decreases if the patent incorporates knowledge spillback from an alliance partner of its applicant firm. Moreover, I examined how the effect of knowledge spillback on scientific impact compares against the effect of inbound knowledge spillover on scientific impact.

The sample for this analysis comprises 1,938,202 USPTO patent applications that were filed by the 323 firms during the period 2000–2020. The dependent variable *scientific impact* counts the forward citations received by a given patent during that period. The independent variables indicate whether a patent constitutes a knowledge spillback or an inbound knowledge spillover. *Knowledge spillback* is a dummy variable that takes the value 1 if the patent receives a knowledge spillback from an alliance partner of the applicant firm, and 0 otherwise. A patent is considered to receive knowledge spillback if it contains backward citations to patents of its applicant firm's alliance partners, which in turn have cited prior patents of the applicant firm. *Inbound knowledge spillover* is a dummy variable with value 1 if the patent receives an inbound knowledge spillover from an alliance partner of the applicant firm, and 0 otherwise. A patent is considered to receive an inbound knowledge spillover if it cites patents of its applicant firm's alliance partners, provided that those citations do not constitute knowledge spillback. The time intervals for capturing knowledge spillover and knowledge spillback were consistent with those used in the paper's main body. I control for the patent's number of *backward citations,* its number of primary and secondary IPC *technology classes*, whether it is a *granted patent*, and whether it is a *co-application* by multiple applicants. I include fixed effects on the patent's application year, the patent's three-digit IPC technology class, the applicant firm, and the applicant firm's industry.

*************Insert Tables 4.6–4.7 here *************

Table 4.6 reports descriptive statistics and pairwise correlations. Because the dependent variable is an integer count with overdispersion, I estimated the models using negative binomial regression.[21] The results are shown in Table 4.7. Model 1 is the baseline model and includes the

[21] PPML, generates consistent findings although the HPC test (Santos Silva et al., 2015) indicates a preference for negative binomial.

control variables. It finds that a patent's scientific impact increases with its number of backward citations, its status as a granted patent, and if it is a co-application. In turn, scientific impact decreases with the number of the patent's technology classes. Models 2 and 3 introduce the independent variables, revealing positive effects of inbound knowledge spillover ($\beta = 0.047$, $p < 0.001$) (Model 2) and of knowledge spillback ($\beta = 0.112$, $p < 0.001$) (Model 3) on a patent's scientific impact. Model 4 presents the full model and finds a positive association of a patent's scientific impact with knowledge spillback ($\beta = 0.138$, $p < 0.001$), as well as with inbound knowledge spillover ($\beta = 0.059$, $p < 0.001$). Average marginal effects indicate that spillback patents accumulate 1.38 more forward citations than patents that receive neither spillback nor spillover, whereas inbound spillover patents accumulate 0.58 more forward citations than patents that receive neither spillback nor spillover. Given a sample mean of 9.19 forward citations per patent, these findings suggest that inventions which incorporate knowledge spillback from partners tend to be, on average, 15.02 percent more scientifically impactful than inventions that do not draw upon partners' knowledge. Moreover, knowledge spillback inventions tend to be, on average, 8.19 percent more impactful than inventions that receive inbound knowledge spillovers from partners.

4.7. DISCUSSION

This paper studies how a firm may benefit from a partner's inventions that are based on knowledge that the firm has spilled to the partner during their alliance. It extends research on learning in alliances not only by introducing knowledge spillback as a novel learning pathway in alliances, but also by outlining conditions that alter the extent by which firms absorb knowledge spillback relative to preceding knowledge spillover. It suggests that firms can gain value from spilled knowledge to alliance partners via absorbing knowledge spillback from these partners.

While my theory predicts an r-shaped association between the firm's absorption of knowledge spillback from its partner and the extent of preceding knowledge spillover to the partner, the observed association between spillback and spillover is in fact inverted U-shaped. There are several possible explanations for why that association turns negative at high levels of knowledge spillover. One explanation is that beyond a certain threshold of knowledge spillover, there remain too few opportunities for the firm to capitalize on the spilled knowledge, prompting the firm to cease further development of that knowledge. Alternatively, the firm may have allowed large amounts of its knowledge to spill to the partner mainly because it had already proceeded to develop other knowledge, which it considers more up to date and valuable. Finally, it is possible that if the partner absorbs a large portion of the firm's spilled knowledge, the partner can combine the various elements of that knowledge with each other, rather than combine them with its own knowledge elements. As a result, the partner's recombinations would appear less novel to the firm, considering that the firm could have generated similar combinations by itself. These possibilities notwithstanding, my findings indicate that knowledge spillovers to partners can benefit the firm by facilitating subsequent learning, at least as long as such spillovers do not become excessive.

My findings further suggest that knowledge spillovers facilitate learning especially if partners combine the spilled knowledge in inventions that appear novel and non-redundant to the firm. Accordingly, the positive association between knowledge spillback and knowledge spillover is reinforced by the cumulativeness of the firm's knowledge. In turn, that association is weakened by the firm's reliance on prior industry knowledge. Moreover, I find that knowledge spillback opportunities are evident mostly in the nonoverlapping nature of the parties' knowledge bases. Future research can seek to uncover the exact reasons for the observed negative effect of knowledge base relatedness on the association between knowledge spillback and spillover.

This study challenges prior research on alliances that has perceived knowledge spillover to a partner as a loss for the source firm. Instead, my findings suggest that knowledge spillover to partners can benefit the source firm if it absorbs the evolving knowledge that spills back from partners. This can enable the firm to recapture losses in outbound spillover rent by converting them into gainful inbound spillover rent (Lavie, 2006). These conclusions provide impetus to the debate concerning the tradeoffs between knowledge acquisition and protection in alliances. According to some recent studies, greater protection of own assets can restrict the firm’s absorption of the partner’s assets and is rather costly (Contractor, 2019; Inkpen et al., 2019; Wadhwa, Bodas Freitas, & Sarkar, 2017). My study refines the advice of such research by showing how knowledge spillovers to partners induce valuable learning opportunities in the form of knowledge spillback.

This study also makes important contributions to the cumulative innovation literature. Prior evidence has shown that it is possible for a firm to absorb external inventions which are based on its spilled knowledge (Alnuaimi & George, 2016; Yang et al., 2010). I find more nuanced results, indicating that the rate by which knowledge spillover generates knowledge spillback varies with the extent of spillover. While earlier findings suggest that greater knowledge relatedness increases a firm's tendency to build on its spilled knowledge (Yang et al., 2010), I find that, among alliance partners, greater knowledge base relatedness decreases the rate at which spillovers result in spillback. Finally, the current study distinguishes itself from earlier research in adopting a dyadic approach to study spillback-spillover dynamics. By considering not only the source’s perspective, but also that of the recipient, this paper underscores how firms’ learning from recombinations of their spilled knowledge is influenced by the interplay of both source-, and recipient-specific factors.

Knowledge spillovers to alliance partners remain a concern for managers (Contractor, 2019). This study suggests that executives should consider the opportunity of knowledge spillback and learn to balance the benefits of asset protection against those of knowledge spillback. Accordingly, when forming alliances in which asset protection may not be a feasible nor a desirable strategy, executives should consider exploring knowledge spillback opportunities, given that knowledge spillback can increase the technological value of the firm's inventions and enable the firm to break the mold of path dependencies in its current knowledge development trajectory.

This study has limitations, which suggest directions for future research. While the current study focuses on firms' learning benefits, it offers no insights into whether firms can capitalize on spillback knowledge to a similar extent as they may capitalize on internally developed knowledge. Moreover, patent data suffer from known limitations (e.g., Corsino et al., 2019; Jaffe & de Rassenfosse, 2017) and provide limited insights into the underlying learning mechanisms. Future research may provide qualitative evidence to complement this study's findings and elucidate the learning processes to offer more detailed insights into how knowledge spillback occurs. Likewise, future research may extend this study's findings by more closely studying its contingencies other than those associated with the relatedness of knowledge. Finally, future research should explore alternative transaction modes through which the firm can tap into a partner's knowledge recombinations which are based on its spilled knowledge. In that regard scholars may investigate the effect of knowledge spillback dynamics on sequential patterns of corporate strategy transactions (Feldman, 2020; Kochura, Mirc, & Lacoste, 2022). For instance, it is conceivable that a firm spills some knowledge to a partner during an alliance, inducing it to subsequently acquire that partner with the aim to absorb the partner's recombinations of its spilled knowledge. A similar dynamic may help explain re-acquisition transactions wherein firms acquire previously divested business units (Dietz & zu Knyphausen-Aufseß, 2017), or patterns of alliance formation following divestitures. Future research may examine the role of knowledge spillback in these sequential transaction patterns.

