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For the degree of Doctor of Philosophy

Is approved by the final examining committee:

Thomas H. Brush
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Javier Gimeno

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Approved by Major Professor(s): Thomas H. Brush and Jeffrey J. Reuer

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Head of the Departmental Graduate Program Date

# THREE ESSAYS ON COMPETITION AND COOPERATION IN R&D ALLIANCES

A Dissertation

Submitted to the Faculty

of

Purdue University

by

Wonsang Ryu

In Partial Fulfillment of the

Requirements for the Degree

of

Doctor of Philosophy

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This dissertation is dedicated to my parents and my wife.

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# ABSTRACT

Ryu, Wonsang. Ph.D., Purdue University, May 2016. Three Essays on Competition and Cooperation in R&D Alliances. Major Professors: Thomas H. Brush and Jeffrey J. Reuer.

In this dissertation, I investigate the interplay between competition and cooperation in R&D alliances. The alliance literature on this issue has emphasized that product market rivalry (i.e., market overlap) between partnering firms aggravates cooperation hazards by increasing the private benefits from opportunism. However, drawing on the multimarket competition literature, I maintain that market overlap between alliance partners can rather curb opportunism by partners because the multimarket contact between them might increase the expected costs of opportunistic behaviors by enabling broad retaliation against such behaviors across the shared markets. Based on this argument, I theorize and corroborate that the mutual forbearance from opportunism that multimarket contact generates not only promotes the formation of R&D collaborations in Essay 1, but also substitutes for hierarchical governance structures in R&D alliances in Essay 2. In Essay 3, I also extend the prior literature on competitive aspects of R&D collaborations that has been mainly interested in knowledge protection concerns in alliances between direct rivals. I join the alliance literature with the agglomeration literature to argue and show that geographic co-location between an allying firm's partner and the major rivals of the allying firm introduces potential indirect

paths of knowledge leakage to rivals, making the allying firm more likely to employ defense mechanisms such as using equity structures and reducing task interdependence.

# CHAPTER 1. INTRODUCTION

Although competition and cooperation are fundamental concepts in the field of strategy and are inherently interdependent, the research streams on the two concepts have often tended to be developed separately, resulting in a lack of understanding on the interplay between them. In a similar vein, the alliance literature, one of the main research streams on cooperative strategy, has also paid relatively less attention to the competitive context of inter-firm collaborations. Though scant, however, there is a stream of research called "competition-oriented cooperation studies (Chen, 2008)"[1], and this literature has contributed to our understanding on the interplay between competition and cooperation by investigating how competitive relationships between alliance partners affect the outcome of their collaborations.

The key argument commonly made by the competition-oriented cooperation literature is that competition undermines cooperation (Harrigan, 1988; Oxley & Sampson, 2004; Park & Russo, 1996), that is, competitive relationships between collaboration partners incentivize them to undertake opportunistic behaviors (e.g., shirking,

[1] The competition-oriented cooperation studies belong to the broad competition-cooperation research that also includes co-opetition studies and cooperation-oriented competition studies according to Chen's (2008) categorization. The competition-oriented cooperation studies are distinguished from the co-opetition studies in that the former focus on partner firms' competition and cooperation within their partnerships, such as strategic alliances, while the latter mainly examine the simultaneous pursuit of competitive and cooperative strategies at the firm level. In addition, competition-oriented cooperation studies and cooperation-oriented studies are opposite to each other in terms of the cause-effect relationship of interest. The former are interested in how competition between partners affect their collaborations, while the latter use cooperation-related variables to predict competitive concerns.

misappropriation, and hold-up) by increasing the return from such behaviors. As a result, collaborations between rivals tend to fail or need extra remedies for these contractual hazards. Furthermore, this stream of research has also claimed that as the partners' competitive domains come to a complete overlap, perfect cooperation in their collaboration approximates a zero-sum game and thus, the cooperation-eroding effect of competition increases with the market overlap between partners (Oxley & Sampson, 2004). Along this line of thought, prior empirical work in this research stream has also tended to use co-presence in the same broadly-defined domain (e.g., 4-digit Standard Industrial Classification [SIC]) to conceptualize the competitive tension between collaboration partners, and it has shown that alliances between partners from the same domain tend to be short-lived and have a narrow scope (Chung, Singh, & Lee, 2000; Gulati, 1995a; Oxley & Sampson, 2004; Park & Russo, 1996; Park & Ungson, 1997).

Although the prior work on the competitive aspects of collaboration has contributed to our understanding on the interplay between competition and cooperation, I observe three important research gaps in the literature. First, the literature has exclusively focused on the benefit of opportunistic behaviors in collaborations between rival firms, ignoring the possibility of the partner's competitive reactions to the opportunistic behaviors and the associated cost. As firms competitively respond to the actions undertaken by others (Porter, 1980; Smith, Grimm, Gannon, & Chen, 1991), opportunistic behaviors also can invoke retaliation, and the loss caused by the retaliation might be larger than the initial gain from the opportunistic behaviors. Furthermore, the cost caused by retaliation against opportunism might increase with the degree of market overlap between partner firms because broad retaliation across more markets can damage the partner firm more seriously. Therefore, the possibility of a competitive response to opportunism and the number of market contacts should be considered to estimate the net effect of competition between collaboration partners on their inclination toward opportunism.

Second, while the existing literature has paid substantial attention to how the competitive relationships in end-product markets that alliance partners have affect their cooperation, it has not been interested in how the end-product market rivalry interacts with other types of inter-firm relationships between alliance partners in influencing the partner's decisions concerning the partnership. Firms compete not only in end-product markets, but also in factor markets. In addition, firms are embedded in cooperative relationships that they have formed through prior cooperation experience. Therefore, considering these distinct interfirm relationships that alliance partners have outside an alliance might enhance our understanding on the interplay between competition and cooperation.

Third, while the competition-oriented cooperation literature has been mainly interested in direct competitive relationships between partner firms, it has paid little attention to indirect competitive linkages surrounding collaborations. In inter-firm partnerships (particularly R&D alliances), valuable knowledge and technologies are inevitably shared between partner firms and therefore, they are concerned about knowledge leakage to the partners, especially when they collaborate with their rivals. This direct knowledge leakage to partnering rivals has been extensively discussed in the literature (Dussauge, Garrette, & Mitchell, 2000; Hamel, Doz, & Prahalad, 1989; Khanna, Gulati, & Nohria, 1998; Oxley & Sampson, 2004). However, knowledge leakage to rivals takes place not only through direct interactions, but also through indirect paths. Although some recent research has begun to address this issue of indirect knowledge leakages (Hernandez, Sanders, & Tuschke, 2015; Mesquita, Anand, & Brush, 2008; Pahnke, McDonald, Wang, & Hallen, 2015), our understanding on this issue is still limited, at least partially due to the prior research's exclusive focus on indirect paths that *formal* interfirm relationships form.

In this dissertation, I aim to fill these three research gaps using R&D alliances in high-technology industries as a theoretical context, because R&D alliances are particularly prone to the risk of opportunism and entail a high level of knowledge loss risk. More specifically, in Essay 1 (Chapter 2), I combine the multimarket competition literature with the alliance literature on partner selection to argue that multimarket contact[2] between alliance partners can facilitate the formation of R&D collaborations by generating mutual forbearance from opportunism.

The multimarket competition literature has argued and shown that as two firms compete against each other in more markets, they mutually forbear from initiating attacks for fear of broad retaliation by the attacked firm across the multiple shared markets (Baum & Korn, 1996; Evans & Kessides, 1994; Gimeno & Woo, 1996; Haveman & Nonnemaker, 2000; Phillips & Mason, 1996). Accordingly, in R&D alliances featuring the risk of opportunism by partners (Pisano, 1989), mutual forbearance generated by multimarket contact between partner firms might also be able to curb opportunism, as opportunistic behaviors are also a form of competitive action that partner firms can

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[2] In this dissertation, I use the terms market overlap, (multi)market contact, and shared markets interchangeably.

undertake within their collaboration. Based on this argument, I claim that the reduced level of the risk of opportunism makes multimarket rivals attractive to each other as a partner for technology cooperation, promoting the formation of R&D alliances between them. I also maintain that this effect is more pronounced not only for technology partnerships with high technological uncertainty, but also for those with a broader vertical scope, as both cases entail greater contractual hazards.

By joining the multimarket competition literature with the alliance literature, Essay 1 (Chapter 2) contributes to the competition-oriented cooperation literature by theorizing and corroborating that market overlap between alliance partners can reduce the risk of opportunism by increasing its cost. Unlike the conventional view that only considers the benefit of opportunism in an agreement with a rival, this argument offers a novel and more complete perspective on the effect of competition between alliance partners on the risk of opportunism by considering the partners' possible retaliatory response to opportunism and the consequential costs.

In Essay 2 (Chapter 3), I examine how multimarket contact between R&D alliance partners affects their alliance governance choices. The conventional view has been that as direct competition between alliance partners aggravates the risk of opportunism by partners, they need to employ more hierarchical governance structures as a remedy for the risk, as they have a higher level of market overlap between them. However, based on the same theory developed in Essay 1 (Chapter 2), I argue that multimarket contact rather reduces the need for hierarchical governance modes by generating mutual forbearance from opportunism. In addition, I further investigate how different dyadic relationships between alliance partners (i.e., competitive relationships in end-product markets and factor markets and previous cooperative relationships) interplay with one another in affecting the partner firms' proclivity toward opportunism and governance choice. Specifically, drawing on the recent multimarket competition literature on factor market rivalry (Markman, Gianiodis, & Buchholtz, 2009), I claim that factor market rivalry intensifies mutual forbearance and thus, the substituting effect of multimarket contact for hierarchical governance structures is intensified when the alliance partners pursue similar technologies. In addition, based on the literature on relational embeddedness (Gulati, 1995a, 1995b), I maintain that the same substituting effect is weakened when alliance partners have previous cooperative ties, because prior collaborative experience and multimarket contact play a redundant role in reducing the risk of opportunism by partners.

Essay 2 (Chapter 3) also contributes not only to the competition-oriented cooperation literature, but also to the relational embeddedness perspective in the alliance literature by showing that three distinct dyadic relationships between alliance partners, i.e., end-product market rivalry, factor market rivalry, and prior collaborative relationships, function as important boundary conditions to each other. The results suggest that the two literatures complement each other and the simultaneous consideration of the findings provides a more complete and comprehensive understanding on how interfirm relationships in which alliance partners are embedded determine cooperation hazards.

In Essay 3 (Chapter 4), I attempt to fill the third research gap that the literature has been mainly interested in knowledge protection concerns in alliances between direct rivals and has paid little attention to indirect competitive linkages surrounding collaborations. Drawing on the agglomeration literature, I maintain that geographic co-location between an allying firm's partner and the major rivals of the allying firm is an important but understudied factor that creates indirect paths of knowledge leakage to the rivals. The agglomeration literature has shown that geographic co-location increases the likelihood of knowledge spillovers to neighboring firms (Jaffe, Trajtenberg, & Henderson, 1993), as well as transactions with them (Narula & Santangelo, 2009). Based on these findings, I maintain that as there are more rivals co-located with the allying firm's partner, the allying firm is more exposed to the risk of knowledge loss to the rivals and is thus more likely to employ defense mechanisms, such as (1) the inclusion of equity arrangements to benefit from enhanced monitoring, control, and incentive alignment that equity involvement can offer and (2) the reduction of task interdependence to reduce knowledge sharing. I further claim that the effects of partners' co-location with rivals on governance choice and task interdependence are intensified by the nearby rivals' absorptive capacity.

Based on the results from Essay 3 (Chapter 4), I also contribute to the emerging literature on indirect competitive linkages by showing that the geographic co-location between an allying firm's partner and the major rivals of the allying firm increases the allying firm's knowledge protection concerns. Geographic co-location as a factor creating indirect paths of knowledge loss to rivals adds two interesting points to the literature. First, while previous research has exclusively focused on indirect channels via *formal* inter-firm relationships (Hernandez et al., 2015; Pahnke et al., 2015), this approach based on the geographic dimension shows that the literature needs to extend the scope of inquiry to *informal* paths, as well. In addition, geographic co-location aggravates the risk of knowledge loss through unintentional knowledge spillovers. Therefore, firms need to be concerned not only about the *misappropriation* of knowledge but also about the risk of unintentional knowledge *spillovers* in R&D alliances.

For an empirical analysis, I use the biopharmaceutical industry as an empirical context for all three essays for several reasons. First, the biopharmaceutical industry is a high-technology industry where R&D alliances are regarded as an important means of R&D activities and thus are frequently observed (Hagedoorn, 2002). Second, the biopharmaceutical industry features clear market definitions based on therapeutic classes that are widely accepted and commonly used by U.S. government authorities and industry players (e.g., cholesterol regulators, anti-ulcerants, and anti-psychotics). As defining markets is critical in all three essays, the clear market definition in the industry is of crucial benefit to this dissertation and for the same reason, prior work in the multimarket competition literature has been carried out in the industry (e.g., Anand, Mesquita, & Vassolo, 2009). Third, the biopharmaceutical industry is characterized by agglomeration (Folta, Cooper, & Baik, 2006). Because Essay 3 (Chapter 4) focuses on the geographic co-location between an allying firm's partner and its major rivals as a theoretical factor to aggravate the allying firm's concern about knowledge leakage to its rivals, I need an empirical setting where firms agglomerate, and the biopharmaceutical industry meets this condition well.

In summary, this dissertation investigates the effects of the direct and indirect competitive relationships alliance partners have outside an alliance on partner selection, governance choice, and task interdependence in R&D alliances. I draw on insight from the multimarket competition literature and the agglomeration literature to shed new light on the competitive aspects of R&D collaborations. Based on the findings from the multimarket competition literature, I argue and show that multimarket contact can not only promote the formation of R&D collaborations, but also substitute for hierarchical governance structures for the collaborative R&D efforts by increasing the costs of opportunism that retaliation can cause. In addition, I join the agglomeration literature with the alliance literature on knowledge protection concerns to theorize that the geographic co-location between an allying firm's partner and the major rivals of the allying firm creates indirect paths of knowledge leakages to rivals, thereby affecting the allying firm's decisions on governance modes and task interdependence. The three studies contribute to the literature on the competitive context of collaborations with new theories and findings.

# CHAPTER 2. THE EFFECT OF MARKET OVERLAP ON PARTNER SELECTION FOR TECHNOLOGY COOPERATION

## 2.1 Introduction

Technology cooperation refers to "interfirm cooperation for which a combined innovative activity or an exchange of technology is at least part of their agreement," and this interfirm arrangement includes various modes ranging from licensing agreements to R&D joint ventures (Hagedoorn, 1993). Rapid technological changes characterizing today's economy render technology cooperation between firms more important than ever to maintain competitive advantages. Since selecting appropriate partners is one of the most critical factors to determine success or failure of any interfirm partnerships (Kale & Singh, 2009), the literature has extensively investigated who partners whom (Gimeno, 2004; Gulati, 1995a; Li, Eden, Hitt, & Ireland, 2008; Reuer & Lahiri, 2014; Rothaermel & Boeker, 2008). Although the literature has tended to focus on resource complementarity as a criterion for partner selection, it has also suggested that other criteria also become critical depending on the partnership context (Kale & Singh, 2009). In particular, when partners' behaviors are difficult to observe and the outcomes of collaborations are highly uncertain (Eisenhardt, 1989; Kirsch, 1996), the risk of opportunism by partners becomes a key criterion for partner selection (Shah & Swaminathan, 2008). Since such exchange hazards often surround technology cooperation (Nelson & Winter, 1977; Pisano, 1989), the risk of opportunism is an important criterion for partner selection for technology cooperation.

In the literature investigating the risk of opportunism by partners, the relationships between potential partners have received substantial scholarly attention. For instance, many studies have supported the idea that previous cooperative relationships between potential partners—prior ties—reduce the risk of opportunism (Dyer & Singh, 1998), therefore making firms select previous partners repetitively (Gulati, 1995a). By contrast, less attention has been paid to how competitive relationships between prospective partners—in particular, market overlap in end-product markets—can have an impact on partner selection. Extant research on market overlap and opportunism has tended to regard market overlap between potential partners as a factor increasing the propensity for opportunism by partners and *ex post* conflicts (Oxley & Sampson, 2004; Park & Russo, 1996). This is because market overlap between potential partners incentivizes the partners to behave opportunistically by increasing the payoff from such behaviors in their partnerships (Khanna et al., 1998). Although this argument has been rarely applied to partner selection, it leads to the prediction that firms would avoid partners with market overlap for technology cooperation at the margin. However, the multimarket competition literature in industrial organization economics and strategy, to which the cooperative strategy literature has paid little attention, provides a novel prediction opposite to the conventional view: market overlap between potential partners reduces the risk of opportunism and therefore facilitates technology partnerships.

More specifically, the multimarket competition literature argues that as firms share more markets, they mutually forbear from taking aggressive actions for fear of broad retaliation across the shared markets (Bernheim & Whinston, 1990; Edwards, 1955). This mutual forbearance hypothesis has been corroborated by many empirical studies showing that multimarket overlap between firms reduces attacks such as price cuts (Gimeno & Woo, 1996; Hannan & Prager, 2004), market entry (Baum & Korn, 1996; Fuentelsaz & Gómez, 2006), and advertising (Strickland, 1985). In this paper, I link this mutual forbearance generated by market overlap to the risk of opportunism by partners. That is, I argue that since opportunistic behaviors are a kind of aggressive action that partners can take in their partnerships, mutual forbearance can also curb such behavior just as it does other kinds of attacks. Based on this argument, I claim that reduced opportunism between partners with market overlap makes them more likely to partner with each other for technology cooperation. Furthermore, I also examine some contingencies that shape this relationship. Given that the preference for partners with low risk of opportunism becomes stronger for cooperative agreements entailing a higher level of contractual hazards, I investigate how technological uncertainty and vertical scope—which are known to increase exchange hazards—condition the effect of mutual forbearance on partner selection.

My theory and empirical results obtained from the global biopharmaceutical industry contribute not only to the literature on partner selection but also to the broader alliance literature by providing a novel view on market overlap and interfirm cooperation. For instance, by linking market overlap to lower resource complementarity, previous research has typically argued that since firms present in the same market niches are likely to possess redundant assets rather than complementary assets, they are unlikely to enter into a partnership (Chung et al., 2000; Gulati, 1995a; Rothaermel & Boeker, 2008).

However, tying market overlap to the risk of opportunism by partners rather than resource complementarity, I claim that market overlap mitigates the risk of opportunism by partners and therefore facilitates technology cooperation. Partners' inclination towards opportunism takes up more importance as a criterion to evaluate and select partners for technology cooperation where the observability of partners' behaviors and the predictability of outcome are inherently low (Nelson & Winter, 1977; Pisano, 1989; Shah & Swaminathan, 2008). My arguments and findings therefore highlight the importance of considering the multimarket context of partnerships and the potential for mutual forbearance from opportunism during their formation of technology cooperation (Ariño & Ring, 2010; Hitt, Ahlstrom, Dacin, Levitas, & Svobodina, 2004; Li et al., 2008; Luo, 1997; Shipilov & Li, 2010) and I identify important boundary conditions for the effect of market overlap on partner selection.

The way that I interpret the impact of market overlap on opportunism by partners is also novel. Previous research has suggested that as two partners share more markets, the benefit of opportunistic action within the collaborative agreement increases and therefore the partners are exposed to a greater risk of opportunism (Oxley & Sampson, 2004). Although this argument provides a useful insight into the incentives partners have in the collaborative agreement, I suggest that it is also necessary to account for the partners' possible responses against opportunism and the related costs causes by these responses. Since market overlap strengthens partners' retaliatory capacity, it can also increase the cost caused by the retaliation against opportunism. Therefore, by integrating the multimarket competition literature that addresses rivals' actions and responses, I enrich the current understanding on the effect of market overlap on opportunism by partners and, in turn, partner selection for technology cooperation.

## 2.2 Theory and Hypotheses

### 2.2.1 Multimarket Contact and Mutual Forbearance

Multimarket contact refers to two firms competing in more than one distinct market (Karnani & Wernerfelt, 1985). According to the multimarket competition literature (Jayachandran, Gimeno, & Varadarajan, 1999; Yu & Cannella Jr., 2013 for a review of the literature), rivals having multimarket contact between them tend to mutually forbear from attacks, therefore lowering the intensity of rivalry (Bernheim & Whinston, 1990; Edwards, 1955). This lowered level of rivalry between multimarket rivals has been corroborated by many previous empirical papers, where the attenuation of rivalry has been measured by greater stability of market shares (Heggestad & Rhoades, 1978; Sandler, 1988), higher profitability (Hannan & Prager, 2009; Parker & Röller, 1997), higher prices (Gimeno & Woo, 1996; Hannan & Prager, 2004), lower entry and exit rates (Baum & Korn, 1996; Fuentelsaz & Gómez, 2006), less frequent competitive behavior (Young, Smith, Grimm, & Simon, 2000; Yu & Cannella Jr., 2007), smaller investments in tangible and intangible resources (Kang, Bayus, & Balasubramanian, 2010; Shankar, 1999), and lower service quality (Prince & Simon, 2009).

Mutual forbearance takes place because multimarket rivals realize that an aggressive action taken in one market may provoke broad retaliation by rivals, not only in the market where the attack was initiated but also in other shared markets. This broad retaliation may eventually result in a larger loss than the initial gain in one market from an attack (Evans & Kessides, 1994; Feinberg, 1985; Haveman & Nonnemaker, 2000; Heggestad & Rhoades, 1978; Phillips & Mason, 1996). That is, the attacked firm's ability to retaliate to cause the attacker serious financial damage will then be taken into account in analyzing the benefit and cost of current attacks. The shadow of the future created by the prospect of broad retaliation functions to deter current attacks.

The potential for mutual forbearance between two firms increases with the degree of multimarket contact between them because multimarket contact provides a better ability and more opportunities to retaliate against current attacks (Jayachandran et al., 1999). As two firms share more markets, retaliation across the shared markets can hurt the attacker more seriously (Edwards, 1955). Also, the larger number of markets of overlap means more areas to retaliate against current attacks (Jayachandran et al., 1999). Furthermore, previous work has also shown that mutual forbearance potential depends not only on the mere number of shared markets but also on some attributes of the shared markets. Mutual forbearance potential increases with the strategic importance of the shared markets because possible retaliation in an unimportant market may not provide deterrence from attacks (Feinberg, 1985; Mester, 1987; Scott, 1982). Furthermore, the asymmetry of strategic importance also affects the degree of deterrence. That is, as two firms are more dissimilar in terms of their presence in the shared markets, the deterrence between them becomes more effective (Bernheim & Whinston, 1990; Gimeno, 1999). This is because if one firm has footholds of small market share in the other firm's important markets and vice versa, they can substantially hurt each other at a small cost, and thus threats of retaliation become more credible (Fuentelsaz & Gómez, 2006;

Gimeno, 1999). In addition, the number of competitors in the shared markets is also an important factor influencing mutual forbearance potential because the detection of deviation from mutual forbearance becomes harder, and retaliation becomes less effective, as there are more other firms in the market (Evans & Kessides, 1994; Feinberg, 1985).

### 2.2.2 Mutual Forbearance from Opportunism in Technology Cooperation

In the context of technology cooperation, mutual forbearance between partners with market overlap can reduce opportunism by partners given the shadow of the future (e.g., Parkhe, 1993) that is created by possible broad retaliation. In a technology cooperation agreement between two partners with no market overlap, one partner who is victimized by the other's opportunistic behavior has several options to respond to the opportunistic behavior. For instance, barring a successful private resolution of a dispute, the partners can appeal to third parties (e.g., courts) if their contracts include provisions that are directly related to the detected opportunistic behavior (Reuer & Ariño, 2007). However, the effectiveness of this option may be restricted owing to the inherent incompleteness of contracts and the costs and lead time involved. Other options include passive responses such as behaving opportunistically in an eye-for-an-eye fashion within the partnership, terminating the relationship, and ruling out an opportunistic partner for future cooperation. These options can also be ineffective because the first two hinder the achievement of cooperation objectives and the last one would also be of limited effectiveness in creating a shadow of the future if the opportunistic partner views the focal agreement in one-off terms.

If two partners have market overlap, however, one partner can effectively respond to the other's opportunistic behavior by retaliating in the overlapped end-product markets. Furthermore, if market overlap between them is substantial and retaliation takes place across the shared markets, it can cause the opportunistic partner substantial damage (Jayachandran et al., 1999). One thing to note is that the market overlap between them provides both partners with retaliatory capacity and, therefore, none of them cannot easily initiate opportunistic behaviors. That is, the partners mutually forbear from opportunistically behaving within the partnership because it may escalate the intensity of their competition in the shared markets. The benefit from opportunistic behaviors in the partnership may be not only uncertain but also marginal relative to the possible costs caused by the intensified competition. In particular, if the two partners with market overlap are currently enjoying substantial rents in the overlapping markets, they may suffer a big loss in going after a small gain by behaving opportunistically in the cooperation. In sum, as two firms have a higher level of mutual forbearance potential generated by their market overlap, they experience a lower risk of opportunism.

The literature on partner selection has argued that partners' inclination toward opportunism becomes a key criterion for partner selection when partners' behaviors are difficult to observe and the outcomes of collaborations are highly unpredictable (Shah & Swaminathan, 2008). Since technology cooperation typically entails such exchange hazards (Nelson & Winter, 1977; Pisano, 1989), firms strongly prefer partners with low risk of opportunism for technology cooperation. Accordingly, as two potential partners have higher potential for mutual forbearance from opportunism, they are more likely to partner with each other for technology cooperation. I therefore posit:

*Hypothesis 1: The likelihood of technology cooperation between two firms is positively related to the degree of mutual forbearance potential between them.*

### 2.2.3 Contingent Effects of Mutual Forbearance Potential on Partner Selection

So far, I have argued that market overlap between two potential partners generates mutual forbearance from opportunism, thereby making them attractive to each other as partners for technology cooperation. However, the attractiveness of partners with market overlap can vary depending on the hazards of opportunism the partners anticipate. That is, when a potential technology partnership is expected to entail a higher level of contractual hazards, firms will put more weight on prospective partners' inclination towards opportunism as a criterion for partner selection (Shah & Swaminathan 2008). Under these conditions, partners with a higher potential for mutual forbearance from opportunism will be even more preferred. By contrast, when opportunism is expected to be lower, the mutual forbearance potential of market overlap would have a lesser impact on partner selection for technology cooperation. Therefore, factors known to influence the hazards of cooperation will also shape the effects of mutual forbearance potential on partner selection.

The TCE literature emphasizes transaction attributes as determinants of contractual hazards (Williamson, 1985). In particular, uncertainty has long been regarded as one of the major factors determining contractual hazards in the literature (Williamson, 1985). As the degree of uncertainty surrounding a transaction increases, it is more difficult for the participating parties to write a complete and enforceable contract. Since technological uncertainty is a key dimension of uncertainty in technology cooperation by definition, I examine whether the mutual forbearance potential created by market overlap will take on greater importance for technology partnerships with higher technological uncertainty. In addition, research on technology cooperation has often emphasized the vertical scope of agreements given the conceptual clarity of this transactional attribute as well as data availability (Li et al., 2008; Oxley, 1997; Oxley & Sampson, 2004; Phene & Tallman, 2012; Reuer, Zollo, & Singh, 2002). This research suggests that cooperative agreements with a broader vertical scope entail a higher level of contractual hazards compared to those with a narrower vertical scope. Therefore, I also investigate whether the effect of mutual forbearance potential on partner selection will be intensified by the vertical scope of technology cooperation.

***Technological Uncertainty.*** The TCE literature has long suggested uncertainty as one of the key transactional attributes determining the level of expected contractual hazards (Williamson, 1985). As uncertainty increases, the occasions for sequential adaptations increase in number and importance and accordingly contractual gaps also enlarge, aggravating exchange hazards (Williamson, 1979). Technology cooperation inevitably entails technological uncertainty due to the inherently uncertain nature of innovative activities (Nelson & Winter, 1977). Technological uncertainty refers to “the probability of improvements in technology; i.e. to new generations of technology which might render obsolete the  current technology development effort” and has tended to be regarded as an exogenous variable given by the area of interest (Robertson & Gatignon, 1998).

When technological uncertainty is high, it is difficult to understand involved cause-effect relationships (Duncan, 1972) and to predict accurately the outcome of a decision (Downey & Slocum, 1975). Therefore, when firms collaborate for the development of a highly uncertain technology, they are likely to go through a series of trials and errors and encounter various unexpected contingencies, which all make it difficult to write a complete and enforceable contract *ex ante*. When contract-based formal governance is not an effective means to reduce contractual hazards, firms can mitigate the risks by selecting partners estimated to be low in inclination toward opportunism. Accordingly, firms who have a high level of market overlap and thus are likely to mutually forbear from opportunistic behaviors become more attractive to each other as partners as the collaboration between them entail a higher level of technological uncertainty. By contrast, when technological uncertainty in a technology cooperation agreement is low, the joint effort can be effectively managed by formal contractual apparatus and thus proclivity for opportunism might become less important as a criterion for partner selection. Therefore, although the reduced risk of opportunism that mutual forbearance between multimarket rivals causes is generally appreciated in searching for partners for R&D activities, firms with a high level of market overlap are more preferred as a partner for technology cooperation entailing a high level of technological uncertainty compared to the case of low technological uncertainty. I therefore posit:

*Hypothesis 2: The positive effect of mutual forbearance potential on partner selection is greater for technology cooperation entailing higher technological uncertainty.*

***Vertical Scope of Technology Cooperation.*** Technology cooperation often includes other downstream activities such as manufacturing and marketing. Research in the field of technology and operations management has highlighted that firms can reduce time-to-market and improve quality of new product introductions by having overlapping activities and using cross-function teams (Loch & Terwiesch, 2000). Although this argument concerns within-firm arrangements, the same logic can apply to interfirm cooperation, leading to the conclusion that including manufacturing and/or marketing functions in interfirm technology cooperation can provide the partners the same benefits of reduced time-to-market and improved quality of new product introductions (Oxley & Sampson, 2004).

However, such merits of collaborations entailing broad vertical scope do not come without important drawbacks. Previous research has also emphasized that broad scope collaborations can exacerbate the potential risk of opportunism and thus influence initial governance choice and *ex post* governance changes. Pisano (1989) argued that when transactions involve a broader range of products or technologies, equity-based governance modes are more likely to be chosen. This is because involving multiple projects aggravates contractual hazards by increasing the number of contingencies that must be written into the initial contract and contributes to the possibility of unanticipated contingencies arising during the course of relationship. Oxley (1997) also maintained that as a technology transfer alliance includes a broader range of products or technologies, the difficulty and costs of monitoring activities inevitably increase, making involved firms choose a more hierarchical governance structure. Consistent with the argument that it is difficult to specify partners' rights and obligations in broad-scope alliances, which entail gaps that become evident during alliance implementation, Reuer and colleagues (2002) report that alliances with broad scope are more likely to be renegotiated. Firms can also contend with these same challenges during partner selection, prioritizing those partners that come with less risk in the first place. Therefore, when firms search for partners for technology cooperation of broader scope, they will prefer partners characterized by low risk of opportunism to a larger extent. Thus, partners with a high level of mutual forbearance potential will become more attractive as partners for technology cooperation of broader scope. All else equal, for narrow-scope partnerships for which opportunism is of lesser concern, the benefits of mutual forbearance potential will be lower. I therefore posit:

> *Hypothesis 3: The positive effect of mutual forbearance potential on partner selection is greater for technology cooperation including manufacturing or/and marketing than for pure technology cooperation.*

## 2.3 Methods

### 2.3.1 Sample and Data

To test how mutual forbearance potential affects partner selection for technology cooperation, I use the global biopharmaceutical industry as the empirical context of my study. This industry is ideal for this purpose for two reasons. First, market definitions in this industry are very clear. In this study, it is critical to define end-product markets to make sure that firms defined as present in the same end-product market actually compete with each other. The global biopharmaceutical industry is clearly classified into therapeutic classes widely accepted by U.S. government authorities and industry participants (e.g., cholesterol regulators, antiulcerants, and antipsychotics) (Anand et al., 2009). Also, because drugs in the same therapeutic class are substitutes for each other in most cases, the biopharmaceutical companies offering their products in the same therapeutic class are direct competitors in the class. Second, this industry exhibits high rates of technology cooperation (Hagedoorn, 1993, 2002), and given the amount of research carried out in this industry, my focus on this empirical context is valuable for purposes of drawing comparisons across studies on the determinants of alliance formation.

In order to examine firms' activities in different markets, I rely on data provided by IMS Health, a leading information provider in the biopharmaceutical industry that collects prescription drug revenue data by therapeutic class for companies around the world. I draw on the IMS Health data focusing on the top 200 prescription drug sales companies in 2007, which occupied more than 90% of total global prescription drug sales in the year. For data on technology cooperation, I use the Thomson Reuters' Recap database. The Recap database compiles alliance information primarily from the filings of biopharmaceutical companies with the Securities and Exchange Commission (SEC). A recent analysis found the Recap database to be robust and representative in its coverage of alliances in the global biopharmaceutical industry (Schilling, 2009), and it has been used widely in the literature (Adegbesan & Higgins, 2011; Lerner, Shane, & Tsai, 2003; Robinson & Stuart, 2007). In addition, I obtain patent data from the U.S. Patent and Trademark Office (USPTO).

### 2.3.2 Variables and Measurement

***Dependent variable.*** I have three different dependent variables in this study. The first dependent variable used to test H1 is $\textit{Technology Cooperation}_{ijt}$ taking the value of one if firms *i* and *j* in a dyad form a technology cooperation agreement in year *t*, and zero otherwise. The unit of analysis of this study is the dyad between two biopharmaceutical firms. Prior studies have often analyzed cooperation between firms at the dyad level (Gimeno, 2004; Gulati, 1995a; Rothaermel & Boeker, 2008). Since the biopharmaceutical industry is not characterized by alliance blocks, the usage of dyads as the unit of analysis is further justified (Rothaermel & Boeker, 2008). Regarded as equal in a priori risk of forming a technology cooperation agreement, all the possible 19,900 dyads ($={}_{200}C_2$) between the 200 firms are constructed and included in the alliance opportunity risk set. They are also tracked from 2007 to 2013 to construct a panel. Since the dependent variable is measured annually, it is also possible for two firms to form multiple agreements in the same year. There were nine such cases in my sample and I included all of them as separate dyad-year observations, giving me in the final sample of 139,309 dyad-year observations.

To test H2, I developed *Technological Uncertainty*$_{ijt}$, which takes three different values: zero when firm *i* and firm *j* in a dyad do not form a technology cooperation agreement in year *t*, one when the two firms enter into a technology cooperation agreement including a low level of technological uncertainty, and two when the two firms enter into a technology cooperation with a high level of technological uncertainty. To distinguish low and high technological uncertainty, I used the estimates of the clinical approval success rate by therapeutic categories that DiMasi, Feldman, Seckler, and Wilson (2010) provide. I defined a technology agreement of which focal therapeutic class has an above-the-mean clinical approval success rate as low technological uncertainty. By contrast, when the focal therapeutic class of a technology cooperation has a below-the-mean clinical approval success rate, the collaboration is defined as one with a high level of technological uncertainty. This categorization is consistent with the definition of technological uncertainty that I draw on in theory development: "the probability of improvements in technology; i.e. to new generations of technology which might render obsolete the  current technology development effort (Robertson & Gatignon, 1998)." Among the 147 technology cooperation agreements in the sample, 84 (57.1%) were defined as low technological uncertainty while 63 (42.9%) high technological uncertainty.

The third dependent variable used to test H3 is *Vertical Scope*$_{ijt}$, a categorical variable taking three different values. This variable takes one when firm *i* and firm *j* in a dyad do not enter into a technology cooperation agreement in year *t*, two when the two firms form a technology-only cooperation (i.e., a cooperation that includes technology-related activities only), three when the two firms form a technology-plus cooperation (i.e., a cooperation that involves manufacturing or/and marketing activities in addition to technology-related activities). Out of the total 147 technology cooperation agreements in the sample, 79 (53.7%) were defined as technology-only while 68 (46.3%) technology-plus.

***Explanatory variables.*** To measure mutual forbearance potential between two firms, I use the measure developed by Singal (1996). This measure has been regarded as the most comprehensive measure of mutual forbearance potential because it takes into account the major factors that have been demonstrated in the literature to affect mutual forbearance potential (Gimeno & Jeong, 2001). Earlier, I argued that mutual forbearance potential depends not only on the mere number of shared markets but also on some features of the shared markets: strategic importance, asymmetry of strategic importance, and the number of competitors. Singal's (1996) measure for mutual forbearance potential takes into account all these factors. That is, the measure basically counts the number of market contacts, but weights each contact by (1) the size of the market, (2) the combined market share of firm *i* and firm *j* in the market, (3) asymmetry of market presence of firm *i* and firm *j* in the market, and (4) the number of firms in the market. Specifically, in the measure provided below, strategic importance is reflected by the size of the market and the combined market share. The measure accounts for asymmetry of strategic importance by including the ratio of the market share of the larger firm to that of the smaller firm at dyad-in-market level. Therefore, this measure increases as the strategic importance of the shared markets are dissimilar to each firm in a dyad. Lastly, it also takes into account the number of firms by putting the number of possible contacts in a market (=$_nC_2$ where *n* indicates the number of competitors in a market) as the denominator.

$$Mutual\ Forbearance\ Potential_{ijm}$$

$$= I_{im} \cdot I_{jm} \cdot \frac{\sqrt{R_m \times 100}}{R_{total}} \cdot \frac{(MS_{im} + MS_{jm})\sqrt{MS_{im}/MS_{jm}}}{N_m(N_m - 1)/2}$$

, for $MS_{im} \geq MS_{jm}$

Where, $I_{i(j)m}$: takes 1 if firm *i*(*j*) is present at a focal market *m*.
$MS_{i(j)m}$: market share of firm *i*(*j*) in market *m*.
$N_m$: number of firms in market *m*.
$R_m$: total revenue in market *m*.
$R_{total}$: total revenue across all markets.
Since the unit of analysis in this study is a dyad, I aggregate $MFP_{ijm}$ across the shared markets to get $MFP_{ij}$ (=$\sum_m MFP_{ijm}$) and use its value in a given year, $MFP_{ijt}$ for each dyad-year observation[3].

***Control variables.*** Following previous studies that modeled the formation of collaboration agreements at the dyad level, I include various controls to avoid spurious correlations. Firms that are larger or superior in resources tend to be more attractive partners. As proxies for resource endowments that a firm can bring to an alliance, I use the firm's size (Gimeno, 2004), number of patents (DeCarolis, 2003; Matraves, 1999; Roberts, 1999), and number of therapeutic classes in which it operates. At the same time,

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[3] In the multimarket competition literature, many different measures have been used to measure multimarket contact and mutual forbearance, but there is no consensus on which measure is the best (Gimeno & Jeong, 2001). Since the measure developed by Singal (1996) is the most comprehensive and complicated one, I also checked the results using the simplest, widely used measure that represents the ratio of the number of market contact between two firms to the sum of the each firm's number of markets (Baum & Korn, 1996; Fuentelsaz & Gómez, 2006). When using this simplest measure, I obtained the qualitatively same results as those from Singal's (1996) measure for H1 and H2, but H3 was not supported.

firms may want to partner with similar firms with respect to resource endowments. Therefore, a pair of firms that are similar in the resource-related variables may be more likely to enter into a cooperation agreement. To control for these effects, I include the size of the larger firm of a dyad measured by annual prescription drug sales and the ratio of sizes in the dyad (i.e., the ratio of the smaller firm's sales to the larger firm's sales) (Burgers, Hill, & Kim, 1993; Gimeno, 2004). For intellectual resources, I also include the number of patents by the firm with the most patents in the dyad as well as the ratio of patent counts (i.e., the number of patents by the firm with less patents divided by the prospective partner's patents). In the same manner, the number of therapeutic classes of the firm with more classes and the ratio of therapeutic classes are also included in the model. Controlling for the number of therapeutic classes is important for another reason: firms operating in many therapeutic classes may be more likely to be selected as cooperation partners because of increased opportunities to partner given their diverse operations.

Although the patent count measures above are included in the model to control for the effects of the absolute and relative magnitudes of the firms' intellectual property, the relatedness of their knowledge base is a different, critical dimension to be considered (Ahuja & Katila, 2001). If firms understand that they can be more innovative when they find partners having knowledge overlap due to absorptive capacity (Cohen & Levinthal, 1990), they may prefer prospective partners who have similar knowledge bases. For example, Rothaermel and Boeker (2008) examined the effect of dyadic technological similarity on the likelihood of alliance formation in the biopharmaceutical industry, measuring technological similarity by the cross-citation rate and common citation rate developed by Mowery, Oxley, and Silverman (1996, 1998). Following their lead, I also include in the model cross citation rate and common citation rate measured as follows:

$$Patent\ Cross\ Citation\ Rate_{ijt} = \left(\frac{Citations\ to\ firm\ i's\ patents\ in\ firm\ j's\ patent_t}{Total\ citations\ in\ firm\ j's\ patents_t}\right) + \left(\frac{Citations\ to\ firm\ j's\ patents\ in\ firm\ i's\ patent_t}{Total\ citations\ in\ firm\ i's\ patents_t}\right)$$

$$Patent\ Common\ Citation\ Rate_{ijt} = \left(\frac{Citations\ to\ firm\ i's\ patents\ to\ patents\ cited\ in\ firm\ j's\ patent_t}{Total\ citations\ in\ firm\ i's\ patents_t}\right) + \left(\frac{Citations\ to\ firm\ j's\ patents\ to\ patents\ cited\ in\ firm\ i's\ patent_t}{Total\ citations\ in\ firm\ j's\ patents_t}\right)$$

where citations are accumulated from year $t$-$6$ to year $t$-$1$.

Some may expect that the effect of market overlap on partner selection might be attributed to collusive purposes rather than reduced opportunism. More specifically, firms may use R&D alliances as a communication channel to facilitate tacit collusion (Vonortas, 2000). To control for this effect, I include the increment of market power potential that two partners can achieve in the shared markets if they behave as one firm. That is, I first calculate the normalized Herfindahl indexes in the shared markets and average them with weights by market size. Then, assuming that the two firms behave as one firm, I calculate a new weighted average of normalized Herfindahl indexes in the shared markets. Finally, I include the difference between the two weighted averages to obtain the increment of market power potential.