4.8. FIGURES AND TABLES

Table 4.1: Descriptive statistics and pairwise correlations

Variables	Mean	Std.Dev.	VIF	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.	16.	17.
1. Knowledge spillback	39.58	112.34																		
2. Knowledge spillover	292.74	763.60	3.97	0.58																
3. Firm age	46.53	39.07	1.50	0.10	0.19															
4. Firm size	33280.01	37695.51	2.94	0.21	0.26	0.44														
5. Firm R&D intensity	0.15	0.45	1.14	-0.03	-0.05	-0.16	-0.14													
6. Firm solvency	1.71	2.96	1.20	-0.03	-0.10	-0.25	-0.22	0.06												
7. Firm GPE	61.92	80.89	2.45	0.31	0.36	0.34	0.60	-0.10	-0.19											
8. Firm patenting experience	8154.31	12814.65	2.91	0.21	0.24	0.40	0.74	-0.10	-0.20	0.50										
9. Firm knowledge cumulativeness	1.59	2.34	2.87	0.06	0.01	-0.09	0.00	0.18	0.07	0.06	0.05									
10. Firm reliance on industry knowledge	2.13	3.98	1.43	-0.04	-0.09	-0.27	-0.19	0.02	0.08	-0.16	-0.17	0.34								
11. Firm scientific impact	11.93	8.83	1.62	0.08	0.07	-0.10	-0.06	0.04	0.15	0.27	-0.18	0.26	0.12							
12. Firm patent purchasing	50.53	489.98	1.36	-0.01	0.01	0.07	0.00	-0.01	-0.03	-0.02	0.01	0.03	0.02	-0.03						
13. Firm inventor mobility	1.63	5.17	1.79	0.15	0.43	0.19	0.19	-0.04	-0.09	0.18	0.18	-0.03	-0.09	-0.02	0.08					
14. Firm rate of knowledge integration	0.13	0.17	1.87	0.28	0.15	0.03	0.22	0.04	0.12	0.28	0.35	0.50	0.17	0.14	-0.02	-0.02				
15. Partner age	45.37	39.78	1.49	0.05	0.05	0.11	0.08	-0.03	-0.05	-0.01	0.08	0.02	-0.06	-0.05	0.06	0.09	-0.02			
16. Partner size	36397.19	66119.51	1.31	0.06	0.13	0.14	0.06	-0.03	-0.07	-0.02	0.08	-0.05	-0.06	-0.07	0.03	0.11	-0.08	0.27		
17. Partner R&D intensity	0.13	0.28	1.14	-0.02	-0.02	-0.10	-0.08	0.09	0.03	-0.05	-0.06	0.16	0.07	0.06	-0.02	-0.04	0.03	-0.18	-0.11	
18. Partner solvency	1.93	3.34	1.22	0.05	0.06	-0.05	-0.04	0.03	0.08	0.03	-0.03	-0.04	-0.02	0.05	-0.03	-0.01	-0.01	-0.27	-0.12	0.15
19. Partner GPE	33.86	67.17	1.73	0.21	0.32	0.10	0.04	-0.03	-0.08	0.06	-0.02	-0.05	-0.00	0.08	0.00	0.04	-0.02	0.12	0.20	-0.03
20. Partner patenting experience	5951.12	10323.62	1.81	0.12	0.28	0.05	-0.02	-0.05	-0.06	-0.07	-0.00	-0.07	0.00	-0.07	0.06	0.27	-0.07	0.31	0.38	-0.08
21. Partner knowledge cumulativeness	1.54	2.25	1.52	0.04	0.10	-0.01	-0.07	0.12	-0.01	-0.03	-0.07	0.10	0.03	0.06	0.03	0.04	0.06	-0.07	0.03	0.12
22. Partner reliance on industry knowledge	2.41	4.19	1.49	-0.03	-0.03	-0.04	-0.03	0.04	-0.03	0.04	-0.02	0.04	0.04	0.04	-0.00	-0.05	0.05	-0.30	-0.13	0.08
23. Partner scientific impact	11.93	9.14	1.65	0.09	0.10	-0.00	0.00	-0.02	0.00	0.29	-0.08	0.05	0.00	0.43	-0.05	-0.02	0.10	-0.17	-0.07	0.11
24. Partner patent purchasing	55.31	504.01	1.39	-0.01	0.03	0.09	0.09	-0.02	-0.03	-0.02	0.04	0.02	0.00	-0.07	0.49	0.13	-0.02	0.09	0.00	-0.02
25. Partner inventor mobility	1.41	4.14	2.28	0.22	0.35	0.16	0.19	-0.05	-0.09	0.16	0.20	-0.02	-0.08	-0.06	0.13	0.53	0.05	0.18	0.11	-0.06
26. Joint venture	0.22	0.42	1.26	0.00	0.02	0.15	0.09	-0.09	-0.12	-0.03	0.04	-0.08	-0.06	-0.17	0.06	0.09	-0.07	0.19	0.08	-0.12
27. Technology transfer	0.07	0.26	1.11	0.02	0.00	-0.04	0.03	0.02	-0.01	0.02	0.05	0.01	0.01	-0.01	0.02	-0.02	0.02	-0.08	-0.00	0.04
28. Value chain function	-0.24	0.69	1.18	-0.01	-0.01	0.01	-0.00	0.12	-0.01	0.03	0.01	0.01	-0.05	0.01	-0.03	-0.02	-0.01	-0.02	-0.05	0.11
29. Alliance scope	0.14	0.12	1.18	0.08	0.06	-0.03	-0.10	0.07	0.00	-0.06	-0.06	0.04	0.06	0.03	-0.03	-0.00	0.05	0.13	-0.04	0.01
30. Business overlap	0.37	0.35	1.27	0.02	0.05	-0.09	-0.12	-0.09	0.00	-0.13	-0.09	-0.04	0.12	-0.12	0.10	0.06	-0.04	-0.03	-0.06	-0.05
31. Cross-national distance	0.01	1.72	1.28	0.04	-0.01	-0.11	-0.06	-0.01	-0.01	-0.10	-0.05	-0.05	0.05	-0.04	-0.01	-0.17	0.02	-0.08	-0.03	-0.03
32. Joint partnering experience	2.66	4.46	2.34	0.20	0.39	0.22	0.23	-0.06	-0.10	0.28	0.18	-0.02	-0.11	0.02	0.03	0.50	-0.01	0.23	0.17	-0.07
33. Knowledge base relatedness	0.53	0.28	1.46	0.19	0.30	-0.03	0.07	0.05	-0.03	0.16	0.06	-0.02	0.02	0.07	0.06	0.16	0.04	-0.12	-0.01	0.00
34. Patent co-applications	8.71	37.31	1.32	0.09	0.17	0.10	0.06	-0.03	-0.08	0.13	0.06	-0.04	-0.06	0.00	0.06	0.30	-0.01	0.14	0.07	-0.04
35. Firm non-spillback citations to partner	455.14	1149.03	3.35	0.61	0.47	0.10	0.21	-0.04	-0.05	0.26	0.20	0.04	-0.06	0.05	0.03	0.31	0.23	0.16	0.13	-0.04
36. Pre-alliance knowledge spillover	382.76	1011.42	2.83	0.42	0.60	0.18	0.26	-0.05	-0.11	0.26	0.20	0.04	-0.06	-0.03	0.04	0.50	0.08	0.08	0.11	-0.03
37. Pre-alliance knowledge spillback	48.51	204.89	1.79	0.40	0.47	0.11	0.19	-0.03	-0.06	0.24	0.23	0.07	-0.02	0.00	0.04	0.25	0.21	0.06	0.06	-0.02
38. λ partner selection	1.02	0.58	2.11	-0.18	-0.34	-0.10	-0.05	0.04	0.05	-0.07	0.00	0.03	0.02	-0.05	-0.06	-0.30	0.02	-0.27	-0.31	0.14

N = 1,539 dyads.