Cross-border technology cooperation may face some unique challenges stemming from information asymmetry, difficulties in monitoring and enforcement, and different institutional frameworks and cultures. Consistent with these observations, Hagedoorn

(2002) found that international R&D alliances are less common than domestic agreements, and the share of domestic R&D alliances has been increasing. To control for this effect, I include a dummy variable, *International Cooperation*, which takes a value of one if two firms in a dyad are headquartered in different countries, and zero otherwise.

Private firms and public firms may be different in terms of business processes and procedures, as well as visibility to prospective partners, and these differences may affect the likelihood of technology cooperation (Rothaermel & Boeker, 2008). I therefore accounted for these possibilities by using two dummy variables, *Private (max)* and *Private (min)*. The former (latter) takes one if the bigger (smaller) firm in a dyad is a private firm and zero otherwise. Lastly, year dummy variables are included in the model to control for macroeconomic or other factors influencing the propensity for the formation of technology cooperation in different years.

### 2.3.3 Statistical Methods

Given that the dependent variable for H1, *Technology Cooperation*$_{ijt}$, is a binary variable, I use a probit model as my base model. In addition, to avoid any potential effects of non-independent observations I also use robust estimation of standard errors using the Huber-White sandwich estimator (White, 1980). H2 compares the effects of mutual forbearance potential on partner selection for technology-only cooperation versus technology-plus cooperation while H3 for technology cooperation with a low level of technological uncertainty versus that with a high level of technological uncertainty.

Therefore, for testing H2 and H3 I use multinomial logit models with robust standard errors, taking non-realized deal as the omitted category[4].

For robustness analyses, I use three methods in addition to the standard models: a random-effects model, a penalized maximum likelihood estimation method (i.e., Firth's logit model), and analysis using a different definition of technology cooperation. First, although I seek to capture as much variation in the dependent variables as possible with controls that are featured in prior studies, there is still a risk of unobserved heterogeneity among the dyads in the model. Therefore, I use random-effects models (i.e., random-effects probit models for H1and random-effect multinomial models for H2 and H3) to mitigate this concern following prior studies on dyad-level alliance formation (Gimeno, 2004; Reuer & Lahiri, 2014).

Second, the usual maximum likelihood estimation, which is used in a standard probit model, can be biased when the count of rare events is small (Cosslett, 1981; Imbens, 1992; Lancaster & Imbens, 1996). Since there are 146 realized technology cooperation agreements in my sample, I use Firth's logit model using the penalized likelihood method for H1 where the model is applicable (Firth, 1993). This penalized likelihood method is a widely accepted, general approach to reducing small-sample bias.

Lastly, I test my hypotheses again treating licensing agreements as non-realized technology cooperation. In my main results, licensing agreements are also treated as

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[4] When I conducted Hausman chi-squared tests of independence of irrelevant alternatives (IIA), I found no support for rejecting the null hypotheses that odds are independent of other alternatives for both technological uncertainty and vertical scope (for technological uncertainty, chi-sqaure (20)=10.4 and $p$=0.960 for non-realized deal, 11.3 and 0.939 for low technological uncertainty, and 9.9 and 0.969 for high technological uncertainty; for vertical scope, chi-sqaure (20)=21.4 and $p$=0.372 for non-realized deal, 13.0 and 0.876 for technology-only cooperation, and 10.1 and 0.966 for technology-plus cooperation). Therefore, my usage of multinomial logit models for testing H2 and H3 was corroborated.

technology cooperation because licensing agreements involve transfer of technology and also confront greater transactional hazards relative to other unilateral agreements such as supply and distribution agreements. Somaya, Kim, and Vonortas (2011) highlighted that licensing has some critical alliance-like features. Rather than selling their intellectual property indiscriminately, licensors often use licensing agreements to access the complementary assets that licensees possess. Furthermore, this tendency is particularly salient in the biopharmaceutical industry which is my empirical setting (Somaya et al., 2011). When licensors are dependent on licensees' complementary assets, the former are exposed to significant risks because the latter "may devote inadequate complementary resources, or learn from the licensor and then commercialize its own technology, or their priorities may change over time, or it may simple be less capable than initially thought" (Somaya et al., 2011: 161). At the same time, licensees also may confront transactional hazards due to the uncertainty that early stage technology entails or if they are required to make the license-specific investments. Despite these unique features of licensing agreements, however, some may argue that unilateral agreements such as licensing agreements are inherently different from bilateral technology collaborations in terms of the potential risk involved. For example, Pisano (1989) argued that parties can delineate property rights at the outset with far less ambiguity in licensing agreements compared to other bilateral transactions. To mitigate this concern, I re-ran the models by excluding licensing agreements and focusing on other forms of technology cooperation, in order to determine if the inclusion or exclusion of licensing agreements influenced my results and interpretations.

## 2.4 Results

Table 2.1 presents descriptive statistics and a correlation matrix for the variables used in the analyses. The correlation between *Mutual Forbearance Potential* and *Technology Cooperation* is positive and significant offering preliminary support for my theory. Though there are many significant pairwise correlations, my models do not present multicollinearity concerns. Individual variance inflation factors (VIF) for the independent variables are all below the recommended cutoff levels of 10 (the maximum value was 5.35 for *International Deal*) and the mean value is 1.66 (Neter, Kutner, Nachtsheim, & Wasseman, 1996).

Table 2.2 reports the main results of this study based on probit and multinomial logit models examining how mutual forbearance potential between two prospective partners affect the likelihood that they will partner each other for technology cooperation (H1) and when this relationship is more or less pronounced (H2 and H3). Model 1 in Table 2.2 contains the control variables only. Some estimation results for several control variables deserve mention. While the coefficient of *Size (Max)* is positive and significant, that of *Ratio of Size* (small firm to large firm) is positive and insignificant, meaning that although larger firms are significantly preferred as partners for technology cooperation, the preference for partners of similar size is not significant. These results are partially consistent with previous work that reported positive and significant coefficients for both (Gimeno, 2004). Positive and significant coefficients are estimated for both *Common Citation Rate* and *Cross-citation Rate* (e.g., Rothaermel & Boeker, 2008). The coefficient of *Increment of H-index* is also positive and significant, suggesting that two firms who

Table 2.1. Descriptive Statistics and Correlation Matrix

| Variables | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) | (15) | (16) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| (1) Technology Cooperation | 1 | | | | | | | | | | | | | | | |
| (2) Technological Uncertainty | **0.945** | 1 | | | | | | | | | | | | | | |
| (3) Vertical Scope | **0.946** | **0.911** | 1 | | | | | | | | | | | | | |
| (4) Mutual Forbearance Potential | **0.073** | **0.094** | **0.091** | 1 | | | | | | | | | | | | |
| (5) Size (Max) | **0.045** | **0.043** | **0.043** | **0.06** | 1 | | | | | | | | | | | |
| (6) Ratio of Size | **-0.007** | **-0.007** | **-0.008** | **-0.016** | **-0.478** | 1 | | | | | | | | | | |
| (7) Patent Count (Max) | **0.028** | **0.026** | **0.028** | **0.057** | **0.531** | **-0.269** | 1 | | | | | | | | | |
| (8) Ratio of Patent Count | -0.002 | -0.001 | -0.002 | **-0.007** | **-0.2** | **0.2** | **-0.234** | 1 | | | | | | | | |
| (9) Class Count (Max) | **0.023** | **0.021** | **0.022** | **0.033** | **0.471** | **-0.263** | **0.23** | **-0.053** | 1 | | | | | | | |
| (10) Ratio of Class Count | **0.006** | **0.007** | **0.006** | **0.013** | **-0.036** | **0.068** | **-0.015** | **0.032** | **-0.165** | 1 | | | | | | |
| (11) Common Citation Rate | **0.026** | **0.029** | **0.024** | **0.013** | **0.087** | **-0.03** | **0.106** | **-0.016** | **0.047** | 0 | 1 | | | | | |
| (12) Cross-citation Rate | **0.019** | **0.024** | **0.024** | **0.006** | **0.035** | **-0.01** | **0.046** | -0.003 | **0.022** | -0.003 | **0.194** | 1 | | | | |
| (13) Increment of H-index | **0.066** | **0.065** | **0.055** | **0.056** | **0.306** | 0.003 | **0.191** | **-0.007** | **0.168** | **0.043** | **0.077** | **0.032** | 1 | | | |
| (14) International Deal | **-0.018** | **-0.016** | **-0.014** | -0.001 | **-0.011** | 0.004 | **-0.024** | **0.02** | **0.092** | -0.001 | **-0.014** | -0.002 | **-0.042** | 1 | | |
| (15) Private (Bigger Firm) | **-0.014** | **-0.012** | **-0.014** | **-0.018** | **-0.267** | **0.249** | **-0.218** | **0.209** | **-0.11** | **0.045** | **-0.037** | **-0.014** | **-0.072** | **0.055** | 1 | |
| (16) Private (Smaller Firm) | **-0.022** | **-0.02** | **-0.02** | **-0.006** | **-0.061** | **-0.043** | **-0.07** | **0.04** | **-0.041** | **0.035** | **-0.035** | -0.005 | **-0.07** | **0.046** | **0.023** | 1 |
| Mean | 0.001 | 1.002 | 1.002 | 0 | 6.04 | 0.375 | 53.55 | 0.3 | 116.86 | 0.434 | 0.001 | 0 | 0 | 0.911 | 0.31 | 0.47 |
| S.D. | 0.032 | 0.049 | 0.05 | 0 | 10.677 | 0.293 | 123.11 | 0.416 | 59.98 | 0.28 | 0.009 | 0.002 | 0 | 0.285 | 0.462 | 0.499 |
| Min | 0 | 1 | 1 | 0 | 0.038 | 0 | 0 | 0 | 1 | 0.004 | 0 | 0 | 0 | 0 | 0 | 0 |
| Max | 1 | 3 | 3 | 0.001 | 61.767 | 1 | 1128 | 1 | 279 | 1 | 1 | 0.408 | 0.012 | 1 | 1 | 1 |

Note: N=139,309. Bolded pairwise correlations are significant at least at 0.05 level.

can achieve a greater increment of market power by coordinating as one firm are more likely to partner each other, which is consistent with Vonortas (2000). A negative and significant coefficient is estimated for *International Deal*, which is consistent with Hagedoorn's (2002) observation of the dominance of R&D partnering in the same regions, especially in biopharmaceuticals. The coefficients of *Private (Max)* and *Private (Min)* both are negative and significant, which means that firms prefer partnering public firms.

Model 2 in Table 2.2 includes *Mutual Forbearance Potential* in addition to the control variables to test H1. Since the coefficient of *Mutual Forbearance Potential* is positive and significant ($b$=0.014 and $p$<0.05), H1 is supported: as two potential partners have a greater level of mutual forbearance potential, they are more likely to select each other as partners for technology cooperation. I calculated the marginal effects of each observation and averaged the responses (Hoetker, 2007). As the value of *Mutual Forbearance Potential* moves from the mean to one and two standard deviation from the mean, the likelihood of technology cooperation increases by 4.2 and 8.6 percent respectively[5].

H2 predicts that the positive effect of mutual forbearance potential on partner selection is larger for technology cooperation agreements entailing high technological uncertainty relative to those with low technological uncertainty. In Model 3 and 4, multinomial logit models are employed to compare how different the effects of mutual

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[5] When I used Baum and Korn's (1996) measure that represents the ratio of the number of market contact between two firms to the sum of the each firm's number of markets, the estimated economic significance was substantially larger than that based on Singal's (1996) measure. When the value of Baum and Korn's (1996) measure moves from the mean to one and two standard deviation from the mean, the probability of technology cooperation increases by 72 and 189 percent.

forbearance potential on the formation of technology cooperation are depending on the level of technological uncertainty. The coefficients for *Mutual Forbearance Potential* in Model 3 and 4 are both positive and significant ($b$=0.017 and $p$<0.05; $b$=0.031 and $p$<0.01). However, the Wald test shows that the coefficient in Model 4 is significantly larger than that in Model 3 (Chi-square (1)=5.16 and $p$=0.023), supporting H2.

H3 states that the tendency for firms to prefer prospective alliance partners with a high level of mutual forbearance potential is more likely when they search for partners for technology partnerships that involve collaboration in other functional activities at the same time (i.e., technology cooperation including manufacturing or/and marketing activities) rather than technology-only cooperation. Model 5 and 6 use multinomial logit models having no deal as the omitted category. While Model 5 estimates the formation of technology-only cooperation, Model 6 is for technology-plus cooperation. The coefficients of *Mutual Forbearance Potential* are all positive and significant in Model 5 and 6 ($b$=0.018 and $p$<0.05; $b$=0.031 and $p$<0.001). Moreover, the coefficient in Model 6 is larger than that in Model 5 and the two values are significantly different at 5 percent level as the Wald test reveals (Chi-square (1)=4.15 and $p$=0.042). Therefore, the preference for partners with a high level of mutual forbearance potential is stronger when firms search for partners for technology cooperation of broader vertical scope, supporting H3.

Table 2.2. Main Results (Probit and Multinomial Logit Models)

| | Model | |
|---|---|---|
| | (1) | (2) |
| Model Specification | Probit | Probit |
| Dependent Variable | Tech. cooperation | Tech. cooperation |
| Hypothesis tested | H1 | H1 |
| Mutual Forbearance Potential | | 0.014*** |
| | | (0.002) |
| Size (Max) | 0.132*** | 0.131*** |
| | (0.025) | (0.025) |
| Ratio of Size | 0.033 | 0.031 |
| | (0.035) | (0.035) |
| Patent Count (Max) | 0.040* | 0.035 |
| | (0.022) | (0.023) |
| Ratio of Patent Count | 0.037 | 0.033 |
| | (0.028) | (0.028) |
| Class Count (Max) | 0.065** | 0.066** |
| | (0.028) | (0.028) |
| Ratio of Class Count | 0.070** | 0.066** |
| | (0.027) | (0.027) |
| Common Citation Rate | 0.018*** | 0.018*** |
| | (0.006) | (0.006) |
| Cross-citation Rate | 0.013*** | 0.013*** |
| | (0.005) | (0.005) |
| Increment of H-index | 0.023*** | 0.023*** |
| | (0.007) | (0.007) |
| International Deal | -0.340*** | -0.343*** |
| | (0.068) | (0.068) |
| Private (Bigger Firm) | -0.168** | -0.166** |
| | (0.083) | (0.083) |
| Private (Smaller Firm) | -0.448*** | -0.446*** |
| | (0.072) | (0.072) |
| Constant | -2.856*** | -2.869*** |
| | (0.101) | (0.103) |
| Year Fixed Effects | Included | Included |
| Wald Chi-square (df) | 380.09*** (18) | 428.55*** (19) |
| Pseudo R-square | 0.129 | 0.133 |
| Log Pseudolikelihood | -1006.12 | -1001.02 |
| Number of Observations | 139,309 | 139,309 |

Note: Robust standard errors in parentheses. All the continuous variables above are standardized for better presentation. *** $p$<0.01, ** $p$<0.05, * $p$<0.1. Two-tailed tests.

Table 2.2. Continued

| | Model | | | |
|---|---|---|---|---|
| | (3) | (4) | (5) | (6) |
| Model Specification | Multinomial logit | Multinomial logit | Multinomial logit | Multinomial logit |
| Dependent Variable | Low tech. uncertainty vs. no deal | High tech. uncertainty vs. no deal | Tech.-only vs. no deal | Tech.-plus vs. no deal |
| Hypothesis tested | H2 | H2 | H3 | H3 |
| Mutual Forbearance Potential | 0.017** | 0.031*** | 0.018** | 0.031*** |
| | (0.008) | (0.005) | (0.008) | (0.005) |
| Size (Max) | 0.322*** | 0.548*** | 0.407*** | 0.431*** |
| | (0.096) | (0.117) | (0.107) | (0.101) |
| Ratio of Size | 0.097 | 0.137 | 0.114 | 0.127 |
| | (0.155) | (0.168) | (0.163) | (0.157) |
| Patent Count (Max) | 0.176* | 0.015 | 0.136 | 0.084 |
| | (0.091) | (0.100) | (0.092) | (0.101) |
| Ratio of Patent Count | 0.115 | 0.164 | 0.124 | 0.163 |
| | (0.123) | (0.143) | (0.125) | (0.140) |
| Class Count (Max) | 0.270** | 0.108 | 0.115 | 0.318** |
| | (0.119) | (0.136) | (0.125) | (0.128) |
| Ratio of Class Count | 0.201* | 0.290** | 0.167 | 0.335*** |
| | (0.121) | (0.124) | (0.120) | (0.126) |
| Common Citation Rate | 0.026* | 0.044*** | 0.038*** | 0.033* |
| | (0.015) | (0.016) | (0.014) | (0.020) |
| Cross-citation Rate | 0.000 | 0.040*** | -0.005 | 0.038*** |
| | (0.041) | (0.011) | (0.059) | (0.010) |
| Increment of H-index | 0.028 | 0.038* | 0.049*** | -0.001 |
| | (0.019) | (0.020) | (0.017) | (0.027) |
| International Deal | -1.180*** | -0.839** | -1.262*** | -0.732** |
| | (0.262) | (0.340) | (0.275) | (0.332) |
| Private (Bigger Firm) | -1.319*** | -0.048 | -0.458 | -0.897* |
| | (0.495) | (0.381) | (0.378) | (0.458) |
| Private (Smaller Firm) | -1.726*** | -1.290*** | -1.921*** | -1.189*** |
| | (0.358) | (0.356) | (0.398) | (0.331) |
| Constant | -6.741*** | -7.099*** | -6.850*** | -7.000*** |
| | (0.452) | (0.481) | (0.488) | (0.458) |
| Year Fixed Effects | Included | Included | Included | Included |
| H2/H3: Chi-square (1) | 5.16** | | 4.15** | |
| Wald Chi-square (df) | 626.46*** (38) | | 601.05*** (38) | |
| Pseudo R-square | 0.130 | | 0.128 | |
| Log Pseudolikelihood | -1092.14 | | -1095.55 | |
| Number of Observations | 139,309 | | 139,309 | |

Note: Robust standard errors in parentheses. All the continuous variables above are standardized for better presentation. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Two-tailed tests.

### 2.4.1 Supplemental Analyses

Table 2.3 shows the results from logit models using penalized likelihood estimation (so-called Firth logit models) to control for rare event bias (Firth, 1993). As shown in Model 2, the positive effect of mutual forbearance potential on the likelihood of technology cooperation being formed is still supported ($b$=0.021 and $p$<0.01).

I also re-tested all the hypotheses using random-effects specifications to control for unobservable heterogeneity. As shown in Table 2.4, random-effects probit models and random-effects multinomial logit models were employed. Although random-effects were significant in all the models, the results were consistent with the main results in Table 2.2.

Finally, since licensing agreements can be less prone to contractual hazards compared to other types of technology collaborations, I examined whether the findings are sensitive to the inclusion or exclusion of these agreements and the results are shown in Table 2.5. Treating licensing agreements as non-realized deals and using random effects models, the estimation results are consistent with the main results in Table 2.2. It therefore appears that consideration of the small number of realized deals among potential transactions, unobserved heterogeneity, and forms of technology cooperation lead to the interpretations consistent with those presented earlier.

Table 2.3. Penalized Likelihood Estimation Results (Firth Logit Models)

| | Model | |
|---|---|---|
| | (1) | (2) |
| Variables | Tech. Cooperation | Tech. Cooperation |
| Mutual Forbearance Potential | | 0.021*** |
| | | (0.006) |
| Size (Max) | 0.412*** | 0.409*** |
| | (0.076) | (0.076) |
| Ratio of Size | 0.118 | 0.114 |
| | (0.107) | (0.108) |
| Patent Count (Max) | 0.122* | 0.111* |
| | (0.062) | (0.064) |
| Ratio of Patent Count | 0.152 | 0.139 |
| | (0.103) | (0.104) |
| Class Count (Max) | 0.202** | 0.207** |
| | (0.097) | (0.097) |
| Ratio of Class Count | 0.250*** | 0.239*** |
| | (0.083) | (0.084) |
| Common Citation Rate | 0.038*** | 0.038*** |
| | (0.012) | (0.012) |
| Cross-citation Rate | 0.039*** | 0.039*** |
| | (0.009) | (0.009) |
| Increment of H-index | 0.032* | 0.033* |
| | (0.018) | (0.018) |
| International Deal | -1.042*** | -1.055*** |
| | (0.200) | (0.200) |
| Private (Bigger Firm) | -0.633** | -0.621** |
| | (0.282) | (0.282) |
| Private (Smaller Firm) | -1.500*** | -1.494*** |
| | (0.247) | (0.247) |
| Constant | -5.692*** | -5.687*** |
| | (0.284) | (0.284) |
| Year Fixed Effects | Included | Included |
| Wald Chi-square (df) | 376.92*** (18) | 390.31*** (19) |
| Penalized Log Likelihood | -966.3 | -956.6 |
| Number of Observations | 139,309 | 139,309 |

Note: Robust standard errors in parentheses. All the continuous variables above are standardized for better presentation. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Two-tailed tests.

Table 2.4. Random-effects Probit and Multinomial Logit Results

| | Model | |
|---|---|---|
| | (1) | (2) |
| Model specification | Random-effects probit | Random-effects probit |
| Dependent Variable | Tech. Cooperation | Tech. Cooperation |
| Hypothesis tested | H1 | H1 |
| Mutual Forbearance Potential | | 0.014*** |
| | | (0.002) |
| Size (Max) | 0.159*** | 0.158*** |
| | (0.035) | (0.034) |
| Ratio of Size | 0.057 | 0.055 |
| | (0.046) | (0.046) |
| Patent Count (Max) | 0.055** | 0.051* |
| | (0.027) | (0.028) |
| Ratio of Patent Count | 0.041 | 0.038 |
| | (0.038) | (0.038) |
| Class Count (Max) | 0.095** | 0.094** |
| | (0.039) | (0.038) |
| Ratio of Class Count | 0.076** | 0.072** |
| | (0.037) | (0.036) |
| Common Citation Rate | 0.024*** | 0.024*** |
| | (0.009) | (0.009) |
| Cross-citation Rate | 0.014* | 0.014* |
| | (0.008) | (0.008) |
| Increment of H-index | 0.030*** | 0.030*** |
| | (0.011) | (0.011) |
| International Deal | -0.451*** | -0.449*** |
| | (0.096) | (0.096) |
| Private (Bigger Firm) | -0.258** | -0.253** |
| | (0.117) | (0.116) |
| Private (Smaller Firm) | -0.526*** | -0.520*** |
| | (0.100) | (0.099) |
| Constant | -3.583*** | -3.571*** |
| | (0.203) | (0.207) |
| Year Fixed Effects | Included | Included |
| Rho | 0.367*** | 0.356*** |
| | (0.055) | (0.057) |
| Wald Chi-square (df) | 158.45*** (18) | 162.22*** (19) |
| Log Pseudolikelihood | -944.04 | -940.79 |
| Number of Observations | 139,300 | 139,300 |

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Two-tailed tests. All the continuous variables above are standardized for better presentation. Since random-effects models allow only one observation for a certain dyad in a certain year, only one observation is randomly selected when there are more than one observation, reducing the same size from 139,309 to 139,300.

Table 2.4. Continued

| | Model | | | |
|---|---|---|---|---|
| | (3) | (4) | (5) | (6) |
| Model specification | Random-effects multinomial logit | Random-effects multinomial logit | Random-effects multinomial logit | Random-effects multinomial logit |
| Dependent Variable | Low tech. uncertainty vs. no deal | High tech. uncertainty vs. no deal | Tech.-only vs. no deal | Tech.-plus vs. no deal |
| Hypothesis tested | H2 | H2 | H3 | H3 |
| Mutual Forbearance Potential | 0.018** | 0.031*** | 0.019** | 0.030*** |
| | (0.008) | (0.004) | (0.008) | (0.004) |
| Size (Max) | 0.320*** | 0.555*** | 0.393*** | 0.445*** |
| | (0.108) | (0.137) | (0.120) | (0.117) |
| Ratio of Size | 0.111 | 0.190 | 0.130 | 0.171 |
| | (0.159) | (0.176) | (0.169) | (0.173) |
| Patent Count (Max) | 0.200** | 0.039 | 0.154* | 0.111 |
| | (0.097) | (0.096) | (0.091) | (0.103) |
| Ratio of Patent Count | 0.101 | 0.147 | 0.109 | 0.146 |
| | (0.136) | (0.152) | (0.129) | (0.152) |
| Class Count (Max) | 0.309** | 0.175 | 0.151 | 0.386*** |
| | (0.130) | (0.157) | (0.135) | (0.144) |
| Ratio of Class Count | 0.149 | 0.254* | 0.107 | 0.304** |
| | (0.129) | (0.135) | (0.130) | (0.134) |
| Common Citation Rate | 0.043* | 0.060*** | 0.058*** | 0.047* |
| | (0.022) | (0.023) | (0.022) | (0.026) |
| Cross-citation Rate | -0.013 | 0.039** | -0.025 | 0.038** |
| | (0.056) | (0.019) | (0.105) | (0.017) |
| Increment of H-index | 0.056* | 0.062** | 0.084*** | 0.011 |
| | (0.032) | (0.029) | (0.033) | (0.036) |
| International Deal | -1.307*** | -0.988*** | -1.423*** | -0.843** |
| | (0.292) | (0.352) | (0.291) | (0.356) |
| Private (Bigger Firm) | -1.340** | -0.137 | -0.480 | -1.061** |
| | (0.582) | (0.444) | (0.420) | (0.490) |
| Private (Smaller Firm) | -1.711*** | -1.205*** | -1.876*** | -1.136*** |
| | (0.367) | (0.366) | (0.405) | (0.341) |
| Constant | -8.475*** | -8.808*** | -8.583*** | -8.751*** |
| | (0.634) | (0.650) | (0.681) | (0.611) |
| Year Fixed Effects | Included | Included | Included | Included |
| Variance(Random Effect) | 3.580*** (0.831) | | 3.610*** (0.820) | |
| H2/H3: Chi-square (1) | 5.81** | | 3.98** | |
| Log Pseudolikelihood | -1027.72 | | -1030.74 | |
| Number of Observations | 139,300 | | 139,300 | |

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Two-tailed tests. All the continuous variables above are standardized for better presentation. Since random-effects models allow only one observation for a certain dyad in a certain year, only one observation is randomly selected when there are more than one observation, reducing the same size from 139,309 to 139,300.

Table 2.5. Random-effects Probit/Multinomial Logit Results Excluding Licensing Agreements

| | Model | |
|---|---|---|
| | (1) | (2) |
| Model specification | Random-effects probit | Random-effects probit |
| Dependent Variable | Tech. Cooperation | Tech. Cooperation |
| Hypothesis tested | H1 | H1 |
| Mutual Forbearance Potential | | 0.016*** |
| | | (0.002) |
| Size (Max) | 0.280*** | 0.277*** |
| | (0.055) | (0.055) |
| Ratio of Size | 0.168*** | 0.164*** |
| | (0.064) | (0.063) |
| Patent Count (Max) | -0.016 | -0.030 |
| | (0.041) | (0.043) |
| Ratio of Patent Count | 0.160*** | 0.151*** |
| | (0.056) | (0.054) |
| Class Count (Max) | 0.021 | 0.020 |
| | (0.060) | (0.059) |
| Ratio of Class Count | 0.019 | 0.010 |
| | (0.054) | (0.052) |
| Common Citation Rate | 0.023** | 0.022** |
| | (0.009) | (0.009) |
| Cross-citation Rate | 0.007 | 0.007 |
| | (0.006) | (0.006) |
| Increment of H-index | 0.019 | 0.019 |
| | (0.012) | (0.012) |
| International Deal | -0.274* | -0.271** |
| | (0.141) | (0.138) |
| Private (Bigger Firm) | -0.498** | -0.479** |
| | (0.196) | (0.189) |
| Private (Smaller Firm) | -0.385*** | -0.374*** |
| | (0.145) | (0.142) |
| Constant | -4.139*** | -4.086*** |
| | (0.377) | (0.392) |
| Year Fixed Effects | Included | Included |
| Rho | 0.421*** | 0.397*** |
| | (.091) | (0.099) |
| Wald Chi-square (df) | 68.53*** (18) | 71.90*** (19) |
| Log Pseudolikelihood | -422.11 | -418.39 |
| Number of Observations | 139,300 | 139,300 |

Note: Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Two-tailed tests. All the continuous variables above are standardized for better presentation. Since random-effects models allow only one observation for a certain dyad in a certain year, only one observation is randomly selected when there are more than one observation, reducing the same size from 139,309 to 139,300.

Table 2.5 Continued

| | Model | | | |
|---|---|---|---|---|
| | (3) | (4) | (5) | (6) |
| Model specification | Random-effects multinomial logit | Random-effects multinomial logit | Random-effects multinomial logit | Random-effects multinomial logit |
| Dependent Variable | Low tech. uncertainty vs. no deal | High tech. uncertainty vs. no deal | Tech.-only vs. no deal | Tech.-plus vs. no deal |
| Hypothesis tested | H2 | H2 | H3 | H3 |
| Mutual Forbearance Potential | 0.020* | 0.041*** | 0.023** | 0.037*** |
| | (0.010) | (0.008) | (0.010) | (0.007) |
| Size (Max) | 0.579*** | 1.135*** | 0.706*** | 0.842*** |
| | (0.154) | (0.216) | (0.179) | (0.182) |
| Ratio of Size | 0.445** | 0.516* | 0.491** | 0.437 |
| | (0.202) | (0.302) | (0.213) | (0.313) |
| Patent Count (Max) | -0.063 | -0.115 | -0.107 | -0.022 |
| | (0.129) | (0.202) | (0.169) | (0.141) |
| Ratio of Patent Count | 0.430** | 0.488** | 0.392** | 0.551** |
| | (0.178) | (0.232) | (0.181) | (0.216) |
| Class Count (Max) | 0.329 | -0.443* | 0.051 | 0.090 |
| | (0.207) | (0.237) | (0.207) | (0.279) |
| Ratio of Class Count | 0.213 | -0.252 | 0.160 | -0.127 |
| | (0.160) | (0.262) | (0.167) | (0.247) |
| Common Citation Rate | 0.052** | 0.037 | 0.067*** | 0.004 |
| | (0.021) | (0.024) | (0.021) | (0.031) |
| Cross-citation Rate | 0.020 | 0.015 | 0.019 | 0.021* |
| | (0.020) | (0.020) | (0.023) | (0.011) |
| Increment of H-index | 0.034 | 0.028 | 0.062* | -0.071 |
| | (0.036) | (0.038) | (0.035) | (0.061) |
| International Deal | -0.644 | -0.840 | -0.937** | -0.340 |
| | (0.462) | (0.543) | (0.444) | (0.602) |
| Private (Bigger Firm) | -19.831*** | 0.036 | -1.387* | -1.298* |
| | (0.271) | (0.712) | (0.708) | (0.705) |
| Private (Smaller Firm) | -1.276** | -0.939 | -1.222** | -1.063* |
| | (0.502) | (0.600) | (0.507) | (0.590) |
| Constant | -9.532*** | -10.926*** | -10.038*** | -10.312*** |
| | (0.958) | (1.355) | (1.075) | (1.283) |
| Year Fixed Effects | Included | Included | Included | Included |
| Variance(Random Effect) | 4.292*** (1.680) | | 4.478*** (1.796) | |
| H2/H3: Chi-square (1) | 8.36*** | | 4.11** | |
| Log Pseudolikelihood | -443.48 | | -442.63 | |
| Number of Observations | 139,300 | | 139,300 | |

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Two-tailed tests. All the continuous variables above are standardized for better presentation. Since random-effects models allow only one observation for a certain dyad in a certain year, only one observation is randomly selected when there are more than one observation, reducing the same size from 139,309 to 139,300.

## 2.5 Discussion

### 2.5.1 Contributions and Implications

This paper makes several theoretical contributions to the alliance literature in general and the specific stream of research on partner selection in particular. First, at the broadest level, my theory and results offer new interpretations and implications for market overlap and interfirm collaborations. As Gulati (1999: 397) has argued, in the alliance literature “the primary focus has been on understanding some of the resource-based considerations that promote the formation of alliances.” In particular, drawing on the resource-based view (or resource dependence theory) and population ecology, the alliance literature has typically argued that market overlap between potential partners makes collaborations between them unlikely. This is because firms competing in the same market niches are similar in terms of resources and capabilities (Hannan & Freeman, 1977) and this lack of complementarity reduces their strategic interdependence and, in turn, motivation to cooperate (Richardson, 1972). Along similar lines, previous studies in the alliance literature have often measured complementarity between firms by counting non-overlapping niches and also have tested the negative effect of market (or niche) overlap on collaborations (Chung et al., 2000; Gulati, 1995a; Rothaermel & Boeker, 2008).

However, by aiming to bridge the literatures on multimarket competition and interfirm collaboration, I offer a new theoretical logic for the linkage between market overlap and partner selection. I have demonstrated that market overlap can facilitate technology cooperation and have identified a new mechanism for why partners can find cooperative agreements with rivals attractive: market overlap generates mutual forbearance from opportunism. Although my new arguments and the conventional view make the opposite predictions about the relationship between market overlap and technology cooperation, I see the different perspectives as being complementary rather than incompatible with each other. They consider different theoretical mechanisms shaping the attractiveness of partners (i.e., based on resource/capability endowments and likelihood of opportunism), so the positive and negative effects of market overlap can co-exist in theory. Furthermore, recent work on partner selection in the alliance literature highlights that the relative importance of criteria for partner selection such as resource complementarity and the risk of opportunism varies depending on alliance context. For example, Shah and Swaminathan (2008) argued that when “outcome interpretability” and “process manageability” are both low, trust becomes a key criterion for partner selection. Because my theory and results are based on technology cooperation where outcome interpretability and process manageability both are low, this can explain the net positive effect of market overlap for the technology partnerships I study. It would be valuable in future research to identify specific conditions under which market overlap has a negative effect on technology cooperation based upon resource considerations rather than mutual forbearance potential. Such research holds the potential to determine the importance of the new motive for partner selection I have identified compared to other criteria that prospective collaborators employ (Ariño & Ring, 2010; Gimeno, 2004; Hitt et al., 2004; Li et al., 2008; Mitsuhashi & Greve, 2009; Reuer & Lahiri, 2014; Rothaermel & Boeker, 2008).

Second, my theoretical arguments for market overlap and the risk of opportunism enrich the conventional view on the competitive aspect of cooperation by considering the cost side of opportunistic behaviors in partnerships. The literature has mainly argued that competitive relationships in end-product markets aggravate hazards of cooperation by increasing the benefit to a firm engaging in opportunism (Oxley & Sampson, 2004; Park & Russo, 1996). Above all, opportunistic behaviors in a partnership with an end-product market rival can directly hurt the rival in a zero-sum game. In addition, although perfect cooperation within the partnership may make the goal of the partnership more likely to be achieved, the outcomes by perfect cooperation within the partnership improve the competitiveness of the rivals equally, which decreases the incentive for perfect cooperation relative to opportunistic action (Khanna et al., 1998). In addition to this conventional view focusing on the immediate pay-off from opportunistic behavior, I suggest that it is also valuable to consider the multi-period consequences of initial opportunism, including the responses by the counterpart in the markets in which the firms compete. If a partner can retaliate against opportunistic action of a firm in multiple markets, the cost of the initial opportunistic action will increase, making the net benefit unclear once such costs are considered. By applying this simple idea from the multimarket competition literature to the partnership context, I suggest that the effects of competition between partners outside an alliance on behavior within an alliance is more complicated than previously considered in the alliance literature.

### 2.5.2 Limitations and Future Research Directions

This study also has a number of specific limitations that extensions to this research might address. To begin with, my study considers technology cooperation in biopharmaceuticals, so it would be interesting to investigate other forms of collaborative agreements in other industry contexts to probe the generalizability of my findings. Such research could be valuable to ascertain the importance of market overlap and mutual forbearance from opportunism relative to other partner selection criteria in other collaborative contexts.

Along similar lines, it is important to note that the market domain of a firm is defined by two theoretical dimensions—the product market dimension and geographical dimension (Jayachandran et al., 1999). Therefore, strictly speaking, multimarket contact should be measured taking the two dimensions into account simultaneously. Due to data limitations to do both at once, this paper considers the product market dimension only and thus the results of this paper would be weakened if the sample firms are not overlapping in their geographical market domains. To mitigate this concern, based on interviews with industry experts, I have focused on the top 200 global firms in biopharmaceuticals as these firms sell their products in major foreign countries and have the financial wherewithal to bear the cost of going through expensive approval procedures in foreign countries. It would therefore be valuable to investigate heterogeneity in firms' geographic markets to consider this potential boundary condition for mutual forbearance in promoting technology cooperation.

Moreover, future research might investigate how overlap in end-product markets interacts with overlap in factor markets to influence mutual forbearance and partner selection for cooperation. Since factor market overlap between two firms may imply resource similarity between them, the resource complementarity view might predict that factor market overlap will demotivate partnerships between them. By contrast, Jayachandran and colleagues (1999) argued that resource similarity facilitates a cooperative arrangement, such as mutual forbearance, by increasing the credibility of retaliation expectations. Later, Markman and colleagues (2009) also claimed that when two firms are highly overlapped both in end-product markets and factor markets, their awareness of the benefit from and motivation for mutual forbearance are both the highest. Therefore, it would be interesting to investigate which effect is more salient under what conditions.

Given that I only consider partner selection in the current study, it would be natural and interesting extension of this study to investigate how the mutual forbearance from opportunism between multimarket rivals affects other collaboration-related decisions and outcomes. There are many opportunities to bring the multimarket competition literature into different streams of research on alliances. For instance, future studies might examine how mutual forbearance potential and firms' cooperative history jointly have an impact on governance choices, alliance design, conflicts between partners, and knowledge transfers or other outcomes of interfirm collaborations. It would be interesting to consider whether multimarket rivals design incentives and administrative controls in collaborative agreements differently from other partners, given the shadow of the future cast on such collaborations. It might also be that such collaborations are subject to different dynamics than other alliances not embedded in a competitive context offering the potential for mutual forbearance from opportunism. Such research could examine whether and how firms retaliate against opportunism in alliances in their shared markets and vice-versa. Finally, my study has only examined the formation phase of alliances and is silent on the execution of technology partnerships as well as the performance consequences of alliances formed between multimarket rivals. Therefore, future research might examine whether the success or failure of collaborations (Park & Russo, 1996) or the intended transfer of (or unintended leakage of ) know-how (Oxley & Wada, 2009) in technology partnerships are apt to be affected by mutual forbearance from opportunism. Many opportunities therefore exist to examine the interplay of collaboration and multimarket competition to build upon this study as a first step in joining these literatures.

# CHAPTER 3. EFFECTS OF MULTIMARKET CONTACT ON THE GOVERNANCE OF R&D ALLIANCES

## 3.1 Introduction

In the alliance literature, governance structure choice has been regarded as one of the most important decisions that firms have to undertake for their collaborative agreements (Li et al., 2008). Transaction cost economics (TCE) has been a primary theoretical foundation in the literature on alliance governance. At the same time, however, its exclusive focus on transactional attributes and related contractual hazards as determinants of governance structures has been criticized by scholars who emphasize that the broader social context in which a transaction is embedded also crucially influences governance choice (Gulati, 1995b; Gulati & Nickerson, 2008; Jones, Hesterly, & Borgatti, 1997). In particular, the stream of research on relational embeddedness has showed that in general previous cooperative relationships between alliance partners mitigate the risk of opportunism by partners and thus reduce the need for hierarchical governance structures for their collaborations (Gulati, 1995b).

It is noteworthy that the alliance governance literature has not achieved comparable progress regarding how competitive relationships between alliance partners influence the decisions concerning alliances and their governance. This is an important research gap because the competitive relationships a firm has with its potential partners—

both in product markets as well as in factor markets—are among the most important contextual conditions that firms consider for their collaborations. Furthermore, I know little about how these different types of dyadic relationships that alliance partners have outside an alliance (i.e., competitive relationships in product and factor markets and other cooperative relationships) jointly affect the governance of alliances. Indeed, some previous work, though scant, has addressed competition between alliance partners and the competitive context of inter-firm collaboration (Dussauge, Garrette, & Mitchell, 2000; Hamel et al., 1989; Khanna et al., 1998). However, this research has not focused upon how different competitive relationships between alliance partners might affect alliance governance. More importantly, previous research has emphasized that market overlap between alliance partners incentivizes them to behave opportunistically by increasing the pay-off from such behavior (Oxley & Sampson, 2004; Park & Russo, 1996). However, based on the multimarket competition literature, I can build upon and extend this argument by taking into account possible future competitive responses by alliance partners and therefore the consequential costs of behaving opportunistically.

The multimarket competition literature has theorized and corroborated that as two firms encounter each other in more markets, or have a higher level of multimarket contact,[6] they mutually forbear from competitive attacks for fear of broad retaliation by the attacked firm across the multiple shared markets (Baum & Korn, 1996; Evans & Kessides, 1994; Gimeno & Woo, 1996; Haveman & Nonnemaker, 2000; Phillips & Mason, 1996). Accordingly, in R&D alliances featuring concerns about opportunism by

[6] In this paper, I use the terms market overlap, (multi)market contact, and shared markets interchangeably.

partners (Pisano, 1989), multimarket contact between partner firms might also curb opportunistic behavior, since opportunism is also a form of competitive action to appropriate value in an R&D collaboration. For this reason, shared markets between R&D partners can enhance incentive alignment, thus making the R&D alliance less likely to be governed by hierarchical governance structures that the alliance governance literature has long suggested as remedies for opportunism.

Furthermore, I also pay attention to other types of dyadic relationships alliance partners have outside an alliance in addition to rivalry in end-product markets. Alliance partners may encounter each other not only in end-product markets, but also in factor markets. In addition, they may be embedded in prior cooperative relationships, so there is an opportunity to consider the competitive and cooperative context of an alliance agreement at the same time. Drawing on the multimarket competition literature on factor market rivalry and the literature on relational embeddedness respectively, I claim that competition in factor markets intensifies the mutual forbearance from opportunism that multimarket contact in end-product markets generates. I also develop the theoretical argument that there is a substituting relationship between previous cooperative experience and multimarket contact in determining the expected level of opportunism by partners.