Table 4.1: Descriptive statistics and pairwise correlations (continued)

	18.	19.	20.	21,	22.	23.	24.	25.	26.	27.	28.	29.	30.	31.	32.	33.	34.	35.	36.	37.
19.	0.10																			
20.	-0.14	0.35																		
21.	0.12	0.11	0.10																	
22.	0.15	-0.04	-0.15	0.45																
23.	0.23	0.21	-0.11	0.26	0.18															
24.	-0.04	0.00	0.04	0.03	0.01	-0.04														
25.	-0.08	0.01	0.27	-0.02	-0.10	-0.02	0.09													
26.	-0.14	-0.05	0.05	-0.08	-0.09	-0.17	0.08	0.11												
27.	0.02	-0.00	0.03	0.05	0.05	0.01	0.01	-0.02	-0.13											
28.	0.02	0.04	-0.00	0.01	-0.03	0.02	-0.03	-0.03	-0.28	0.09										
29.	-0.07	0.02	0.02	0.02	-0.00	-0.01	-0.04	0.04	0.08	-0.21	-0.18									
30.	-0.08	-0.11	0.07	-0.01	0.03	-0.13	0.09	0.11	0.07	-0.12	-0.13	0.16								
31.	0.05	0.21	-0.04	-0.03	0.04	-0.03	-0.01	-0.19	-0.04	-0.06	-0.02	0.03	0.06							
32.	-0.07	0.01	0.25	-0.01	-0.11	0.04	0.03	0.62	0.15	-0.05	-0.05	0.06	0.13	-0.21						
33.	0.05	0.06	0.09	-0.04	0.08	0.11	0.06	0.21	-0.09	0.06	0.01	-0.04	0.19	-0.01	0.28					
34.	-0.08	0.04	0.11	-0.03	-0.07	0.01	0.04	0.43	0.09	-0.04	0.02	0.06	0.04	-0.13	0.36	0.12				
35.	-0.04	0.34	0.32	0.05	-0.08	0.09	0.01	0.45	0.03	-0.01	-0.01	0.08	0.08	-0.01	0.39	0.29	0.22			
36.	-0.03	0.14	0.34	0.09	-0.03	0.00	0.07	0.43	0.04	0.06	-0.04	0.03	0.10	-0.12	0.49	0.28	0.16	0.52		
37.	-0.05	0.06	0.18	0.00	-0.05	0.02	0.02	0.42	0.06	0.05	-0.05	0.02	0.10	-0.08	0.38	0.19	0.13	0.49	0.50	
38.	0.11	-0.35	-0.49	-0.02	0.18	-0.10	-0.04	-0.36	-0.10	-0.00	0.01	-0.01	-0.02	0.23	-0.43	-0.32	-0.18	-0.38	-0.34	-0.24

Table 4.2: First-stage probit regression for partner selection

Variables	Model (1)	
Firm age	0.040	(0.032)
Firm size	0.044	(0.035)
Firm solvency	-0.000	(0.021)
Firm R&D intensity	-0.002	(0.023)
Firm GPE	-0.023	(0.032)
Firm patenting experience	-0.032	(0.043)
Partner age	-0.108***	(0.025)
Partner size	-0.012	(0.019)
Partner solvency	0.020	(0.020)
Partner R&D intensity	0.011	(0.018)
Partner GPE	0.137***	(0.022)
Partner patenting experience	0.144***	(0.023)
Joint partnering experience	0.053*	(0.026)
Cross-national distance	-0.156***	(0.023)
Knowledge base relatedness	0.231***	(0.020)
Pre-alliance knowledge spillover	0.029	(0.025)
Pre-alliance knowledge spillback	-0.001	(0.020)
Partner relative size	0.548***	(0.021)
Year fixed effects	Included	
Industry fixed effects	Included	
Country fixed effects	Included	
Constant	-0.730**	(0.197)
N population	7,607	
N selected	1,539 (20.23%)	
Log likelihood	-2827.3	

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

Table 4.3a: Second-stage PPML regression for knowledge spillback

Variables	Model (1)		Model (2)		Model (3)		Model (4)		
Knowledge spillover			0.298***	(0.035)	1.083***	(0.075)	0.535***	(0.101)	[0.163]
Knowledge spillover ^{2}					-0.102***	(0.010)	-0.060***	(0.010)	[0.019]
Firm age	-0.221	(0.142)	-0.140	(0.113)	-0.289**	(0.108)	-0.247*	(0.105)	[0.131]
Firm size	-0.045	(0.148)	0.046	(0.121)	0.064	(0.094)	0.085	(0.096)	[0.129]
Firm R&D intensity	-0.104	(0.530)	0.177	(0.405)	-0.083	(0.453)	-0.196	(0.482)	[0.537]
Firm solvency	0.011	(0.073)	-0.010	(0.064)	-0.028	(0.061)	-0.065	(0.062)	[0.095]
Firm GPE	0.130	(0.100)	-0.092	(0.077)	0.054	(0.072)	0.163*	(0.071)	[0.111]
Firm patenting experience	0.550***	(0.138)	0.353***	(0.102)	0.274**	(0.099)	0.278**	(0.096)	[0.127]
Firm knowledge cumulativeness	-0.018	(0.140)	-0.046	(0.141)	-0.197	(0.128)	-0.106	(0.124)	[0.207]
Firm reliance on industry knowledge	-0.488+	(0.257)	-0.603*	(0.240)	-0.305	(0.199)	-0.320	(0.203)	[0.239]
Firm scientific impact	0.083	(0.130)	-0.027	(0.112)	-0.061	(0.116)	-0.039	(0.116)	[0.142]
Firm patent purchasing	-0.226	(0.172)	-0.231	(0.145)	-0.115	(0.089)	-0.142+	(0.084)	[0.177]
Firm inventor mobility	0.053	(0.035)	0.035	(0.031)	-0.043	(0.031)	0.027	(0.029)	[0.047]
Firm rate of knowledge integration	0.371***	(0.085)	0.464***	(0.081)	0.532***	(0.076)	0.482***	(0.067)	[0.103]
Partner age	0.094	(0.081)	0.054	(0.072)	0.145*	(0.059)	0.092+	(0.053)	[0.074]
Partner size	0.143**	(0.054)	0.003	(0.117)	0.112**	(0.041)	0.161***	(0.033)	[0.059]
Partner R&D intensity	0.149*	(0.072)	0.172*	(0.069)	0.096	(0.068)	0.082	(0.059)	[0.128]
Partner solvency	0.210***	(0.045)	0.057	(0.044)	0.068	(0.042)	0.138***	(0.035)	[0.069]
Partner GPE	-0.179***	(0.050)	-0.111*	(0.043)	-0.157***	(0.039)	-0.087*	(0.036)	[0.060]
Partner patenting experience	-0.002	(0.098)	-0.052	(0.103)	-0.094	(0.088)	-0.148+	(0.080)	[0.098]
Partner knowledge cumulativeness	0.236**	(0.074)	0.104+	(0.062)	0.215***	(0.064)	0.317***	(0.069)	[0.111]
Partner reliance on industry knowledge	-0.234*	(0.098)	-0.045	(0.067)	-0.296***	(0.088)	-0.398***	(0.094)	[0.133]
Partner scientific impact	0.215**	(0.069)	0.230***	(0.066)	0.215***	(0.051)	0.133*	(0.058)	[0.073]
Partner patent purchasing	-0.014	(0.181)	0.054	(0.071)	-0.014	(0.061)	0.009	(0.056)	[0.133]
Partner inventor mobility	0.123***	(0.032)	0.135***	(0.031)	0.135***	(0.026)	0.130***	(0.025)	[0.038]
Joint venture	-0.399**	(0.122)	-0.310**	(0.115)	-0.259**	(0.099)	-0.266**	(0.098)	[0.154]
Technology transfer	0.392+	(0.232)	0.508**	(0.187)	0.311+	(0.168)	0.362*	(0.167)	[0.226]
Value chain function	-0.125*	(0.051)	-0.099*	(0.047)	-0.067+	(0.036)	-0.098**	(0.036)	[0.055]
Alliance scope	0.205***	(0.051)	0.152***	(0.046)	0.193***	(0.045)	0.167***	(0.043)	[0.063]
Business overlap	0.216**	(0.084)	0.244***	(0.059)	0.121*	(0.049)	0.106*	(0.048)	[0.069]
Cross-national distance	0.254***	(0.072)	0.049	(0.069)	0.109+	(0.056)	0.189***	(0.052)	[0.077]
Joint partnering experience	-0.174***	(0.053)	-0.096*	(0.046)	-0.094*	(0.048)	-0.134**	(0.044)	[0.059]
Knowledge base relatedness	0.400***	(0.076)	0.188*	(0.077)	0.191**	(0.069)	0.292***	(0.071)	[0.094]
Patent co-applications	0.186***	(0.053)	0.187***	(0.044)	0.131***	(0.026)	0.147***	(0.026)	[0.042]
Firm non-spillback citations to partner	0.427***	(0.042)	0.349***	(0.052)	0.204***	(0.049)	0.349***	(0.039)	[0.062]
Pre-alliance knowledge spillover	0.197***	(0.036)	0.032	(0.037)	-0.034	(0.036)	0.127***	(0.035)	[0.061]
Pre-alliance knowledge spillback	-0.089**	(0.033)	-0.106***	(0.030)	-0.065*	(0.027)	-0.068**	(0.025)	[0.050]
λ partner selection	-0.353*	(0.154)	-0.414**	(0.137)	-0.224+	(0.120)	-0.433***	(0.114)	[0.171]
Control function							0.146***	(0.022)	[0.033]
Year fixed effects	Included		Included		Included		Included		
Industry fixed effects	Included		Included		Included		Included		
Country fixed effects	Included		Included		Included		Included		
Constant	2.674***	(0.192)	2.874***	(0.169)	2.469***	(0.159)	2.496***	(0.145)	[0.221]
Observations	1,539		1,539		1,539		1,539		
Log pseudo-likelihood	-22277		-19079		-14497		-13090		

Standardized coefficients. Robust standard errors in parentheses. Bootstrap standard errors (1,000 replications) in brackets for control-function estimates. Significance: *** p < 0.001, ** p < 0.01, * p < 0.05, + p < 0.10.

Table 4.3b: Second-stage PPML regression for knowledge spillback (moderation analysis)

Variables	Model (5)	Model (6)	Model (7)	Model (8)	Model (9)	Model (10)	Model (11)	Model (12)
Control variables	Included	Included	Included	Included	Included	Included	Included	Excluded
Knowledge spillover	0.752***	0.657***	0.526***	0.535***	0.655***	0.733***	1.215***	1.579***
	(0.099) [0.170]	(0.093) [0.171]	(0.104) [0.168]	(0.099) [0.174]	(0.089) [0.192]	(0.096) [0.192]	(0.069)	(0.085)
Knowledge spillover ^{2}	-0.059***	-0.055***	-0.060***	-0.062***	-0.059***	-0.064***	-0.095***	-0.122***
	(0.009) [0.017]	(0.009) [0.020]	(0.011) [0.020]	(0.010) [0.019]	(0.009) [0.019]	(0.009) [0.017]	(0.008)	(0.012)
Firm knowledge cumulativeness	-0.059	-0.050	-0.124	-0.076	-0.061	-0.091	-0.104	0.377***
	(0.124) [0.207]	(0.121) [0.196]	(0.135) [0.229]	(0.121) [0.252]	(0.121) [0.238]	(0.126) [0.248]	(0.126)	(0.066)
Firm reliance on industry knowledge	-0.349+	-0.334	-0.345	-0.295+	-0.375*	-0.433*	-0.389*	-0.472***
	(0.212) [0.249]	(0.203) [0.238]	(0.220) [0.247]	(0.171) [0.245]	(0.184) [0.249]	(0.197) [0.252]	(0.182)	(0.132)
Knowledge base relatedness	0.406***		0.295***	0.270***		0.388***	0.332***	0.444***
	(0.067) [0.087]		(0.073) [0.096]	(0.068) [0.087]		(0.068) [0.083]	(0.064)	(0.085)
Knowledge base relatedness (< mean)		0.791***			0.738***			
		(0.227) [0.256]			(0.221) [0.254]			
Knowledge base relatedness (> mean)		0.225+			0.209+			
		(0.118) [0.144]			(0.114) [0.142]			
Knowledge spillover ×	-0.162***					-0.200***	-0.248***	-0.296***
Knowledge base relatedness	(0.028) [0.054]					(0.030) [0.055]	(0.032)	(0.031)
Knowledge spillover ×		-1.896***			-1.803***			
Knowledge base relatedness (< mean)		(0.302) [0.438]			(0.302) [0.435]			
Knowledge spillover ×		-0.078*			-0.112***			
Knowledge base relatedness (> mean)		(0.034) [0.065]			(0.033) [0.070]			
Knowledge spillover ×			0.023		0.122*	0.178**	0.129*	0.305***
Firm knowledge cumulativeness			(0.046) [0.079]		(0.057) [0.073]	(0.061) [0.089]	(0.060)	(0.059)
Knowledge spillover ×				-0.081	-0.209*	-0.250**	-0.245*	-0.199***
Firm reliance on industry knowledge				(0.065) [0.093]	(0.081) [0.122]	(0.090) [0.116]	(0.098)	(0.059)
Control function	0.116***	0.106***	0.149***	0.143***	0.109***	0.122***		
	(0.018) [0.032]	(0.017) [0.032]	(0.024) [0.034]	(0.021) [0.033]	(0.017) [0.033]	(0.018) [0.035]		
Year fixed effects	Included	Included	Included	Included	Included	Included	Included	Excluded
Industry fixed effects	Included	Included	Included	Included	Included	Included	Included	Excluded
Country fixed effects	Included	Included	Included	Included	Included	Included	Included	Excluded
Constant	2.553***	2.667***	2.482***	2.530***	2.697***	2.581***	3.237***	2.581***
	(0.141) [0.199]	(0.165) [0.226]	(0.154) [0.226]	(0.142) [0.229]	(0.163) [0.235]	(0.142) [0.204]	(0.247)	(0.144)
Observations	1,539	1,539	1,539	1,539	1,539	1,539	1,539	1,539
Log pseudo-likelihood	-12484	-11648	-13083	-13041	-11443	-12148	-13040	-31567

Standardized coefficients. Robust standard errors in parentheses. Bootstrap standard errors (1,000 replications) in brackets for control-function estimates.
Significance: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, + $p < 0.10$.