By theorizing upon how different dyadic relationships located outside an alliance affect incentive alignment and governance choice, I make several contributions to research on alliance governance as well as to the multimarket competition literature. Beyond joining these two streams of research that have previously developed separately, I contribute to the literature on the competitive aspects of collaborations by suggesting that overlap across markets can reduce the risk of opportunism by increasing its cost. My study therefore offers a novel and more complete perspective on how the competitive context of collaboration affects alliance governance choice. My theory emphasizes that competition does not always undermine cooperation. Also, my theory and results contribute to an understanding of how three different dyadic relationships between alliance partners, i.e., end-product market rivalry, factor market rivalry, and prior collaborative relationships, interplay with one another in influencing partners' alliance governance choices.

I also contribute to the multimarket competition literature by proposing that market contact can influence firms' decisions through efficiency considerations, rather than market power considerations. Previous studies on multimarket competition have interpreted mutual forbearance as tacit collusion, which enables firms to obtain monopolistic rents (Jayachandran et al., 1999; Yu & Cannella Jr., 2013). However, by emphasizing how multimarket contact can generate mutual forbearance that can support the governance of alliances through incentive alignment, my arguments and findings suggest that multimarket contact can also enhance transactional efficiency, broadening the domains to which mutual forbearance through multimarket competition can apply.

## 3.2 Theory and Hypotheses

### 3.2.1 Multimarket Contact and Alliance Governance

In the study of inter-organizational collaboration, misaligned incentives and the consequential opportunism have been a central theme in multiple theoretical traditions such as organizational economics (Oxley, 1997; Pisano, 1989), the social-structural perspective (Gulati, 1995b; Robinson & Stuart, 2007), and the social-psychological trust-based perspective (Ring & van de Ven, 1994; Zaheer, McEvily, & Perrone, 1998) (Gulati, Wohlgezogen, & Zhelyazkov, 2012). However, despite the probable impact of competitive relationships between alliance partners on their incentive alignment, previous research has not paid systematic attention to this issue.

Though scant, some existing research that Chen (2008) named as the "competition-oriented cooperation" literature has examined the tension between competition and cooperation and how competition between alliance partners affect their decisions upon alliances and collaboration outcomes. For example, Oxley and Sampson (2004) posited that in R&D alliances market overlap between partner firms reduces the likelihood of a broad alliance scope including manufacturing and marketing in addition to R&D activities. Park and Russo (1996) also showed that joint ventures between direct competitors are more likely to fail than those in which partners do not compete. These previous studies were based on the argument that competition in end-product markets, or market overlap between alliance partners, incentivizes alliance partners to opportunistically behave by increasing the pay-off from such behaviors. Competition outside an alliance effectively makes the collaboration a zero-sum game (Oxley & Sampson, 2004). Also, existing research has considered whether or not alliance partners are present in the same end-product markets to conceptualize direct competition between them. Although this formulation captures the competitive tension that exists between alliance partners, it does not distinguish the nature and breadth of partners' competitive relationships, which carry different consequences for partners' incentives and alliance governance. As I will argue below, appreciation of the number of market contacts sheds new light on the cost of opportunism in alliances and the implications this has for alliance governance.

When firms decide whether or not to undertake an action such as opportunistic behavior in alliances, they evaluate the benefits and costs of the action. Since rivals react to the actions taken by each other, expected costs of an opportunistic behavior should include the damage that the rivals' response would entail. The multimarket competition literature is a research stream that has focused on investigating the competitive actions and responses between multimarket rivals (see Jayachandran et al. (1999) and Yu & Cannella Jr. (2013) for reviews). To my knowledge, this literature has not examined the effect of multimarket contact on alliance governance. However, as I will demonstrate, this literature would predict that multimarket contact between alliance partners discourages opportunistic behavior by increasing its cost and thereby makes hierarchical governance modes less likely to be needed for an alliance. This is opposite to the existing view in the alliance literature that market overlap increases the likelihood of hierarchical governance mode due to aggravated contractual hazards, regardless of the number of market contacts (Oxley & Sampson, 2004).

The core concept of the multimarket competition literature is the so-called mutual forbearance hypothesis—as two firms share more markets, they tend to mutually forbear from attacks, therefore lowering the intensity of rivalry (Bernheim & Whinston, 1990; Edwards, 1955). The reason why mutual forbearance takes place is that multimarket rivals appreciate that an attack taken in one market may provoke broad retaliation by the attacked firms, so competitive responses would occur not only in the market where the attack was initiated but also in other shared markets. As a consequence, the attacking firm may incur a larger loss than the gain from the initial attack (Karnani & Wernerfelt, 1985). Many previous empirical studies have shown that mutual forbearance between multimarket rivals attenuates rivalry, as indicated by higher prices (Gimeno & Woo, 1996; Hannan & Prager, 2004), higher profitability (Hannan & Prager, 2009; Parker & Röller, 1997), lower entry and exit rates (Baum & Korn, 1996; Fuentelsaz & Gómez, 2006), greater stability of market shares (Heggestad & Rhoades, 1978; Sandler, 1988), less frequent competitive behavior (Young et al., 2000; Yu & Cannella Jr., 2007), lower service quality (Prince & Simon, 2009), and smaller investments in tangible and intangible resources (Kang et al., 2010; Shankar, 1999).

The multimarket competition literature also argues that as two firms share more markets (i.e., have a higher level of multimarket contact), mutual forbearance between them becomes stronger. This is because multimarket contact enhances two conditions that are required for mutual forbearance: (1) deterrence from attacks (Bernheim & Whinston, 1990; Edwards, 1955) and (2) mutual understanding of rivals' capabilities and strategies and consequently an appreciation of their interdependence (Baum & Korn, 1996). Deterrence between two firms is proportional to the degree of multimarket contact between them because more shared markets provide a greater ability, as well as more opportunities, to retaliate against current attacks (Jayachandran et al., 1999). Multimarket contact also promotes mutual forbearance by helping multimarket rivals to recognize that their market prospects are highly interdependent, and that they can be better off by mutually forbearing from rather than initiating attacks. For two firms to appreciate this interdependence and implicitly agree on mutual forbearance, both firms should have a high level of awareness of each other's capabilities, tactics and strategies, and reputation for retaliation. This high level of mutual awareness is more likely to be achieved as two firms encounter each other in more markets (Jayachandran et al., 1999).

Opportunistic behaviors are also a kind of competitive action that alliance partners can take within an alliance itself. Just as mutual forbearance deters rivals from taking aggressive actions such as price cuts and market entry, it can also curb opportunism in alliances. That is, the possibility of broad retaliation increases the expected cost of the opportunistic behaviors and thereby reduces the incentives for alliance partners to behave opportunistically. Accordingly, as two R&D alliance partners share more markets, they tend to have stronger deterrence and better understanding of their interdependence and, as a result, are more likely to mutually forbear from behaving opportunistically; therefore, two R&D alliance partners with a higher level of multimarket contact have a lower concern about opportunism by partners.

The alliance governance literature has long argued that hierarchical governance structures involving equity arrangements effectively mitigate the risk of partners' opportunism by enhancing monitoring, control, and incentive alignment (Kogut, 1988; Pisano, 1989). Despite these benefits, however, the high costs associated with establishing and maintaining hierarchical governance structures justify alliance partners' employing those remedies only when the expected level of opportunism by partners is substantial. Consistently, since two potential R&D alliance partners who share more markets are more likely to mutually forbear from opportunism, they have a lesser need to choose hierarchical governance modes to alleviate the risk of opportunism. By contrast, when such mutual forbearance from opportunism is not available due to lower levels of multimarket contact, they will be more likely to need the benefits of monitoring, control, and incentive alignment that hierarchical governance structures provide. I therefore posit:

*Hypothesis 1. As two partner firms to an R&D collaboration have a higher level of multimarket contact, the likelihood of the partners employing a more hierarchical governance structure decreases.*

### 3.2.2 Other Competitive and Cooperative Relationships between Partners

I have argued that multimarket contact between alliance partners effectively substitutes for hierarchical governance structures by generating mutual forbearance from opportunism in R&D collaborations. Although I have focused on competitive relationships between alliance partners in end-product markets, they may also have different dyadic relationships between them. That is, they may compete against each other in factor markets as well, just as they might also be embedded in pre-existing cooperative relationships. Given that the relational context in which alliance partners are embedded might affect their incentive alignment, the interplay between different types of dyadic relationships is worth investigating to have a more complete and comprehensive understanding of the effects of dyadic relationships alliance partners have outside an alliance on their governance choice. As I argue below, these other competitive and cooperative relationships between partners represent important boundary conditions for the effects of multimarket contact on alliance governance captured by my first hypothesis.

More specifically, if factor market competition makes multimarket contact more or less likely to generate mutual forbearance or if cooperative relationships affect the expected level of opportunism between alliance partners, these interfirm relationships will also shape the efficacy of multimarket contact as a remedy for opportunism and hence partners' reliance on hierarchical governance structures. Therefore, drawing on recent work in the multimarket competition literature that examines how factor market rivalry affects mutual forbearance (Markman et al., 2009), I examine how firms' pursuit of similar or different technological resources reinforces or dampens the effect of multimarket contact on alliance governance choice in R&D collaborations. In addition, drawing on previous research on relational embeddedness (Gulati, 1995a; Gulati, 1995b), I investigate how the substituting effect of multimarket contact for hierarchical governance structures becomes stronger or weaker for partners having previous collaborations with each other.

***Moderating effect of technology overlap.*** While the multimarket competition literature has predominantly emphasized competition in end-product markets, firms also compete in factor markets (Dierickx & Cool, 1989) and overlap in factor markets may likewise affect mutual forbearance by reinforcing deterrence from attacks and mutual understanding of firms' interdependence (Markman et al., 2009). Since firms may rely on different factors to produce the same or substituting products, even rivals in the same end-product markets have different levels of overlap in factor markets between each other. Given the same number of end-product market contacts, overlap in factor markets provides extra contacts between firms. Since these extra contacts can promote deterrence and understanding of interdependence between multimarket rivals, overlap in factor markets reinforces mutual forbearance between them.

Deterrence from attacks becomes stronger as two firms have greater overlap in factor markets in addition to end-product markets because the contacts in factor markets also provide better ability and more opportunities to retaliate against current attacks. Simultaneous retaliation in both end-product and factor markets can damage the attacker more seriously. Also, even when retaliation in end-product markets is prohibitively costly, firms sharing factor markets still can retaliate in different factor markets (Markman et al., 2009). For instance, they can seize the top talent or important specialized input suppliers of the attacking firms. In addition, encounters in factor markets enhance partners' understanding of each other's capabilities and strategies that support their positions in end product markets (Porter, 1980: 47–71). It also makes them conceive of each other as more significant competitors and therefore pay more attention to each other (Porac & Thomas, 1990; Reger & Huff, 1993). For these reasons, overlap in factor markets helps multimarket rivals in end-product markets better understand their interdependence.

In high-technology industries, the most important strategic factor to determine competitive advantages is technology (DeCarolis & Deeds, 1999). Therefore, technology overlap between two firms is the most critical aspect of factor market rivalry between them (DeCarolis, 2003). Since the trajectories of technology development in firms tend to be path-dependent (Coombs & Hull, 1998), two firms who are highly overlapped in technology space are likely to compete for the same pools of labor and input suppliers over a long period of time. Hence, technology overlap between multimarket rivals in end-product markets facilitates the formation of mutual forbearance from opportunism. Therefore, given a certain level of multimarket contact, technology overlap facilitates the formation of mutual forbearance from opportunism and thus further reduces the need for hierarchical governance structures to support R&D collaborations. I therefore posit:

*Hypothesis 2. The negative effects of multimarket contact on the usage of hierarchical governance in R&D alliances will be more pronounced when the partners have technological overlap.*

***Moderating effect of prior ties.*** Although I have argued that multimarket contact between R&D alliance partners reduces the risk of opportunism by partners, they are also embedded in social networks of cooperative relationships that shape expectations of opportunism. When trust is defined as "a type of expectation that alleviates the fear that one's exchange partner will act opportunistically (Bradach & Eccles, 1989: 104)," organizational researchers have argued and empirically shown that interfirm trust increases with repeated interactions (Anderson & Weitz, 1989; Gulati & Sytch, 2008; Parkhe, 1993). Therefore, the number of previous experience of interactions (i.e., prior ties) with a potential partner is expected to reduce potential hazards of opportunism and, in turn, may affect the effect of multimarket contact on alliance governance choice. Gulati (1995a) has shown that past alliances between firms enhance the likelihood of a future exchange in the form of a new partnership between them, and he has also demonstrated that the reduced risk of opportunism leads them to opt for a non-equity structure rather than an equity alliance that would bring greater joint controls and enhanced incentive alignment through shared equity (Gulati, 1995b).

I argue that since multimarket contact and prior ties fulfill a redundant role of reducing the risk of opportunism by partners, they substitute for each other in affecting alliance partners' decisions regarding remedies for such a risk. When two potential alliance partners have prior ties and thus expect a lower level of opportunism by partners, the relative contribution that multimarket contact makes to mitigating cooperation hazards will tend to be lower. However, when prior ties between firms are lacking and the risk of opportunism is greater, it can be especially beneficial to have the shadow of the future and mutual forbearance from opportunism emerging from multimarket contact to support R&D collaborations. Therefore, the substituting effect of multimarket contact for hierarchical governance structures is expected to be most pronounced for first-time collaborators exposed to a greater risk of opportunism and will diminish for firms with a more extensive cooperative history. I therefore posit:

*Hypothesis 3. The negative effects of multimarket contact on the usage of hierarchical governance in R&D alliances will diminish with prior ties.*

## 3.3 Methods

### 3.3.1 Data and Sample

To empirically investigate how multimarket contact between alliance partners affects their governance choices for R&D alliances in high-technology industries, I used the global biopharmaceutical industry as my research setting, for several reasons. First, the biopharmaceutical industry is a high-technology industry where R&D intensity is substantial. Second, market definition in this industry is very clear. Like other empirical work in the multimarket competition literature, in my study markets should be defined to ensure that two firms defined to be present in the same market actually compete against each other. Markets in this industry are defined by therapeutic classes that are widely-accepted and commonly-used by U.S. government authorities and industry players (e.g., cholesterol regulators, antiulcerants, and antipsychotics) (Anand et al., 2009). Since different products in the same therapeutic class are generally substitutes for each other, firms offering their products in the same therapeutic class compete with each other. Third, alliances are frequently observed in the industry (Hagedoorn, 2002), and many studies of alliance governance have been carried out in biopharmaceuticals (Gulati & Singh, 1998; Phene & Tallman, 2012; Pisano, 1989; Robinson & Stuart, 2007), which facilitates comparisons between my study and extant research.

In order to examine firms' presence in different end-product markets, I used data provided by IMS Health that contains prescription drug sales by therapeutic class for biopharmaceutical companies around the world; in the data, there were 338 distinct therapeutic classes and each therapeutic class was defined as a distinct market. For the alliance data, I relied on Thomson Reuters' Recap database. As Schilling (2009) has shown, the Recap database is the most robust and representative in its coverage of alliances in the global biopharmaceutical industry and thus has been widely used in previous work on R&D collaborations in this industry (Adegbesan & Higgins, 2011; Lerner et al., 2003; Robinson & Stuart, 2007). To develop patent-related variables, I drew on patent data from the U.S. Patent and Trademark Office (USPTO).

To construct my base sample, I first extracted all the R&D partnerships reported in the Recap database between 2007 and 2013. Using the definition of R&D partnerships by Hagedoorn (2002), I included contractual partnerships, such as joint R&D pacts and joint development agreements, and equity-based partnerships such as minority equity R&D partnerships and R&D joint ventures. Pure patent licensing agreements were excluded. Since my theory on the effects of multimarket contact on alliance governance is fundamentally dyadic, I excluded 167 alliances that were formed between more than two firms, leaving 3,523 observations in my sample. Out of the 3,523 R&D partnerships, 201 (5.7%) were equity-based alliances, including minority equity partnerships and joint ventures while the remaining 3,322 (94.3%) were non-equity alliances. Then, for the firms involved in those R&D collaboration agreements, I examined their activities in end-product markets from the IMS Health data to measure their competitive relationships, as described below.

### 3.3.2 Measures

***Dependent variable.*** The dependent variable, *Equity Alliance*$_{ij}$, takes the value of one if two R&D alliance partners, firm *i* and firm *j*, choose an equity-based governance structure (either minority investment or joint venture), and zero for non-equity deals.[7] The dependent variable therefore captures the degree of hierarchy in alliances. Equity involvement is the most critical control mechanism to enhance incentive alignment,

[7] To check if there are R&D alliances where the governance modes change (e.g., from non-equity to equity or from equity to non-equity) in my sample, I collected all the repeated alliances between the sample partners and checked the detailed specifics of the alliances. To my best knowledge, however, there was no such case.

monitoring, and enforcement (Hennart, 1988; Pisano, 1989). Therefore, bifurcation of the hybrid governance structures on the markets-hierarchies governance continuum into non-equity and equity alliances has been the most commonly used approach in the alliance governance literature (Gulati, 1995b; Hagedoorn & Narula, 1996; Li et al., 2008; Li, Eden, Hitt, Ireland, & Garrett, 2012; Osborn & Baughn, 1990; Phene & Tallman, 2012; Pisano, 1989; Robinson & Stuart, 2007). I also use this categorization for clarity, simplicity, and comparability with previous work. In supplemental analyses presented below, I also follow previous research on alliance governance in biopharmaceuticals in separating minority equity partnerships and joint ventures (Gulati & Singh, 1998).

***Explanatory variables.*** The key independent variable of this study used for hypothesis testing is $\textit{Multimarket Contact}_{ij}$, which measures the degree of multimarket contact between firm *i* and firm *j* in the year of R&D partnership. Following the literature (Baum & Korn, 1996; Fuentelsaz & Gómez, 2006), I operationalize the variable as follows:

$$\textit{Multimarket Contact}_{ij} = \frac{\sum_m I_{im} \times I_{jm}}{\sum_m I_{im} + \sum_m I_{jm}}$$

In this expression, *m* represents the set of markets. For market definition, I treat each therapeutic class (e.g., cholesterol regulator, antiulcerants, and antipsychotics) as a distinct end-product market. $I_{im}$ ($I_{jm}$) is an indicator taking the value of one if firm *i* (firm *j*) is present in market *m* in the year of R&D partnership, and zero otherwise. The multimarket contact measure represents the number of market contact between the two firms over the sum of the each firm's number of markets. Many different measures for multimarket contact have been developed and used in the multimarket competition literature. Basically, the measures are constructed from counts of market contacts, but different weights are often employed. Since reliability as well as discriminant and predictive validity have been found to differ across the measures and no consensus exists as to which one is best (Gimeno & Jeong, 2001), I choose this simple measure to be parsimonious (Gimeno & Woo, 1996).[8]

To test the moderating effects of partners' overlap in factor markets (i.e., H2), I construct a measure of technology overlap, or the extent to which two alliance partners draw upon similar technological resources in factor markets. For this variable, I employ the angular measure initially developed by Jaffe (1986) that has been widely accepted and extensively used in the literature for this purpose (Gomes-Casseres, Hagedoorn, & Jaffe, 2006; Li et al., 2008):

$$Technology\ Overlap_{ij} = \frac{\boldsymbol{F}_i \boldsymbol{F'}_j}{\sqrt{(\boldsymbol{F}_i \boldsymbol{F'}_i)(\boldsymbol{F}_j \boldsymbol{F'}_j)}}$$

where $\boldsymbol{F}_i = [F_i^1, F_i^2, \cdots, F_i^s, \cdots, F_i^{462}]$ and $\boldsymbol{F}_j = [F_j^1, F_j^2, \cdots, F_j^s, \cdots, F_j^{462}]$

Given that my sampled firms have patented in 462 distinct three-digit USPTO patent classes, $F_i^s$ ($F_j^s$) is the number of patents that Firm *i* (Firm *j*) have applied in patent class *s* for the last ten years before the year of their R&D partnership (Benner & Waldfogel, 2008); these patent applications are all approved in the end. Therefore, $\boldsymbol{F}_i$ ($\boldsymbol{F}_j$) represents Firm *i* (Firm *j*)'s distribution of patents across various patent classes. *Technology Overlap* ranges from zero to one, where values closer to one indicate greater overlap between two

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8 For robustness check, I also used Baum and Korn's, (1999) measure weighting each market contact with its importance. However, the results did not change significantly (results available upon request).

firms in technology space. As a robustness check, I also used a five-year time window to count the number of patent applications, but obtained the qualitatively same results as those presented below.

To examine the potential role that partners' cooperative history plays as a boundary condition for the effects of multimarket contract on R&D alliance governance (i.e., H3), I constructed a measure of *Prior Ties* by counting the number of previous agreements two firms in a dyad entered into in the past ten years before the focal deal. Including this variable in the models is also helpful for controlling the direct effects of previous cooperative experience on governance choice. As above, I also examined this variable for a five-year time-frame and found the results to be robust.

***Control variables.*** In addition to the above covariates, I incorporate variables in the models that might be related to firms' alliance governance choices or their competitive relationships. First, at transaction level I control for the degree of exploration and the scope of the collaboration. As activities in a given R&D project are more explorative, appropriation concerns become stronger because adequate specification of property rights can be problematic (Freeman, 1997; Mowery & Rosenberg, 1991). In my context, the degree of exploration is well approximated by phases in new drug development. The new drug development process is typically categorized into discovery, lead molecule, formulation, preclinical, clinical phases I/II/III, and FDA approval phases from the beginning to the end, where earlier phases entail greater exploration (Robinson & Stuart, 2007). Therefore, I categorize the first four phases as early stage (i.e., high degree of exploration) through an indicator variable. As a robustness check, I also examined phase fixed effects and obtained qualitatively similar results as those presented below. Also, since alliance scope has been shown to affect the level of appropriation risk (Oxley & Sampson, 2004), I include a dummy variable taking the value of one if a given R&D alliance also contains either manufacturing or marketing activities, and zero otherwise.

Although I focus on relational embeddedness (i.e., *Prior Ties*) for my theory development, the social-structural perspective in the alliance literature has found that structural embeddedness also affects alliance formation and governance choices (Gulati & Gargiulo, 1999). Since they are related concepts, controlling for structural embeddedness can help to show the effect of relational embeddedness on governance choice independent of structural embeddedness. To control for structural embeddedness, I used measures for indirect ties and degree centrality. To measure indirect ties, I count the number of indirect ties at degree distance two using the complete network in the biopharmaceutical field reported in the Recap database (Powell, Koput, & Smith-Doerr, 1996). Degree centrality is measured by the total number of ties the firm had entered within the entire industry network. Prior ties between alliance partners in a dyad were excluded from measuring degree centrality to ensure that the latter is independent from the former. Specifically, I construct two dyad-level measures, *Degree Centrality (Max)* and *Ratio of Degree Centrality*. While the former refers to the level of degree centrality of the firm who has the larger value in a dyad, the latter means the ratio of degree centrality of the smaller firm to that of the larger firm in the dyad.

I also control for some other firm-level factors that may influence their alliance governance choices. When a partner firm is large, equity sharing can be prohibitively expensive, particularly when both partners are large. Also, prior research argued that asymmetrical sizes between alliance partners may affect their governance choices by causing more conflicts (Li et al., 2012). To control for these effects, I include in the model the sales of the larger firm in a given dyad (i.e., *Sales (Max)*) and the ratio of sales of the smaller firm to those of the larger firm in a given dyad (i.e., *Ratio of Sales*) (Gimeno, 2004).

The knowledge bases of alliance partners may also affect their decisions regarding governance structures. Firms with significant knowledge bases may prefer more hierarchical governance structures because they tend to have greater concerns about coordination and misappropriation (Phene & Tallman, 2012). To control for these effects, I construct *Patent Counts (Max)* and *Ratio of Patent Counts*. While the former counts the number of patents by the firm with the most patents in the dyad, the latter represents the ratio of patent counts (i.e., the number of patents by the firm with less patents divided by the number of patents by the partner). In addition, each partner's knowledge in the technological areas of the given alliance can influence governance structures more than its overall knowledge base does. Thus, I developed *Focal Knowledge (Max) and Ratio of Focal Knowledge.* To operationalize these variables, I mapped the technological areas reported for each alliance in the Recap database with the three-digit USPTO patent classes and then based on the mapping I counted the patents applied for the past ten years prior to the given alliance in the relevant patent classes. Using these patent counts in the technological areas of the given alliance, I measure the two variables in the same way as I do for overall patent counts.

I also include three different classes of fixed effects in the models. Because the types of technologies and diseases involved in a focal alliance may influence the governance structure of the alliance, technological domain fixed effects and disease fixed effects are included in the model. Finally, to capture any broader, economy-wide factors influencing the propensity for firms to include equity arrangements, year fixed effects are also included.

### 3.3.3 Statistical Methods

Because the dependent variable of this study, *Equity Alliance*$_{ij}$, is a binary variable, I use a probit regression model with robust errors as my base model. For robustness analyses, I use three additional statistical methods: ordered probit models, probit models with sample selection, and probit models with continuous endogenous regressors. First, although bifurcation of hybrid governance structures into equity and non-equity alliances is widely accepted in the literature (Gulati, 1995b; Li et al., 2008; Osborn & Baughn, 1990; Phene & Tallman, 2012; Pisano, 1989), this categorization of collaborations does not fully capture differential degrees of hierarchical control across different hybrid governance structures. I therefore estimated ordered probit models using three governance categories for the dependent variable, following Gulati and Singh (1998). Specifically, I categorize alliances into non-equity alliances, minority equity partnerships, and joint ventures. Gulati and Singh (1998) argued that joint ventures are more hierarchical than minority investments because the former are superior in monitoring and enforcement. The separate administrative hierarchy of managers in a joint venture not only makes detailed information on daily operations more accessible but also reinforces control by fiat (Gulati & Singh, 1998). Therefore, non-equity alliances, minority equity partnerships, and joint ventures can be ordered in their degree of hierarchy from lowest to highest for the hybrid portion of the markets-hierarchies governance continuum.

Second, since my sample consists of realized alliance deals only, selection bias may be a concern. To mitigate this concern, I use bivariate probit models with sample selection, which are the equivalent of Heckman's (1979) selection model except that the outcome equation (i.e., second-stage equation) is also a probit model. To run the first-stage selection model, I add 10 random unrealized alliance dyads for each of the realized alliances in my sample. As an instrument in the first-stage model, I use the average number of the two partner firms' previous licensing agreements with universities, following Robinson and Stuart (2007). Since partner firms licensing patents granted to universities may be regarded as an attractive partner, it may affect the likelihood of alliance formation, but it is unlikely to be related to their alliance governance structures.

Third, I also use probit models with continuous endogenous regressors to address a possible alternative explanation that multimarket rivals might refrain from opportunism due to the high value of the collaborations between them, rather than possible retaliation. Some might argue that R&D collaborations between multimarket rivals could be extremely damaging if key knowledge is leaked to the partners and thus multimarket rivals partner with each other only when the upside of the partnership is substantial. This logic might also predict the low use of hierarchical governance structures in the R&D alliances between multimarket rivals because the participating firms would abstain from opportunistic behaviors not to ruin the high potential partnerships. That is, this logic suggests that the mechanism through which multimarket contact reduces the likelihood of hierarchical governance modes being chosen is not the possible costs caused by retaliation against opportunism, but the possible costs of losing the high value collaboration due to opportunism. If this alternative explanation is true, my probit models have an endogeneity problem (more specifically, omitted variable bias) because my main theoretical variable (i.e., *Multimarket Contact*) will be (positively) correlated with the unobservable value of the given R&D alliance. To address this endogeneity problem, I run probit models with continuous endogenous variables using the logarithm of the sum of each partner's number of markets as an instrument (Wooldridge, 2002). The requirement for the instrument variable is that it should be correlated with the degree of multimarket contact, but not with governance choice. When a firm is present in many markets, this firm is more likely to be overlapped with other firms for a simply probabilistic reason. Therefore, when two potential partners compete in many markets, they are likely to have a high level of market overlap. However, the number of markets where two partner firms are present is unlikely to affect their governance choice, especially when their sizes are controlled.

## 3.4 Results

Table 3.1 presents descriptive statistics and a correlation matrix for the variables used in the analyses. The correlation between *Multimarket Contact* and *Equity Alliance* is negative and significant as predicted. Although there are many pairs of variables that show significant pairwise correlations, my models do not suffer from multicollinearity issues. The variance inflation factor for *Degree Centrality* (*Max*) is the highest (5.00), but is still below the recommended cutoff level of 10 (Neter et al., 1996). Table 3.2 shows the results from probit regression models examining how the degree of multimarket contact between two alliance partners affects their alliance governance choice (Hypothesis 1) and how this relationship is moderated by technology overlap and prior ties (Hypothesis 2 and 3 respectively). Model 1 contains control variables only, and Model 2 adds the direct effect of multimarket contact. The coefficient of *Multimarket Contact* in Model 2 is negative and significant ($b$=-10.98 and $p$<0.05), supporting Hypothesis 1. That is, as alliance partners have a higher level of multimarket contact, they are less likely to choose equity structure in their R&D collaborations. To estimate the economic significance of this variable, I examined how changes in *Multimarket Contact* affect the likelihood of equity alliance being chosen. Using the values of *Multimarket Contact* at its mean and mean plus one standard deviation, I calculated the response for each observation and then averaged those responses (Hoetker, 2007; Train, 1986). I observed that an increase in *Multimarket Contact* by one standard deviation from the mean reduces the predicted probability for equity arrangements by 55.2 percent.

Models 3-7 test the moderating effects of technology overlap and prior ties. Since the coefficient of the interaction term between *Multimarket Contact* and *Technology Overlap* in Model 4 is negative and significant ($b$=-565.4 and $p$<0.01), Hypothesis 2 is supported. That is, the negative effect of multimarket contact on the likelihood of equity structure being chosen is intensified when two alliance partners are also overlapped in technology space. Models 5 and 6 test Hypothesis 3 predicting that the effect of multimarket contact on governance choice is dampened as two alliance partners have more previous collaborations together. The coefficient of the interaction term between

*Multimarket Contact* and *Prior Ties* in Model 6 is estimated to be positive and significant in Model 6 ($b$=8.413 and $p$<0.01) as predicted in Hypothesis 3. In addition, the results from Model 7 where both moderating effects of technology overlap and prior ties are estimated together are consistent with the individual results in Model 4 and 6. Although the hypothesized moderating effects are supported by the interpretation of the relevant coefficients, the effect—and even the sign—of an interaction also depends upon the coefficients of the composite variables and the values of all other variables in probit models (Hoetker, 2007). Therefore, I provide graphical presentations of the interaction effects, following Hoetker (2007). For this exercise, while I used certain values of interest for the explanatory variables (i.e., *Multimarket Contact*, *Technology Overlap*, and *Prior Ties*), I used observed values for all other right-hand side variables to calculate the average response (Hoetker, 2007; Train, 1986). The graph in Panel A (Panel B) in Figure 3.1 shows how the relationship between *Multimarket Contact* and predicted probability for equity alliance changes depending on the values of *Technology Overlap* (*Prior Ties*). Specifically, when the value of *Technology Overlap* increases from its mean to one and two standard deviation above the mean, the downward slope becomes steeper, presenting that the negative effect of multimarket contact on the likelihood of equity alliance being chosen is reinforced as R&D alliance partners have a higher degree of technology overlap. By contrast, as the value of *Prior Ties* moves from zero to one and two, the downward slope becomes flatter in Panel B in Figure 3.1, supporting that the substituting effect of multimarket contact for hierarchical governance structures is weakened as two R&D alliance partners have more previous collaboration experience.

Table 3.1. Descriptive Statistics and Correlation Matrix

| Variables | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) | (15) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| (1) Equity Alliance | 1 | | | | | | | | | | | | | | |
| (2) Multimarket Contact | **-0.04** | 1 | | | | | | | | | | | | | |
| (3) Technology Overlap | 0.02 | **0.17** | 1 | | | | | | | | | | | | |
| (4) Prior Ties | -0.01 | **0.09** | **0.15** | 1 | | | | | | | | | | | |
| (5) Early Stage | **0.03** | **-0.07** | 0.01 | **0.04** | 1 | | | | | | | | | | |
| (6) Alliance Scope | **0.04** | **0.11** | **0.14** | **0.07** | **-0.13** | 1 | | | | | | | | | |
| (7) Indirect Ties | -0.03 | **0.33** | **0.17** | **0.16** | **-0.04** | -0.01 | 1 | | | | | | | | |
| (8) Degree Centrality (Max) | 0.02 | **0.14** | **0.20** | **0.22** | **0.09** | -0.01 | **0.27** | 1 | | | | | | | |
| (9) Ratio of Degree Centrality | -0.03 | **-0.01** | **-0.03** | **-0.04** | **-0.07** | 0.01 | 0.00 | **-0.28** | 1 | | | | | | |
| (10) Size (Max) | 0.03 | **0.20** | **0.16** | **0.14** | **0.10** | -0.01 | **0.18** | **0.55** | **-0.07** | 1 | | | | | |
| (11) Ratio of Size | **-0.06** | **-0.09** | **-0.14** | **-0.08** | **-0.09** | **-0.08** | **-0.04** | **-0.19** | **0.04** | **-0.37** | 1 | | | | |
| (12) Focal Knowledge (Max) | 0.01 | **0.13** | **0.2** | **0.11** | **0.16** | 0.01 | **0.18** | **0.49** | **-0.14** | **0.49** | **-0.27** | 1 | | | |
| (13) Ratio of Focal Knowledge | **-0.04** | **-0.06** | **-0.15** | **-0.1** | **-0.25** | -0.02 | **-0.04** | **-0.34** | **0.22** | **-0.28** | **0.32** | **-0.33** | 1 | | |
| (14) Patent Counts (Max.) | -0.02 | **0.06** | **0.09** | **0.06** | -0.01 | 0.03 | **0.1** | **0.36** | **-0.11** | **0.32** | **-0.23** | **0.37** | **-0.21** | 1 | |
| (15) Ratio of Patent Counts | **-0.04** | -0.01 | **-0.1** | **-0.08** | **-0.07** | **-0.04** | 0 | **-0.33** | **0.27** | **-0.27** | **0.32** | **-0.22** | **0.54** | **-0.22** | 1 |
| Mean | 0.06 | 0.01 | 0.12 | 0.10 | 0.43 | 0.14 | 0.81 | 66.67 | 0.23 | 7.39 | 0.54 | 116.5 | 0.49 | 233.3 | 0.31 |
| Standard Deviation | 0.23 | 0.04 | 0.26 | 0.38 | 0.50 | 0.35 | 5.87 | 101.2 | 0.34 | 14.30 | 0.49 | 320.4 | 0.48 | 649.0 | 0.43 |
| Min | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Max | 1 | 0.41 | 1 | 5 | 1 | 1 | 147 | 450 | 1 | 61.80 | 1 | 4083 | 1 | 14533 | 1 |

Note: N=3,523. Bolded pairwise correlations are significant at least at 0.05 level.

Table 3.2. Probit Regression Results

| | Models | | | | | | |
|---|---|---|---|---|---|---|---|
| Variables | (1) H1 | (2) H1 | (3) H2 | (4) H2 | (5) H3 | (6) H3 | (7) H2 & H3 |
| Multimarket Contact | | -10.98** | -10.98** | -7.04 | -10.68** | -17.60** | -11.27* |
| | | (5.15) | (5.11) | (4.47) | (4.97) | (8.377) | (6.10) |
| Technology Overlap | | | 0.06 | 0.08 | | | 0.09 |
| | | | (0.14) | (0.14) | | | (0.14) |
| Multimarket Contact × | | | | -565.4*** | | | -554.6*** |
| Technology Overlap | | | | (173.4) | | | (172.15) |
| Prior Ties | | | | | -0.08 | -0.10 | -0.10 |
| | | | | | (0.10) | (0.10) | (0.10) |
| Multimarket Contact × | | | | | | 8.41** | 7.94*** |
| Prior Ties | | | | | | (3.69) | (3.04) |
| Early Stage | 0.05 | 0.04 | 0.04 | 0.04 | 0.04 | 0.04 | 0.04 |
| | (0.08) | (0.08) | (0.08) | (0.08) | (0.08) | (0.08) | (0.08) |
| Alliance Scope | 0.04 | 0.07 | 0.06 | 0.07 | 0.07 | 0.07 | 0.07 |
| | (0.11) | (0.10) | (0.10) | (0.10) | (0.10) | (0.10) | (0.10) |
| Indirect Ties | -0.10** | -0.09** | -0.09** | -0.09** | -0.09** | -0.08** | -0.08** |
| | (0.04) | (0.04) | (0.04) | (0.04) | (0.04) | (0.04) | (0.04) |
| Degree Centrality (Max) | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| Ratio of Degree Centrality | -0.09 | -0.07 | -0.07 | -0.07 | -0.06 | -0.06 | -0.06 |
| | (0.13) | (0.12) | (0.13) | (0.13) | (0.12) | (0.12) | (0.13) |
| Size (Max) | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| Ratio of Size | -0.18* | -0.19* | -0.18* | -0.18* | -0.19* | -0.19* | -0.18* |
| | (0.10) | (0.10) | (0.10) | (0.10) | (0.10) | (0.10) | (0.10) |
| Focal Knowledge (Max) | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| Ratio of Focal Knowledge | 0.02 | 0.01 | 0.01 | 0.01 | 0.00 | 0.00 | 0.01 |
| | (0.09) | (0.09) | (0.09) | (0.09) | (0.09) | (0.09) | (0.09) |
| Patent Counts (Max) | -0.00** | -0.00*** | -0.00*** | -0.00** | -0.00*** | -0.00*** | -0.00*** |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| Ratio of Patent Counts | -0.22** | -0.22** | -0.22** | -0.22** | -0.22** | -0.22** | -0.23** |
| | (0.11) | (0.11) | (0.11) | (0.11) | (0.11) | (0.11) | (0.11) |
| Constant | -1.27*** | -1.26*** | -1.27*** | -1.28*** | -1.26*** | -1.26*** | -1.28*** |
| | (0.15) | (0.15) | (0.15) | (0.15) | (0.15) | (0.15) | (0.16) |
| Year Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Technology Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Disease Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Log likelihood | -682.4 | -676.5 | -676.4 | -674.6 | -676.3 | -675.9 | -673.9 |
| Wald Chi-squared | 1672.2*** | 1559.4*** | 1529.4*** | 1708.9*** | 1556.9*** | 1558.7*** | 1710.6*** |
| Observations | 3,523 | 3,523 | 3,523 | 3,523 | 3,523 | 3,523 | 3,523 |

Note: Robust standard errors in parentheses. *** $p$<0.01, ** $p$<0.05, * $p$<0.1. Two-tailed tests.

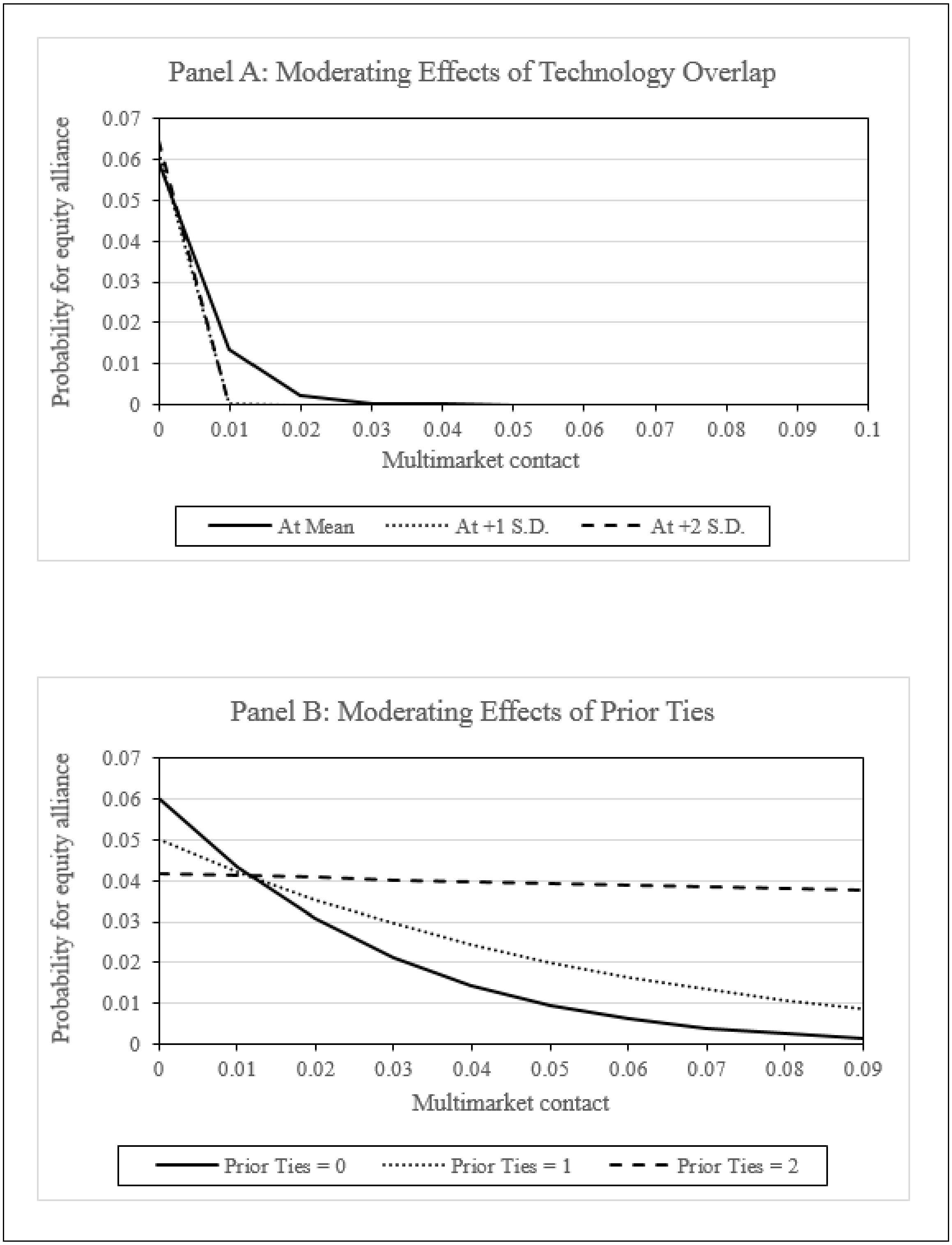


Figure 3.1. The Contingent Effects of Multimarket Contact

### 3.4.1 Supplemental Analyses

Table 3.3, 3.4, and 3.5 present the results of robustness checks using ordered probit models, probit models with sample selection, and probit models with continuous endogenous regressors respectively. As shown in Table 3.3, the results from ordered probit models provide support to the hypotheses as before. In addition, the second cut point is significantly larger than the first one in all models, justifying my categorization scheme.