Figure 4.1: Knowledge spillover by knowledge spillback (Hypothesis 1)

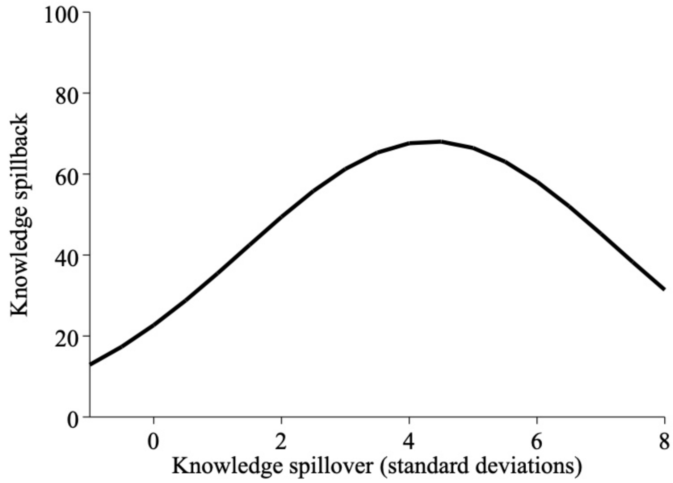

Figure 4.2: Moderating effect of firm's and partner's knowledge base relatedness (Hypothesis 2)

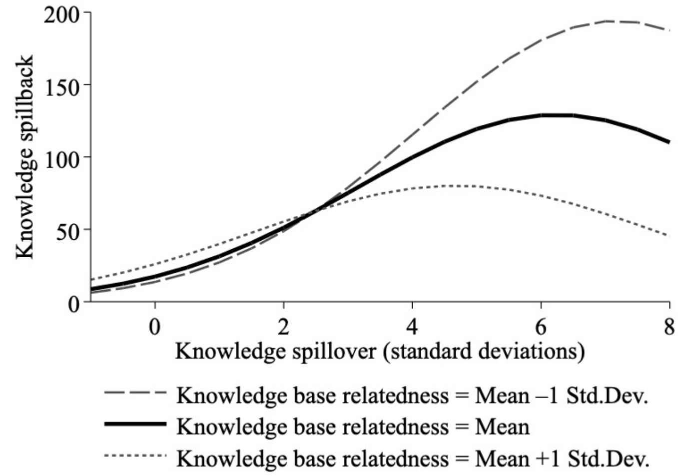

Figure 4.3: Moderating effect of firm's knowledge cumulativeness (Hypothesis 3)

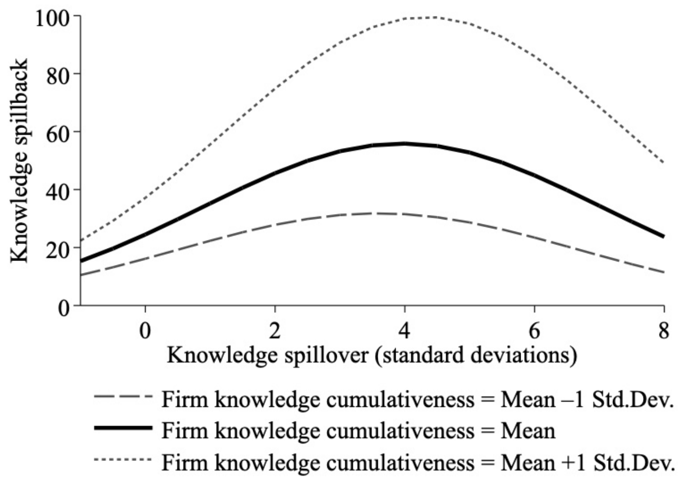

Figure 4.4: Moderating effect of firm's reliance on industry knowledge (Hypothesis 4)

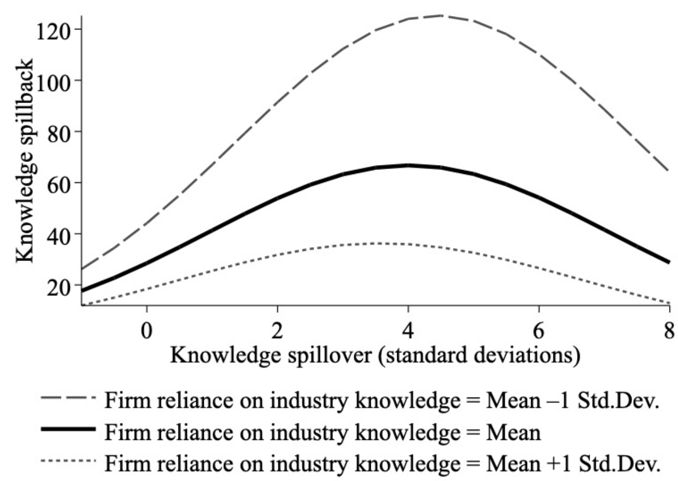

Table 4.4: Descriptive statistics and pairwise correlations for control group of non-alliance dyads

Variables	Mean	Std.Dev.	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.
1. Knowledge spillback	8.46	49.92											
2. Knowledge spillover	96.88	397.44	0.54										
3. Firm age	46.53	39.10	0.09	0.15									
4. Firm size	33280.01	37695.51	0.15	0.15	0.44								
5. Firm R&D intensity	0.15	0.45	-0.02	-0.02	-0.16	-0.14							
6. Firm solvency	1.71	2.96	-0.02	-0.06	-0.25	-0.22	0.06						
7. Firm GPE	61.92	80.89	0.17	0.21	0.34	0.60	-0.10	-0.19					
8. Firm patenting experience	8154.31	12814.65	0.17	0.13	0.40	0.74	-0.10	-0.20	0.50				
9. Firm knowledge cumulativeness	1.59	2.34	0.06	0.01	-0.09	0.00	0.18	0.07	0.06	0.05			
10. Firm reliance on industry knowledge	2.13	3.98	-0.02	-0.05	-0.27	-0.19	0.02	0.08	-0.16	-0.17	0.34		
11. Firm scientific impact	11.93	8.83	0.05	0.06	-0.10	-0.06	0.04	0.15	0.27	-0.18	0.26	0.12	
12. Firm patent purchasing	5.28	63.67	0.01	0.03	-0.00	0.03	-0.01	-0.02	-0.00	0.05	-0.02	-0.01	-0.02
13. Firm inventor mobility	0.62	3.37	0.01	0.01	0.03	0.04	-0.01	-0.03	-0.01	0.04	-0.02	-0.03	-0.05
14. Firm rate of knowledge integration	0.13	0.17	0.18	0.11	0.03	0.22	0.04	0.12	0.28	0.35	0.50	0.17	0.14
15. Partner age	43.98	64.83	0.02	0.04	0.03	0.04	-0.02	-0.00	0.02	0.03	0.00	-0.03	0.03
16. Partner size	23832.70	39255.88	0.05	0.06	0.10	0.06	-0.02	-0.02	-0.05	0.05	-0.03	-0.02	-0.04
17. Partner R&D intensity	0.11	0.23	0.01	0.02	-0.09	-0.08	0.12	0.02	-0.05	-0.06	0.08	0.09	0.04
18. Partner solvency	1.94	3.16	-0.03	-0.02	-0.06	-0.03	-0.00	0.01	0.03	-0.04	-0.01	0.03	0.03
19. Partner GPE	27.34	52.62	0.11	0.11	0.01	-0.02	-0.03	0.04	0.03	-0.06	-0.02	0.04	0.19
20. Partner patenting experience	2904.36	7306.99	0.18	0.24	0.02	0.04	-0.04	-0.02	-0.06	0.02	-0.03	-0.01	-0.07
21. Partner knowledge cumulativeness	1.13	2.14	0.05	0.18	-0.03	-0.06	0.03	0.01	-0.03	-0.05	0.00	0.07	0.07
22. Partner reliance on industry knowledge	2.44	4.42	-0.00	0.04	-0.03	-0.07	0.03	0.03	-0.03	-0.05	-0.01	0.07	0.07
23. Partner scientific impact	11.88	14.23	0.03	0.05	0.04	0.01	-0.02	-0.04	0.19	-0.06	-0.03	0.01	0.27
24. Partner patent purchasing	3.57	36.19	0.07	0.19	0.09	0.05	-0.01	-0.02	0.04	0.05	-0.02	-0.03	0.01
25. Partner inventor mobility	0.53	2.81	0.01	-0.01	0.01	-0.02	-0.02	-0.02	-0.03	-0.01	-0.02	-0.01	-0.03
26. Business overlap	0.30	0.40	0.08	0.11	-0.09	-0.12	-0.05	-0.00	-0.12	-0.09	-0.02	0.12	-0.12
27. Cross-national distance	0.00	1.61	-0.02	0.01	0.03	0.03	-0.08	-0.05	0.02	0.03	-0.08	-0.11	-0.04
28. Joint partnering experience	0.34	1.37	0.22	0.16	0.09	0.16	-0.04	0.01	0.23	0.11	0.01	-0.04	0.10
29. Knowledge base relatedness	0.38	0.30	0.19	0.24	0.04	0.14	0.05	-0.02	0.19	0.11	0.03	-0.01	0.11
30. Patent co-applications	2.70	19.93	0.02	0.00	-0.01	-0.02	-0.02	-0.03	-0.02	-0.00	-0.02	-0.00	-0.02
31. Firm non-spillback citations to partner	166.01	709.18	0.53	0.49	0.06	0.15	-0.02	0.04	0.16	0.14	0.05	-0.03	0.06
32. Pre-alliance knowledge spillover	124.03	527.00	0.42	0.63	0.14	0.16	-0.02	-0.06	0.18	0.17	0.01	-0.05	0.01
33. Pre-alliance knowledge spillback	14.21	77.48	0.44	0.42	0.10	0.13	-0.02	-0.04	0.12	0.13	0.05	-0.03	0.01