Table 3.4 shows the results from bivariate probit models with sample selection. In the first-stage selection model (Model 1), the coefficient for the average number of licensing agreements with universities is positive and significant ($b$=0.05 and $p$<0.01). The Wald chi-square tests show that the selection bias is not significant in my sample. Furthermore, the results from the bivariate probit models with sample selection again lead to the same interpretations as those presented above.

Lastly, Table 3.5 presents the results from probit models with endogenous regressors. The Wald test of the exogeneity of the instrumented variable (i.e., *Multimarket Contact*) does not reject the null that the instrumented variable is exogenous ($\chi^2(1)$=1.27 and $p$=0.26), which recommends that a standard probit model is appropriate. Furthermore, the coefficient of *Multimarket Contact* is still negative and significant ($b$=-15.4 and $p$<0.01), supporting the negative main effect of multimarket contact on the likelihood of equity arrangements being included.

Table 3.3. Ordered Probit Regression Results

| | Models | | | | | | |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Variables | H1 | H1 | H2 | H2 | H3 | H3 | H2 & H3 |
| Multimarket Contact | | -10.92** | -10.91** | -7.01 | -10.60** | -17.55** | -11.22* |
| | | (5.11) | (5.07) | (4.41) | (4.91) | (8.27) | (6.05) |
| Technology Overlap | | | 0.05 | 0.07 | | | 0.08 |
| | | | (0.14) | (0.14) | | | (0.14) |
| Multimarket Contact × Technology Overlap | | | | -566.8*** | | | -552.0*** |
| | | | | (166.3) | | | (165.4) |
| Prior Ties | | | | | -0.08 | -0.10 | -0.10 |
| | | | | | (0.10) | (0.10) | (0.10) |
| Multimarket Contact × Prior Ties | | | | | | 8.44** | 7.87*** |
| | | | | | | (3.66) | (3.03) |
| Early Stage | 0.05 | 0.04 | 0.04 | 0.04 | 0.04 | 0.04 | 0.04 |
| | (0.08) | (0.08) | (0.08) | (0.08) | (0.08) | (0.08) | (0.08) |
| Alliance Scope | 0.06 | 0.08 | 0.08 | 0.08 | 0.09 | 0.09 | 0.09 |
| | (0.10) | (0.10) | (0.10) | (0.10) | (0.10) | (0.10) | (0.10) |
| Indirect Ties | -0.10** | -0.09** | -0.09** | -0.09** | -0.08** | -0.08** | -0.08** |
| | (0.04) | (0.04) | (0.04) | (0.04) | (0.04) | (0.04) | (0.04) |
| Degree Centrality (Max) | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| Ratio of Degree Centrality | -0.10 | -0.08 | -0.08 | -0.08 | -0.08 | -0.07 | -0.07 |
| | (0.12) | (0.12) | (0.12) | (0.12) | (0.12) | (0.12) | (0.12) |
| Size (Max) | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| Ratio of Size | -0.17* | -0.18* | -0.18* | -0.18* | -0.18* | -0.18* | -0.18* |
| | (0.10) | (0.10) | (0.10) | (0.10) | (0.10) | (0.10) | (0.10) |
| Focal Knowledge (Max) | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| Ratio of Focal Knowledge | 0.02 | 0.01 | 0.01 | 0.02 | 0.01 | 0.01 | 0.01 |
| | (0.09) | (0.09) | (0.09) | (0.09) | (0.09) | (0.09) | (0.09) |
| Patent Counts (Max) | -0.00*** | -0.00*** | -0.00*** | -0.00*** | -0.00*** | -0.00*** | -0.00*** |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| Ratio of Patent Counts | -0.20* | -0.20* | -0.20* | -0.20* | -0.20* | -0.21* | -0.21* |
| | (0.11) | (0.11) | (0.11) | (0.11) | (0.11) | (0.11) | (0.11) |
| Constant cut1 | 1.30*** | 1.29*** | 1.29*** | 1.30*** | 1.29*** | 1.29*** | 1.30*** |
| | (0.15) | (0.15) | (0.15) | (0.15) | (0.15) | (0.15) | (0.15) |
| Constant cut2 | 2.80*** | 2.81*** | 2.81*** | 2.82*** | 2.80*** | 2.81*** | 2.82*** |
| | (0.19) | (0.19) | (0.19) | (0.19) | (0.19) | (0.19) | (0.19) |
| Log likelihood | -708.0 | -702.1 | -702.1 | -700.3 | -701.9 | -701.5 | -699.5 |
| Wald Chi-squared | 846.9*** | 966.0*** | 864.6*** | 1127.1*** | 872.1*** | 908.6*** | 1211.6*** |
| Observations | 3,523 | 3,523 | 3,523 | 3,523 | 3,523 | 3,523 | 3,523 |

Note: Robust standard errors in parentheses. *** $p$<0.01, ** $p$<0.05, * $p$<0.1. Two-tailed tests.

Table 3.4. Probit Regression Results with Sample Selection

| | Model | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| | Selection | Outcome | | | |
| Variables | | H1 | H1 | H2 | H2 |
| Multimarket Contact | | | -10.98** | -10.95** | -7.02 |
| | | | (5.17) | (5.12) | (4.47) |
| Technology Overlap | | | | 0.07 | 0.09 |
| | | | | (0.14) | (0.14) |
| Multimarket Contact × Technology Overlap | | | | | -565.2*** |
| | | | | | (172.8) |
| Early Stage | | 0.05 | 0.04 | 0.04 | 0.04 |
| | | (0.08) | (0.08) | (0.08) | (0.08) |
| Alliance Scope | | 0.04 | 0.07 | 0.07 | 0.07 |
| | | (0.10) | (0.10) | (0.10) | (0.10) |
| Indirect Ties | 7.09*** | -0.09** | -0.09** | -0.09** | -0.09** |
| | (0.06) | (0.04) | (0.04) | (0.04) | (0.04) |
| Degree Centrality (Max) | 0.01*** | 0.00 | 0.00 | 0.00 | 0.00 |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| Ratio of Degree Centrality | -0.53*** | -0.10 | -0.07 | -0.07 | -0.07 |
| | (0.02) | (0.13) | (0.13) | (0.13) | (0.13) |
| Size (Max) | 0.00*** | 0.00 | 0.00 | 0.00 | 0.00 |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| Ratio of Size | -0.13*** | -0.18* | -0.19* | -0.18* | -0.18* |
| | (0.04) | (0.11) | (0.10) | (0.11) | (0.11) |
| Focal Knowledge (Max) | | 0.00 | 0.00 | 0.00 | 0.00 |
| | | (0.00) | (0.00) | (0.00) | (0.00) |
| Ratio of Focal Knowledge | | 0.01 | 0.01 | 0.01 | 0.01 |
| | | (0.09) | (0.09) | (0.09) | (0.09) |
| Patent Counts (Max) | 0.00** | -0.00** | -0.00*** | -0.00*** | -0.00** |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| Ratio of Patent Counts | 0.02 | -0.22** | -0.22** | -0.22** | -0.22** |
| | (0.03) | (0.11) | (0.11) | (0.11) | (0.11) |
| Avg. Licensing with Univ. | 0.05*** | | | | |
| | (0.01) | | | | |
| Inverse Mills Ratio | | 0.03 | 0.00 | 0.01 | 0.01 |
| | | (0.10) | (0.10) | (0.10) | (0.10) |
| Constant | -1.32*** | -1.32*** | -1.26*** | -1.28*** | -1.29*** |
| | (0.04) | (0.21) | (0.21) | (0.21) | (0.21) |
| Year Fixed Effects | | Yes | Yes | Yes | Yes |
| Technology Fixed Effects | | Yes | Yes | Yes | Yes |
| Disease Fixed Effects | | Yes | Yes | Yes | Yes |
| Log Pseudolikelihood | | -9568.5 | -9562.6 | -9562.5 | -9560.7 |
| Wald Chi-squared | | 1544.8*** | 1717.4*** | 1642.7*** | 1903.0*** |
| Wald Test of Rho = 0: $\chi^2(1)$ | | 0.09 | 0.00 | 0.01 | 0.01 |
| (p-value) | | (p=0.77) | (p=0.99) | (p=0.93) | (p=0.92) |
| Observations | | 3,523 | 3,523 | 3,523 | 3,523 |

Note: Robust standard errors in parentheses. *** $p$<0.01, ** $p$<0.05, * $p$<0.1. Two-tailed tests. Even when we included *Multimarket Contact* in the selection stage, we obtained the qualitatively same results.

Table 3.4. Continued

| | Model | | |
|---|---|---|---|
| | (6) | (7) | (8) |
| | Outcome | | |
| Variables | H3 | H3 | H2/H3 |
| Multimarket Contact | -10.67** | -17.62** | -11.23* |
| | (4.99) | (8.38) | (6.07) |
| Technology Overlap | | | 0.09 |
| | | | (0.14) |
| Multimarket Contact × Technology Overlap | | | -554.5*** |
| | | | (171.6) |
| Prior Ties | -0.08 | -0.10 | -0.10 |
| | (0.10) | (0.10) | (0.10) |
| Multimarket Contact × Prior Ties | | 8.42** | 7.93*** |
| | | (3.72) | (3.04) |
| Early Stage | 0.04 | 0.04 | 0.04 |
| | (0.08) | (0.08) | (0.08) |
| Alliance Scope | 0.07 | 0.07 | 0.07 |
| | (0.10) | (0.10) | (0.10) |
| Indirect Ties | -0.08** | -0.09** | -0.08** |
| | (0.04) | (0.04) | (0.04) |
| Degree Centrality (Max) | 0.00 | 0.00 | 0.00 |
| | (0.00) | (0.00) | (0.00) |
| Ratio of Degree Centrality | -0.06 | -0.06 | -0.06 |
| | (0.13) | (0.13) | (0.13) |
| Size (Max) | 0.00 | 0.00 | 0.00 |
| | (0.00) | (0.00) | (0.00) |
| Ratio of Size | -0.19* | -0.19* | -0.18* |
| | (0.10) | (0.11) | (0.11) |
| Focal Knowledge (Max) | 0.00 | 0.00 | 0.00 |
| | (0.00) | (0.00) | (0.00) |
| Ratio of Focal Knowledge | 0.00 | 0.00 | 0.01 |
| | (0.09) | (0.09) | (0.09) |
| Patent Counts (Max) | -0.00*** | -0.00*** | -0.00** |
| | (0.00) | (0.00) | (0.00) |
| Ratio of Patent Counts | -0.22** | -0.22** | -0.23** |
| | (0.11) | (0.11) | (0.11) |
| Inverse Mills Ratio | 0.00 | -0.00 | 0.01 |
| | (0.10) | (0.10) | (0.10) |
| Constant | -1.26*** | -1.26*** | -1.29*** |
| | (0.21) | (0.21) | (0.21) |
| Year Fixed Effects | Yes | Yes | Yes |
| Technology Fixed Effects | Yes | Yes | Yes |
| Disease Fixed Effects | Yes | Yes | Yes |
| Log Pseudolikelihood | -9562.4 | -9562.0 | -9560.0 |
| Wald Chi-squared | 1823.7*** | 1723.1*** | 14208*** |
| Wald Test of Rho = 0: $\chi^2(1)$ (p-value) | 0.00 (p=0.99) | 0.00 (p=0.98) | 0.01 (p=0.92) |
| Observations | 3,523 | 3,523 | 3,523 |

Note: Robust standard errors in parentheses. *** $p$<0.01, ** $p$<0.05, * $p$<0.1. Two-tailed tests. Even when we included *Multimarket Contact* in the selection stage, we obtained the qualitatively same results.

Table 3.5. Probit Regression Results with Continuous Endogenous Regressors

| | Model | |
|---|---|---|
| | (1) | (2) |
| Variables | Equity Alliance | Multimarket Contact |
| Multimarket Contact | -15.374** | |
| | (5.983) | |
| Early Stage | 0.022 | -0.004*** |
| | (0.082) | (0.001) |
| Alliance Scope | 0.116 | 0.008*** |
| | (0.105) | (0.003) |
| Indirect Ties | -0.076* | 0.002*** |
| | (0.043) | (0.000) |
| Degree Centrality (Max) | 0.001 | -0.000 |
| | (0.001) | (0.000) |
| Ratio of Degree Centrality | -0.026 | 0.006*** |
| | (0.131) | (0.002) |
| Size (Max) | 0.000 | -0.000 |
| | (0.000) | (0.000) |
| Ratio of Size | -0.169* | 0.036*** |
| | (0.101) | (0.007) |
| Focal Knowledge (Max) | 0.000 | 0.000 |
| | (0.000) | (0.000) |
| Ratio of Focal Knowledge | -0.015 | -0.003** |
| | (0.088) | (0.001) |
| Patent Counts (Max) | -0.001** | -0.000 |
| | (0.000) | (0.000) |
| Ratio of Patent Counts | -0.209* | 0.002 |
| | (0.108) | (0.001) |
| Log (Sum of Num. of Markets) | | 0.011*** |
| | | (0.002) |
| Constant | -1.256*** | -0.035*** |
| | (0.154) | (0.007) |
| Year Fixed Effects | Yes | Yes |
| Technology Fixed Effects | Yes | Yes |
| Disease Fixed Effects | Yes | Yes |
| Log Pseudolikelihood | 6585.6 | |
| Wald Chi-squared | 1598.8*** | |
| Rho | 0.170 | |
| | (0.148) | |
| Simga | 0.031*** | |
| | (0.003) | |
| Wald Test of Rho = 0: $\chi^2(1)$ | 1.27 | |
| (p-value) | (0.260) | |
| Observations | 3,523 | |

Note: Robust standard errors in parentheses. *** $p$<0.01, ** $p$<0.05, * $p$<0.1. Two-tailed tests.

In addition, the alternative explanation that multimarket rivals might abstain from opportunism not to lose their high value collaboration is based on the assumption that multimarket rivals normally avoid partnering with each other due to high risks and collaborate only when their collaboration is expected to be extremely valuable. Accordingly, this assumption is likely to predict that the average effect of multimarket contact on the likelihood of alliance formation would be negative. However, though not reported in Table 3.4, when I include *Multimarket Contact* in the first-stage selection equation, the coefficient of *Multimarket Contact* is positive and significant ($b$=1.50 and $p$<0.05); that is, multimarket contact promotes alliance formation. Therefore, at least in my sample I could conclude that the mechanism through which multimarket contact influences opportunism and governance choice is the possible costs caused by retaliation against opportunism rather than the possible costs of losing a high value collaboration due to opportunism.

## 3.5 Discussion

### 3.5.1 Contributions and Implications

In broad terms, my paper's theoretical contribution lies in bringing together the bodies of literature on multimarket contract as well as alliance governance, and I also make theoretical contributions to each of these literatures. First, my theory and findings contribute to the competition-cooperation research, in particular the "competition-oriented cooperation" literature (Chen, 2008)[9] by highlighting the importance of considering partners' potential competitive reactions and the number of market contacts between partners in predicting the effects of competition on cooperation. The competition-oriented cooperation literature has examined how various competitive attributes affect outcomes of collaborations (Browning, Beyer, & Shetler, 1995; Dussauge et al., 2000; Harrigan, 1988; Khanna, Gulati, & Nohria, 1998). The main view in this literature has been that competitive relationships in end-product markets incentivize alliance partners to behave opportunistically by increasing the private benefits from such behaviors in alliances (Oxley & Sampson, 2004). In addition, the previous work has tended to rely on alliance partners' co-presence in the same broadly-defined industry (e.g., at the 4-digit SIC level) to conceptualize their competitive tension in theory development.

By contrast, however, my theory based on the multimarket competition literature argues that as alliance partners encounter each other in *more end-product markets*, they can *retaliate* against each other's opportunistic behaviors across multiple markets more effectively and thus they tend to mutually forbear from such behaviors. That is, my theory emphasizes the need to take into account partners' potential competitive reactions and the costs caused by them, which is made possible by accommodating the partners' contacts in different end-product markets. As a consequence, I provide evidence that in some cases partner competition can actually support collaboration rather than undermine it. I conclude that competition can therefore have complex effects on alliances and the

[9] Chen (2008) categorized competition-cooperation studies into "co-opetition," "competition-oriented cooperation," and "cooperation-oriented competition" studies.

governance of collaborative agreements, so I would call for more research on the competitive context of alliances in future studies of interfirm cooperation.

Second, my arguments and findings contribute to the alliance literature that emphasizes economic—either cooperative or competitive—relationships in which firms are embedded as determinants of opportunism and governance choice. While the literature has paid substantial attention to previous cooperative relationships, it has paid very little attention to competitive relationships and thus I had little understanding on possible interactions between different types of dyadic relationships located outside an alliance. My results show that when various transactional attributes related to R&D alliances in the biopharmaceutical industry (e.g., development phases, scope, technologies, and diseases) are controlled, mutual forbearance generated by multimarket contact (i.e., competition between partners outside an alliance) can substitute for hierarchical governance structures as remedies for opportunism; furthermore, this substituting relationship is intensified and dampened by rivalry in factor markets (i.e., technology space in my case) and prior collaborative experience respectively. The broader competitive and cooperative context of a given alliance therefore determines the implications of multimarket contact on alliance governance. It would be valuable in future research to give more attention to the competitive context of collaboration and its interplay with cooperative relationships between firms. This point also motivates more research integrating the cooperative strategy literature and the competitive strategy literature, which have tended to develop separately in recent years.

Finally, my theory and evidence contribute to the multimarket competition literature by developing novel implications of multimarket contact and the mutual forbearance it creates. Previous work in the multimarket competition has entirely regarded mutual forbearance as tacit collusion that takes place across markets (Jayachandran et al., 1999; Yu & Cannella Jr., 2013), in other words, firms' "subordination in their rivals' territories in exchange for the rivals' subordination in the firms' important markets (Gimeno, 1999)." Accordingly, from the conventional viewpoint, the motivation behind mutual forbearance is monopolistic rent seeking. The empirical research in this literature is constituent with this focus by emphasizing collusive outcomes of multimarket contact such as higher prices (Gimeno & Woo, 1996; Hannan & Prager, 2004), higher profitability (Hannan & Prager, 2009; Parker & Röller, 1997), and greater stability of market shares (Heggestad & Rhoades, 1978; Sandler, 1988). In contrast, I argue and show that multimarket contact can also enhance transaction efficiency by curbing opportunism through mutual forbearance; this benefit from multimarket contact and mutual forbearance has nothing to do with monopolistic rent because it takes place within the R&D alliance, not in end-product markets where combined market power can earn monopolistic rent. Therefore, I extend the domain of multimarket competition research from collusion-based monopolistic rent seeking to efficiency-based exchanges in the context of collaborative agreements. Broadly speaking, while the multimarket competition literature has exclusively examined the effects of multimarket contact on firms' competitive strategy, I suggest that linking the implications and findings from the literature with cooperative strategy is an important but understudied research topic.

### 3.5.2 Limitations and Future Research Directions

Extensions might address several limitations of this study and pursue several other research opportunities besides the ones I have already mentioned. To begin with, it would be interesting to examine particular aspects of alliance governance to investigate the implications of multimarket contact through finer-grained analyses of collaborations. For instance, extensions might consider particular dimensions of hierarchical controls such as command structures, authority systems, incentive systems, standard operating procedures, dispute resolution procedures, and non-market pricing systems (e.g., Gulati & Singh, 1998). Since equity arrangements tend to make an interfirm exchange more hierarchical on all these dimensions at once, they are regarded to be the main determinant of hierarchy in alliances. However, firms can incorporate certain benefits of hierarchical control into contract designs (Argyres & Mayer, 2007), and the level of hierarchical control varies within each of the discrete governance structures (e.g., non-equity alliances, minority equity partnerships, and joint ventures) (Reuer & Ariño, 2007). In addition, given that opportunism can appear in various forms and at different levels, it would be interesting to examine specific types of opportunism and whether mutual forbearance through multimarket contact is uniformly important. As one example, multimarket contact might be able to effectively deter opportunism in non-core R&D activities, but when it comes to a disruptive technology, the deterrence from opportunism that multimarket contact provides might be insufficient to safeguard against opportunism (Anand et al., 2009; Jayachandran et al., 1999). In such a case, multimarket rivals may write simple contract provisions on peripheral areas due to reduced risk of opportunism but incorporate stringent provisions pertaining to property rights.