	12.	13.	14.	15.	16.	17.	18.	19.	20.	21	22.	23.	24.	25.	26.	27.	28.	29.	30.	31.	32.
13.	0.04																				
14.	0.01	-0.02																			
15.	0.07	0.00	-0.01																		
16.	0.12	0.02	-0.07	0.22																	
17.	-0.02	-0.01	0.08	-0.12	-0.12																
18.	-0.02	0.00	-0.01	-0.19	-0.20	0.18															
19.	0.10	-0.01	-0.02	0.07	0.43	-0.05	-0.06														
20.	0.08	0.01	-0.03	0.23	0.36	-0.04	-0.11	0.38													
21.	0.04	0.00	-0.00	-0.06	0.03	0.04	-0.03	0.15	0.12												
22.	-0.02	-0.02	-0.00	-0.17	-0.07	0.10	0.03	0.01	-0.10	0.38											
23.	-0.00	0.02	0.02	-0.08	0.00	0.06	0.15	0.28	-0.05	0.15	0.18										
24.	0.12	-0.01	-0.01	0.04	0.03	-0.01	0.03	0.02	0.07	0.01	-0.02	-0.01									
25.	0.00	0.46	-0.02	-0.01	0.05	-0.02	0.01	0.02	-0.02	0.04	0.00	0.01	-0.02								
26.	0.04	-0.05	-0.03	-0.00	-0.08	0.06	0.01	-0.01	0.14	0.09	0.04	-0.04	0.04	-0.03							
27.	-0.02	0.02	-0.02	-0.05	-0.07	-0.00	0.06	-0.15	0.01	-0.10	-0.09	-0.11	-0.05	0.04	0.09						
28.	0.05	0.01	0.08	0.02	0.18	-0.03	-0.05	0.46	0.20	0.07	-0.00	0.11	-0.00	0.02	0.02	-0.12					
29.	0.04	-0.03	0.07	0.02	0.12	0.02	0.05	0.24	0.17	0.09	0.09	0.26	0.06	-0.04	0.15	-0.16	0.22				
30.	0.01	0.25	-0.01	0.01	0.06	-0.02	0.00	0.05	0.01	-0.01	0.00	0.02	-0.01	0.36	-0.00	0.02	0.03	-0.01			
31.	0.10	-0.02	0.23	0.12	0.12	-0.01	-0.06	0.27	0.30	0.08	-0.04	0.05	0.04	-0.01	0.14	0.00	0.43	0.26	0.00		
32.	0.04	0.00	0.10	0.04	0.07	0.02	-0.02	0.09	0.29	0.16	0.03	0.02	0.15	-0.02	0.12	-0.03	0.22	0.24	-0.01	0.41	
33.	0.03	-0.00	0.14	0.06	0.07	0.00	-0.04	0.13	0.22	0.07	-0.02	0.02	0.09	0.00	0.11	-0.01	0.22	0.20	-0.01	0.40	0.43

N = 1,539 dyads.

Table 4.5: Knowledge spillback in alliances versus non-alliance dyads. PPML regression for knowledge spillback

Variables	Alliance sample		Non-alliance sample		Nested Sample		
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)	
Control variables	Included	Included	Included	Included	Included	Included	
Firm knowledge cumulativeness	-0.189	-0.172	0.486+	0.273	0.050	0.027	
	(0.131)	(0.130)	(0.281)	(0.335)	(0.142)	(0.136)	
Firm reliance on industry knowledge	-0.377+	-0.488*	-1.745***	-1.805***	-0.740**	-0.761**	
	(0.229)	(0.211)	(0.489)	(0.491)	(0.266)	(0.264)	
Knowledge base relatedness	0.367***	0.456***	0.667***	0.635***	0.529***	0.577***	
	(0.073)	(0.072)	(0.103)	(0.112)	(0.075)	(0.068)	
Knowledge spillover	0.499***	0.604***	0.530***	0.448*	0.710***	0.749***	
	(0.107)	(0.116)	(0.156)	(0.207)	(0.132)	(0.203)	
Knowledge spillover ^{2}	-0.057***	-0.057***	-0.031***	-0.024**	-0.069***	-0.075***	
	(0.011)	(0.011)	(0.008)	(0.009)	(0.013)	(0.016)	
Knowledge spillover ×		-0.182***		0.038		-0.006	
Knowledge base relatedness		(0.032)		(0.054)		(0.060)	
Knowledge spillover ×		0.194**		0.172		-0.069	
Firm knowledge cumulativeness		(0.068)		(0.120)		(0.128)	
Knowledge spillover ×		-0.303**		0.011		-0.039	
Firm reliance on industry knowledge		(0.097)		(0.167)		(0.272)	
Alliance					0.788***	0.683***	
					(0.140)	(0.140)	
Knowledge spillover × Alliance					-0.319**	-0.269	
					(0.118)	(0.187)	
Knowledge spillover ^{2} × Alliance					0.035*	0.039*	
					(0.014)	(0.017)	
Knowledge spillover ×						-0.107+	
Knowledge base relatedness × Alliance						(0.063)	
Knowledge spillover ×						0.219	
Firm knowledge cumulativeness × Alliance						(0.139)	
Knowledge spillover ×						-0.218	
Firm reliance on industry knowledge × Alliance						(0.274)	
Chi-squared of joint effect of Alliance and its					13.43**	41.83***	
moderated functions					(p = 0.001)	(p = 0.000)	
Control function	0.162***	0.158***	0.054	0.049	0.140***	0.137***	
	(0.022)	(0.022)	(0.055)	(0.060)	(0.020)	(0.022)	
Year fixed effects	Included	Included	Included	Included	Included	Included	
Industry fixed effects	Included	Included	Included	Included	Included	Included	
Country fixed effects	Included	Included	Included	Included	Included	Included	
Constant	2.121***	2.150***	0.314	0.313	1.085***	1.152***	
	(0.110)	(0.108)	(0.267)	(0.271)	(0.151)	(0.139)	
Observations	1,539	1,539	1,539	1,539	1,539	3,078	3,078
Log pseudo-likelihood	-13839	-12858	-9819.1	-9722.5	-13839	-26846	-25940

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

Figure 4.5: Knowledge spillover by knowledge spillback.
Comparison of alliances versus non-alliance dyads

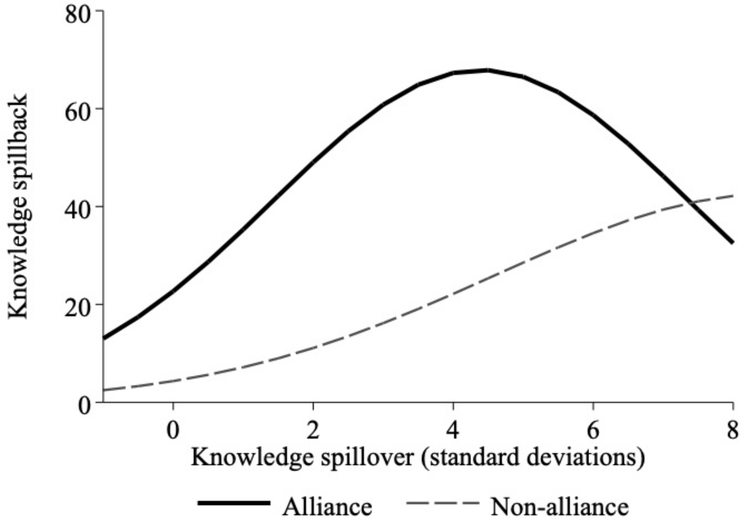

Table 4.6: Descriptive statistics and pairwise correlations for patent-level dataset

Variables	Mean	Std. Dev.	1.	2.	3.	4.	5.	6.
1. Scientific impact	9.19	25.76						
2. Knowledge spillback	0.03	0.17	0.03					
3. Inbound knowledge spillover	0.12	0.33	0.06	-0.07				
4. Backward citations	15.10	46.83	0.06	0.09	0.06			
5. Technology codes	2.83	2.84	-0.08	-0.01	0.02	0.07		
6. Granted patent	0.49	0.50	0.03	0.04	0.07	0.16	0.18	
7. Co-application	0.35	0.48	0.01	-0.03	0.05	-0.00	0.01	0.00

N = 1,938,202 patent applications.

Table 4.7: Patent-level negative binomial regression for scientific impact

Variables	Model (1)	Model (2)	Model (3)	Model (4)
Backward citations	0.002***	0.002***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
Technology codes	-0.033***	-0.033***	-0.033***	-0.033***
	(0.002)	(0.002)	(0.002)	(0.002)
Granted patent	0.823***	0.823***	0.823***	0.824***
	(0.004)	(0.004)	(0.004)	(0.004)
Co-application	0.075***	0.073***	0.075***	0.072***
	(0.018)	(0.018)	(0.018)	(0.018)
Inbound knowledge spillover		0.047***		0.059***
		(0.005)		(0.005)
Knowledge spillback			0.122***	0.138***
			(0.008)	(0.008)
Year fixed effects	Included	Included	Included	Included
Patent class fixed effects	Included	Included	Included	Included
Firm fixed effects	Included	Included	Included	Included
Industry fixed effects	Included	Included	Included	Included
Constant	-3.321***	-3.296***	-3.312***	-3.279***
	(0.167)	(0.167)	(0.167)	(0.167)
Observations	1,938,202	1,938,202	1,938,202	1,938,202
Log likelihood	-6385388	-6385273	-6385142	-6384965

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

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APPENDIX: DATABASE CONSTRUCTION

This appendix describes the methodology used to assemble the databases underlying the empirical analyses in each of the dissertation's chapters. Although the three chapters rely on distinct data and measures corresponding to each chapter's research goal and sampling requirements, the same methodology was applied for constructing the underlying databases. I combined data from three main sources: (a) alliance data from SDC Platinum (Refinitiv, 2020), (b) patent data from Orbis Intellectual Property (Orbis IP) (Bureau van Dijk, 2020a), and (c) firm data from Compustat (Standard & Poor's, 2020a; 2020b). Furthermore, I included subsidiary data from Orbis (Bureau van Dijk, 2020b) and LexisNexis Corporate Affiliations (LexisNexis, 2020), mergers and acquisitions data from SDC Platinum (Refinitiv, 2020) and Zephyr (Bureau van Dijk, 2020c), as well as historical company name changes from CRSP Monthly Stock (Center for Research in Security Prices, 2020). I matched SDC alliance participants to Compustat parent firms, subsidiaries to their Compustat parent firms, acquisition data to Compustat parent firms and their subsidiaries, and patent data from Orbis IP to Compustat parent firms and their subsidiaries.

Data collection and matching firms between databases

I relied on alliance data from SDC Platinum to select firms and their alliances. Firm-level accounting and financial data were obtained from Compustat, accessed via WRDS (Wharton Research Data Services). The Compustat database comprises two sections: One section contains data about firms listed in North America (Compustat North America), the other contains data about firms listed outside of North America (Compustat Global). Since I sampled alliances formed by firms that are listed in various countries, I considered firms from both Compustat North America and from Compustat Global. In SDC each alliance participant firm is identified by its six-digit CUSIP number (the acronym derives from "Committee on Uniform Identification Procedures").

As CUSIP identifiers are also available in Compustat's North America database, I relied on the firms' CUSIP to match SDC alliance participants to firms listed in Compustat North America. Compustat's Global database instead identifies firms via their ISIN (International Securities Identification Number) but does not provide their CUSIP. Hence, matching of SDC alliance participants to firms listed in Compustat Global was achieved by using combinations of the firms' company names, locations, and stock ticker symbols.

Patent data were obtained from Bureau van Dijk's Orbis IP database. Orbis IP contains data on more than 120 million corporate patents worldwide. The patent data of Orbis IP are compiled from different sources, including LexisNexis IP, PATSTAT, and the databases of various national patent offices. Patents in Orbis IP are linked to their applicant firms[1] via their Bureau van Dijk ID (BVDID), an alphanumeric unique company identifier. The BVDID consists of a country code plus the national company registration number (e.g., the Federal Employer Identification Number in the United States, or the "Codice Fiscale" in Italy). To match Compustat firms to Orbis IP patent applicants, I used the firms' ISIN, which is available in both Compustat Global and in Orbis IP. Since Compustat North America does not provide the ISIN identifier, firms listed in North America were matched to Orbis IP patent applicants using a combination of their company names, locations, and ticker symbols.

I manually verified all matches between SDC, Compustat, and Orbis IP, and I tracked changes in the firms' names, legal forms, or stock identifiers to resolve discrepancies. To obtain a list of historical names and stock identifiers along with their date of change, I relied on historical securities data from WRDS's "CRSP Monthly Stock" file for US-listed firms, and on the historical

[1] The applicant of a patent is typically the inventor of the technology (exceptions apply after the death of an inventor). If an invention was made by an employee, the employer firm becomes the applicant of the patent, unless otherwise specified in the inventor's employment contract.

names listed in Orbis, or on filings with national registers for non-US-listed firms.

Ownership structure and timeline

I assume that the knowledge embodied by a patent enters the knowledge base of its applicant firm at the priority date.[2] As any type of property, a patent may be sold by the applicant to another entity, which is termed reassignment. Changes of patent ownership are registered with the responsible patent office, resulting in a change of the patent's assignee. Whereas the patent's assignee (i.e., the owner) can change over time, the original applicant remains the same. I assume that the knowledge embodied by a patent stays with the applicant firm rather than the assignee, should assignee and applicant differ at the time of an alliance.[3] However, because a patent's applicant is not always the legal entity in which the invention actually took place (some firms maintain dedicated subsidiaries for managing the firm's intellectual property), I construct consolidated portfolios of patent applications that account for applications filed by each Compustat parent firm along with applications filed by the firm's subsidiaries. To this end, I consider a firm's wholly-owned subsidiaries[4] throughout five levels of corporate ownership.

To account for changes in a firm's corporate structure over time, I constructed a timeline of subsidiary ownership. I obtained data on the Compustat parent firms' corporate structures from Orbis and LexisNexis Corporate Affiliations. In order to reconstruct the subsidiary ownership at

[2] The priority date is the first date of filing of a patent application, anywhere in the world (usually in the applicant's national patent office). It is the closest date to the actual time of invention that is being documented in a patent (OECD, 2009). If for the same invention a patent application was filed in different countries, the priority date of each patent will be the same, while the application dates may differ for each patent.
[3] This assumption is backed by theoretical considerations: To apply for a patent, a firm has to successfully acquire, internalize, and implement the relevant knowledge, which can be seen as a strong indicator that the firm actually possesses the knowledge embodied in the patent (Cohen & Levinthal, 1990). By contrast, a patent of which the firm only acquires ownership does not necessarily reflect the firm's knowledge, given that the patented technology was invented by an unrelated party. Hence, although the firm has purchased the right to dispose of the knowledge contained in such a patent, it may or may not have absorbed it. That is because the absorption of knowledge requires the firm to apply and develop its acquired knowledge rather than merely owning and storing it (Zahra & George, 2002).
[4] I focus on wholly-owned subsidiaries because partial ownership is a weak indicator for operational control and knowledge access. Furthermore, in conglomerates or business groups, cross holdings between legally distinct constituent firms can be extensive, diluting firm boundaries when defined based on partial ownership.

the time of an alliance, I identified any completed M&A deals in which the firm either gained or ceded full ownership in any of its subsidiaries. Data on the timing of the M&A deals were obtained from SDC as well as from Bureau van Dijk's Zephyr database. I used information from the previously described matching between SDC's CUSIP and Orbis's BVDID to identify M&A deals in which the Compustat firms were either the acquirer or divesting party. To match SDC acquisition targets to Orbis subsidiaries, I relied on a combination of their ticker symbols and standardized company names.[5] To avoid erroneous matches, I cross-checked in Orbis whether each matched target is (or was) a subsidiary of the acquiring or divesting firm, respectively. Matching Zephyr targets to Orbis subsidiaries was achieved by using the BVDID, which is available as an identifier in both databases. In ambiguous cases I also relied on the Corporate Affiliations database to manually verify matches. A single entry was retained for targets identified in both SDC and Zephyr.

While I account for patents of subsidiaries throughout five levels of ownership, data about ownership changes at lower levels were not available for each transaction. Consider the case where parent firm A owns subsidiary A1, and subsidiary A1 owns subsidiary A1a. Eventually, firm A divests subsidiary A1. Unless specified in the data, it remains unclear what happens to A1a in this case. For most M&A transactions I could resolve such uncertainty by relying on data available in the Corporate Affiliations database. However, this was not feasible for transactions involving relatively small subsidiaries, on which Corporate Affiliations does not have data. In the absence of other information, I assumed that A1a is divested along with A1. By analogy, I assume that in an acquisition, direct subsidiaries of an acquired target were not previously owned by the acquiring firm, unless the data indicated otherwise.

[5] To standardize company names, I omitted the legal form endings and other general words (e.g., INC, CO, CORP, LTD, PLC, LAB), to maximize match rates (e.g., "XEROX CORP" was standardized to "XEROX," "ABBOTT LABORATORIES" to "ABBOTT," "SAMSUNG ELECTRONICS CO LTD" to "SAMSUNG ELECTRONICS").

Assigning patents to firms

Before assigning the patent data extracted from Orbis IP to Compustat parent firms and their subsidiaries, I cleaned the patent data in several steps. First, I eliminated patents with incomplete or erroneous data records that had neither a priority date nor an application date assigned to them. Second, for patents that had an application date assigned but no priority date, I used the application date in lieu of the priority date. This applied to recent patents that do not have any other family members or related documents. For these patents the priority date and application date are equivalent. Third, I split patent applications into separate entries for each applicant, creating duplicate entries for patents with co-applicants. This allowed for assigning the same patent to multiple firms if the patent was co-applied for by more than one firm and/or subsidiary.

Next, I assigned the cleaned set of Orbis IP patents to their applicant firms and subsidiaries. While in Orbis IP most patents are linked to their applicant firms via their BVDID, not all patents have an applicant-firm BVDID assigned to them. Some of these patents belong to defunct entities for which Orbis IP does not keep an active BVDID. Other patents were not yet indexed by Orbis IP to their applicant firms at the time of data collection.[6] To match these patents to the firms, I used the list of current and historical company names as they were recorded in Compustat, Orbis, and CRSP Monthly Stock. I assigned BVDIDs to the unmatched patents by matching the patents' applicant names as indicated in Orbis IP to the sampled firms' company names. To do so, I relied on the cosine similarity of their vectorized character strings and on the Levenshtein edit distance, using R's "stringdist" package (van der Loo, 2014). To avoid erroneous matches, I also required that for a patent to be assigned to a firm, the matched applicant's name should not be more similar

[6] Orbis IP regularly updates its database, including historical data. For patents with data updates, new links to company identifiers have to be created and existing links have to be updated. This can cause temporarily missing links in patents with recent data updates.

to the company name of any other sampled firm. To ensure accuracy, I manually compared the unique matched applicant names with the firms' current and historical company names, and I dropped those few patents whose matched applicant names did not unequivocally resemble the firms' current or historical names.

After assigning the patents to their applicant firms, I linked subsidiary patent applications to their parent firm BVDID to generate portfolios of patent applications at the parent-firm level. I removed duplicate patent entries that were generated in a parent firm's portfolio if the parent and a subsidiary were co-applicants of a patent. I assumed that the knowledge embodied in patent applications by an acquired subsidiary becomes accessible to the new parent after the completion of the acquisition. Therefore, in an alliance, the pool of the partner's patents to which the firm can potentially cite includes patents that were applied for by the partner's subsidiaries before they were acquired. However, I discarded any patents by acquired subsidiaries that were applied for prior to the acquisition from the firm's pool of citing patents. I further discarded patents from both the pools of citing and cited patents that were applied for by a subsidiary after it had been sold or divested (Puranam & Srikanth, 2007). The implications of these assumptions are detailed in the table below:

Priority date of patent is	Patent of subsidiary can be	
	i) a citing patent	ii) a cited patent
a) before acquisition	No	Yes
b) after acquisition	Yes	Yes
c) before divestiture	Yes	Yes
d) after divestiture	No	No

Consolidating patent families

Each patented invention can comprise multiple patent documents—e.g., an initial application, a revised application, the granted patent, a supplementary correction, etc. Some companion documents contain additional citations, technology classifications, or other information that are important to consider, but which are not contained in the main document of the patent application. Yet, because each document refers to the same patent application, keeping separate entries for each document can generate duplicated data. To avoid such duplicates, I consolidated patent entries across all documents that are associated with a given patent application. Each of these documents is distinguished from the main document via a "kind code" suffixed to its publication number (e.g., A1, A2, B1). To create aggregate entries per patent application, I stripped the kind codes of the patent publication numbers for each companion document and collapsed the data across all documents with the same stripped publication number. USPTO patent applications at this level of consolidation formed the basis for all patent-based measures computed for chapter three of the dissertation, as well as for certain robustness tests performed in chapter one and chapter two.

A patented invention can also comprise multiple patent applications filed with different patent offices. Collectively, these patent applications are called a "patent family." According to the OECD, "a patent family comprises all the patent documents covering the same invention. As a rule, a patent family consists of the priority application to a national office and equivalent foreign versions of the applications" (1994: 28). Relying on patent families helps to overcome the home-country bias of single patent office applications. This bias may arise if firms prefer applying for patents at their national patent office. For example, many European firms file their patents at the EPO and not at the USPTO. As a result, solely relying on USPTO patent applications may underestimate the patenting activity outside North America (de Rassenfosse, Dernis, Guellec, Picci, & de la Potterie, 2013). To consolidate patent data at the family level, I relied on the EPO's DOCDB (Document Database) definition of the patent family. Each patent in the DOCDB family covers the same technical content. Patent applications that are members of one patent family have the same priority date in common with all other members. However, the number of citations, documents cited, or associated technology classifications can differ between family members, as they are subject to the different requirements of each patent office. Patent families may contain three different types of patents:

1. Extension: An application filed in a patent office other than the priority office. If the extension does not introduce new technical content, it becomes part of the same family as the priority application. Still, content and format of the application may vary to some degree depending on the requirements of the respective patent office (e.g., some patent offices may require more citations to be included than others).
2. Continuation: An application where claims have been added to an invention that has been disclosed in the priority application. If the continuation does not introduce new technical content, it becomes part of the same family as the priority application.
3. Division: An application that is covering a distinct invention which has already been disclosed in the priority application. If the division does not introduce new technical content, it becomes part of the same family as the priority application.

The above patent types are not mutually exclusive, as any combination of them is possible. Hence, they are not formally distinguished by the issuing patent offices. I generated a unique identifier for each patent family, consisting of the member patents' alphabetically ordered publication numbers. I consolidated all patent data at the family level by collapsing the member patents' entries under the family identifier and removing duplicated entries. Collapsing patent data such as citations at the patent-family level purges the data of redundant information and mitigates biases arising from inflationary patenting and citing behavior of applicant firms (Kuhn, Younge, & Marco, 2020). Each consolidated patent family consists of at least one patent (which is the case if there are no other family members). When the same invention was applied for a patent in three patent offices, the patent family consists of at least three family members. Patent families consisting of USPTO, EPO, and JPO patents formed the basis for all patent-based measures computed for chapters one and two of this dissertation, as well as for robustness tests performed in chapter three.