Future studies might also examine the performance implications of multimarket contact. Deterrence from opportunism generated by multimarket contact not only may save costs associated with governing and managing R&D collaborations but also may enhance the outcomes of cooperative agreements. For example, because reduced opportunism between multimarket rivals decreases the likelihood of conflicts, R&D alliances between them may be more robust than those between alliance partners that do not share multiple markets (Hennart, Roehl, & Zietlow, 1999; Park & Ungson, 1997). In addition to shaping alliance survival, multimarket contact and the reduced opportunism it entails may result in better R&D performance while limiting *ex post* conflicts such as patent litigation.

In this paper, I considered the moderating effects of external factors regarding factor markets and previous collaboration experience. However, the multimarket competition literature has suggested that internal factors can also influence the generation of mutual forbearance through affecting internal coordination within firms. For example, Golden and Ma (2003) argued that mutual forbearance is facilitated when firms have integrating mechanisms and incentive systems for internal cooperation within them. Yu and colleagues (2009) also found that local subsidiaries further reduce aggressive actions in their local countries when multinational companies (MNC) who are mutually forbearing have a higher level of ownership in their local subsidiaries, and the cultural distance between MNC's home country and the subsidiary's host country is closer. Such research might reveal whether internal organization, combined with the competitive context of collaborative, have an impact on the governance of alliances and their outcomes for partners.

Finally, it would also be valuable to carry out longitudinal analyses of firms' competitive relationships and their collaborations. Whether on-going alliances are affected by changes in firms' incentives based on shifting market overlaps and factor market competition is worthy of study. Given that my study has emphasized how firms' competitive relationships influence alliance governance, it would also be valuable to examine how firms' investments in alliances potentially shape their subsequent competitive behaviors. For instance, the accumulation of collaborative agreements between two firms might promote tacit collusion and monopolistic rent-seeking in other markets the partners share (Vonortas, 2000). Moreover, inasmuch as alliance termination represents a loss in firms' opportunities to deter competitive actions, this might also have spillover effects in firms' competitive relationships that future research could investigate.

## 3.6 Conclusion

In this paper, I theorized how mutual forbearance generated by multimarket contacts between R&D alliance partners can curb opportunism in a collaborative agreement, thereby enabling the partners to govern an alliance without resorting to hierarchical governance structures. My main theoretical contribution lies in extending theory in the multimarket competition literature to research on alliance governance, and I also showed how certain conditions intensify or weaken the effects of multimarket contacts. Beyond making specific contributions to the separate streams of research on alliances and multimarket competition, my paper joins them and more broadly aims to advance knowledge on the interplay of competition and cooperation. Transcending the conventional view that competition and cooperation are opposites or can undermine each other, recent work has begun to connect the separate streams of research on competitive strategy and cooperative strategy (Brandenburger & Nalebuff, 2011; Gnyawali & Madhavan, 2001; Khanna et al., 1998), though the interplay of competition and cooperation remains a “particularly vexing organizational paradox” (Chen, 2008). My theory and evidence on the alliance governance implications of multimarket contact promote a novel view that competition can enhance transactional efficiency in governing alliances under certain conditions, and I hope that this study encourages new research on the ways in which competition shapes inter-firm cooperation and vice-versa.

# CHAPTER 4. THE EFFECT OF PARTNERS' GEOGRAPHIC LOCATION ON KNOWLEDGE LEAKAGE TO RIVALS

## 4.1 Introduction

Competition and cooperation are fundamental concepts in the field of strategy. Despite their inherent interdependence, however, the research streams on the two concepts have often developed separately, resulting in a lack of systematic understanding on the interplay between them (Chen, 2008). For example, the alliance literature has paid relatively little attention to the competitive context of collaborations. The literature that has addressed this issue has been mainly interested in knowledge protection concerns in alliances between direct rivals, as competition between alliance partners might aggravate the risks of knowledge misappropriation. Studies have investigated asymmetric learning between alliance partners (Hamel et al., 1989), learning dynamics between alliance partners (Khanna et al., 1998), the effects of competition between alliance partners on alliance scope (Oxley & Sampson, 2004), and collaboration failure (Park & Russo, 1996).

However, even when an allying firm partners with a firm who is not a direct rival (e.g., when a downstream firm collaborates with an upstream firm), the allying firm might still have to pay close attention to knowledge protection concerns if knowledge can be (1) *unintentionally* spilled over through the partner to the major rivals of the allying firm or (2) misappropriated jointly by the partner firm and rivals. Some recent work has begun to investigate the risk of indirect ties to rivals. For example, Pahnke, McDonald, Wang, and Hallen (2015) examined the negative effects of competitive exposure to rivals via shared intermediary organizations (i.e., venture capitalists). Similarly, Hernandez, Sanders, and Tuschke (2015) focused on knowledge spillover concerns created when board interlocks result in indirect connections to rival firms. I build upon and extend this work by suggesting that firms must be concerned with more than just the formal relationships that create indirect ties to rivals. Specifically, I draw upon agglomeration theory to suggest that co-location between an allying firm's partner and major rivals of the allying firm ("rivalry in partner location") is an important but understudied factor affecting the risk of knowledge loss and therefore carries implications for alliance governance and design (Gulati & Singh, 1998; Pisano, 1989). My arguments are informed by prior research in the geography of knowledge, especially in the agglomeration literature, that has established knowledge spillovers are spatially restricted and represent a significant feature of geographic clusters (Audretsch & Feldman, 1996; A. B. Jaffe, Trajtenberg, & Henderson, 1993). Geographic proximity to rival firms also increases the potential for knowledge misappropriation because proximity increases the likelihood that the partner and a rival may form a relationship themselves (Chakrabarti & Mitchell, 2013; Narula & Santangelo, 2009).

In this paper, I specifically investigate how incumbent firms address the risk of rivals' gaining access to firm knowledge in these situations. I theorize and empirically corroborate that the allying firm mitigates these concerns when rivalry in partner location is higher by (1) using equity structures to provide enhanced monitoring, control, and incentive alignment and (2) choosing less interdependent R&D projects to reduce knowledge sharing and interactions. Furthermore, given that actual competitive damage by knowledge leakage to rivals depends not only on the amount of knowledge at risk of leakage but also on the rivals' capabilities to take advantage of the leaked knowledge, I further claim that the relationship between rivalry in partner location and these defensive mechanisms will be intensified when rivals surrounding the allying firm's partner have greater absorptive capacity.

With my theory and results, I make several contributions to the alliance literature and the agglomeration literature. First, I contribute to the literature on the competitive aspects of collaborations by highlighting how an understudied but interesting competitive issue, i.e., indirect links to rival firms resulting from the geographic location of partners, affects governance choice and alliance design. There has been a recent call for more research on the interplay between cooperation and competition. Some alliance research has responded to this call, but it has focused mainly on the effect of dyadic competitive relationships between alliance partners (Khanna et al., 1998; Oxley & Sampson, 2004; Park & Russo, 1996), and some related literature has also considered the role of indirect ties that exist due to formal relationships (Hernandez et al., 2015; Pahnke et al., 2015). I enrich the literature on the competitive aspects of collaborations by extending the scope of research inquiries from dyadic and formal indirect ties to a broader set of competitive relationships that affect collaborations.

I also contribute to the alliance literature by suggesting conditions in which incumbent firms address the competitive context of collaborations through their alliance design choices. This extends prior work that has largely focused on how technology ventures can protect themselves from their larger, more powerful incumbent firm partners (Diestre & Rajagopalan, 2012; Katila, Rosenberger, & Eisenhardt, 2008; Yang, Zheng, & Zhao, 2014). The knowledge protection concerns of incumbent firms remain relatively less explored, which is noteworthy because these firms are also exposed to the risk of knowledge loss. My work explicates geographic proximity between technology ventures and incumbents' rivals as an understudied factor affecting incumbent firms' knowledge control concerns.

Finally, I also contribute to the agglomeration literature by adding new theoretical arguments and findings to the research on the potential downsides or drawbacks of agglomeration. Indeed, since Marshall's (1920) pioneering work, the agglomeration literature has considered knowledge spillovers to be a key benefit attracting firms to geographic clusters. Moreover, technology ventures located in geographic clusters have been argued to be particularly attractive alliance partners given their access to the cluster's pool of knowledge spillovers (Rothaermel, 2002). I highlight that partnering with these firms may also entail risks in cases where the technology venture shares a location populated with rivals of the incumbent firm. In this respect, my work is broadly similar in spirit to Shaver and Flyer (2000) in highlighting the downsides of location in a geographic cluster as well as its benefits. Although partnering with a technology firm in a cluster does provide access to the pool of knowledge spillovers, it also increases the risk that the incumbent firm's knowledge could spill out into that pool and be accessed by rivals. In these particular situations, incumbent firms can respond by structuring the relationship to provide better protection of its knowledge.

## 4.2 Theory and Hypotheses

### 4.2.1 Theoretical Background

***Cooperation and Competition in R&D Alliances.*** The formation of research and development (R&D) alliances between companies in high technology industries is a common phenomenon, with a number of potential strategic and cost-economizing motives driving their prevalence (Eisenhardt & Schoonhoven, 1996; Hagedoorn, 2002). In addition to their potential benefits, however, these relationship raise significant concerns related to the protection of technical knowledge because achieving the objectives of an R&D alliance often requires firms to share valuable knowledge. Accordingly, concern over knowledge leakage and misappropriation has been a core theme of research in the alliance literature (Gulati & Singh, 1998; Oxley, 1997; Pisano, 1990). For example, since Hamel and colleagues (1989) pointed out that asymmetric learning in cooperative ventures between U.S. and Japanese competitors critically contributed to the latter's global success over the former, the research stream that Chen (2008) termed the "competition-oriented cooperation" literature has emphasized the risks of knowledge leakage and misappropriation in R&D alliances between rivals. For example, Dussauge, Garrette, and Mitchell (2000) argued and empirically corroborated that alliance partners who are direct competitors to each other have strong incentives to acquire partner capabilities and, as a result, are more likely to reorganize or take over the alliance. In addition, based on the rationale that end-market competition between alliance partners increases the pay-off from free-riding or misappropriation, Oxley and Sampson (2004) claimed and showed that alliance partners with market overlap tend to limit R&D alliance activities to R&D alone rather than extend them to related manufacturing and/or marketing activities in order to reduce knowledge losses.

Although the previous competition-oriented cooperation literature has focused mostly on the dyadic competitive relationship between alliance partners, more recent work has begun to extend the scope of inquiry from dyadic ties to a broader set of relationships. This work recognizes that risks exist, even when not directly partnering with rivals. For example, Mesquita, Anand, and Brush (2008) considered buyers' sharing knowledge and developing new technologies with suppliers in vertical supply alliances. They suggested that this knowledge was subject to use by partner suppliers with other buyers and argued that focal buyers need to invest in partnership-specific assets and capabilities and use relational governance mechanisms to address this risk. Other research from outside the alliance context has highlighted that firm knowledge may be exposed to rivals via other formal relationships that create indirect ties to rivals. For example, Pahnke and colleagues (2015) investigated the situation where an entrepreneurial firm is indirectly connected to rival firms via common venture capitalists, showing that information leakage via these indirect ties to competitors negatively affected entrepreneurial firms' innovation activities. In addition, Hernandez and colleagues (2015) examined the hazards of knowledge leakage to rivals via indirect ties formed by board interlock networks. The authors argued that firms control such risks by terminating and avoiding ties that could create indirect paths to rivals; they also address risks by embedding themselves in dense networks where social monitoring is more prevalent. While this literature is not concerned with interfirm collaboration per se, it highlights the point that firms should consider risks not only from partnering directly with rivals but also from indirect competitive relationships surrounding collaborations. I next explain how similar knowledge concerns can arise from ties that exist even in the absence of formal relationships, such as when partners are located in geographic proximity to rivals.

***Geographic Co-location and Knowledge Protection Concerns.*** Knowledge spillovers are more intense between spatially proximate firms relative to distant counterparts. Geographic proximity enables face-to-face communication that is critical to transferring tacit knowledge (Daft & Lengel, 1986). There has been a substantial body of empirical research corroborating that geographic proximity fosters knowledge spillovers. For instance, Jaffe and colleagues (1993) supported geographic localization of knowledge spillovers by showing that patent citations are more likely to come from the same state and Metropolitan Statistical Area (MSA) compared with the pre-existing concentration of related research activity. Similarly, Rosenkopf and Almeida (2003) noted a positive relationship between geographic proximity and knowledge flows measured by patent citations in the semiconductor industry.

The benefits of localized knowledge spillovers have also been repeatedly highlighted in the agglomeration literature as one of the key benefits of co-location in a geographic cluster, which Porter (1998) defines as a geographically proximate group of interconnected firms and related institutions in a particular field. Co-location in a cluster fosters knowledge spillovers not only due to geographic proximity but also the formal and informal channels it provides. Firms co-located within a cluster generally prefer in-cluster transactions and exchanges and thus tend to be formally interconnected through, for example, licensing, technology partnerships, strategic alliances, and supply contracts (McCann & Folta, 2011). In addition, clusters feature informal channels of knowledge spillovers such as social meetings, trade meetings, and interfirm mobility of workers (Almeida & Kogut, 1999; Saxenian, 1996).

Although much of the agglomeration literature emphasizes the benefits of access to knowledge spillovers, they also represent a risk to firms who possess knowledge. Consistent with this view, Shaver and Flyer (2000) argued that firms with better technologies or human capital would be less likely to locate in a cluster because they contribute more to the pool of spillovers, which benefits rivals and reduces their own relative advantages. This is because the knowledge that spills over to the competitors is likely to be more valuable than the knowledge the firm itself obtains. I contend a similar spillover concern arises via the indirect path of partnering. Given that geographic proximity and co-location in a cluster facilitates knowledge spillovers, an allying firm is prone to knowledge leakage to its rivals when its R&D partner firm is co-located with more of the allying firm's major rivals (henceforth, "rivalry in partner location"). In particular, knowledge spillovers by informal channels such as interpersonal networks and labor mobility can take place even when the partner firm does not have any intention of misappropriation.

Rivalry in partner location also raises the potential risks associated with knowledge misappropriation. When partnering with firms who are not rivals, the misappropriation concern is that partners may share the focal firm's knowledge with rivals. This concern is heightened when rivalry in partner location is higher, for two reasons. First, co-location increases the likelihood that the partner firm may form a future formal relationship with the allying firm's rivals and jointly misappropriate the allying firm's knowledge, as geographic proximity has been demonstrated to promote both alliances (Narula & Santangelo, 2009) and acquisitions (Chakrabarti & Mitchell, 2013; Narula & Santangelo, 2009). Second, the benefits of co-location noted above in promoting transfer of tacit knowledge also apply to knowledge a partner elects to misappropriate via transfer to rivals. In such cases, the effectiveness of the transfer is enhanced due to the geographic co-location.

Prior to turning to my specific hypotheses regarding the mechanisms utilized to address these concerns associated with rivalry in partner location, I explain my choice of theoretical context. In the development of hypotheses below, I focus on a situation where (1) an incumbent firm and an R&D, or technology, venture who are not direct competitors enter into an R&D alliance and (2) the technology venture is co-located with the incumbent firm's major rivals. Although the risk created by rivalry in partner location applies to some degree to all R&D alliances, I focus on R&D alliances between technology ventures and incumbent firms for two important reasons. First, because of liability of newness or smallness (Bruderl & Schussler, 1990; Stinchcombe, 1968) and the lack of downstream capabilities, first-order knowledge leakage to technology ventures is less concerning to incumbent firms.

However, second-order knowledge leakage to the incumbent firms' rivals via technology ventures could be substantially harmful because the rivals could immediately take advantage of the leaked knowledge to undermine the incumbent firms in product markets. Second, given my interest in mechanisms chosen to address the risk associated with rivalry in partner location, it is important to examine partnerships in which the partner exposed to the risk has the ability to influence the structuring of the partnership. In R&D alliances between technology ventures and incumbent firms, the latter typically have significant bargaining power and thus are very likely to influence the design of the alliance (e.g., Mason & Drakeman, 2014). I turn now to an explanation of the defense mechanisms that incumbent firms adopt when facing higher risks of rivalry in partner location.

### 4.2.2 Hypotheses Development

***Knowledge Protection and Choice of Equity as a Governance Mechanism.*** Since knowledge is intangible, R&D partners have difficulty measuring and monitoring each other's behaviors and outcomes. In addition, R&D activities entail a high level of uncertainty. These attributes of R&D alliances make it difficult to write enforceable contractual agreements and accordingly participating firms are subject to opportunistic behaviors (Oxley, 1997). As a remedy for such contractual hazards, equity arrangements have long been suggested in the alliance literature. Equity ownership helps align partners' incentives (Williamson, 1991), delineates rights and obligations between partners (Grossman & Hart, 1986), and also provides hierarchical controls in the form of command structures, authority systems, standard operating procedures, dispute resolution procedures, and non-market pricing systems (Gulati & Singh, 1998; Pisano, 1989). Equity participation in R&D alliances between technology ventures and incumbent firms may take several forms, including minority investment of the incumbent firm in the technology venture or the formation of a joint venture. In both cases, I anticipate that the inclusion of equity in R&D alliances will increase the incumbent firm's ability to mitigate spillovers and misappropriation of its knowledge to rivals co-located with the technology venture by enhancing monitoring, control, and incentive alignment.

The inclusion of equity first fosters monitoring, as it provides greater access to information. For example, equity investments often include representation on the invested partner's board. Board participation provides observational and/or voting rights enabling the investing partner to better monitor its partner's behavior, for example the use of contributed assets and development of new assets (Kumar & Seth, 1998; Pisano, 1989). Enhanced monitoring allows the incumbent firm to limit the amount of unnecessary information sharing with the technology venture. As less unnecessary information is shared with the partner, the total knowledge that may spill over to rivals or be misappropriated is reduced. Moreover, increased ability to monitor fosters the early discovery of possible spillovers of knowledge, allowing the incumbent firm to quickly take steps to address the situation in the event of unintended knowledge spillovers.

Second, equity ownership provides greater control and influence for the incumbent firm. For example, the incumbent firm's existing ownership position gives it preferential access should the technology venture desire to be acquired. Even if the incumbent firm elects not to acquire the technology venture itself, the incumbent firm can use its voting rights try to block transactions between the technology venture and the nearby rivals, such as R&D alliances and acquisitions (García-Canal, 1996; Mjoen & Tallman, 1997; Yan & Gray, 1994). Even when the incumbent firm's voting right may not be strong enough to veto an R&D alliance with or an acquisition by a nearby rival, the incumbent firm's ownership in the technology venture and its intellectual property rights can help safeguard certain knowledge.

A third benefit of equity participation is that it can help align the incentives of the partners and, as a result, prevent opportunistic behaviors. In general, equity participation enhances incentive alignment mainly by two mechanisms. First, equity participation penalizes opportunism through reductions in the value of equity holding (Pisano, 1989: 112). Second, since shares of ownership reflect relative contributions of each partner, the alliance partners are incentivized to make the requisite *ex ante* commitments and thus the risk of reneging on a future commitment is attenuated (Pisano, 1989: 112).

Given these monitoring, control, and incentive alignment benefits from equity arrangements, an incumbent firm will turn to equity arrangements to a larger extent when it faces a higher level of risk for knowledge acquisition by its rivals via its partners. When an incumbent firm collaborates with a technology venture, the risk of knowledge spillovers to and misappropriation by the major rivals of the incumbent firm increases as the technology venture is surrounded by more of the incumbent firm's major rivals. Therefore, as the degree of rivalry in partner location increases, the incumbent firm will have a greater need for the monitoring, control, and incentive alignment benefits that equity arrangements offer. Therefore, I posit:

*Hypothesis 1. The greater the degree of rivalry in partner location, the greater the likelihood the R&D alliance is equity-based.*

***Knowledge Protection and Choice of Interdependence Level.*** In the previous section, I discussed the usage of equity-based governance structures to address knowledge protection concerns. In addition to such governance decisions, however, the alliance literature has also suggested other alliance design decisions that can be responsive to firms' concerns about rivalry in partner location.

In particular, a critical aspect of alliance design related to partners' tasks and interactions is the level of interdependence (Aiken & Hage, 1968; Thompson, 1967; Van De Ven, Delbecq, & Koenig, 1976). Viewing organizations as information processing systems facing uncertainty, Tushman and Nadler (1978) posited that the amount of task interdependence between subunits increases the need for effective coordination and joint problem solving; this heightened need for interaction then increases work-related uncertainty and, as a result, required information processing. Similarly, focusing on the context of alliances, Krishnan, Martin, and Noorderhaven (2006) argued that high interdependence between alliance partners requires them to share valuable knowledge-intensive resources. Therefore, if the tasks in an R&D alliance between an incumbent firm and a technology venture are interdependent, they have to share more knowledge between them and, therefore, are exposed to a larger risk of knowledge leakage.

Indeed, the alliance literature has paid substantial attention to interdependence between alliance partners, but interdependence has typically been considered as a given task attribute affecting governance choice rather than a decision variable that alliance partners have to consider (Aggarwal, Siggelkow, & Singh, 2011; Gulati & Singh, 1998). However, alliance partners can decide the level of interdependence by choosing different types of interdependence for their R&D collaborations. Thompson (1967) classified the types of interdependence based on input-output relationships. The types of interdependence are pooled, sequential, and reciprocal in order of increasing complexity. Pooled interdependence refers to no direct input-output relationship between subunits; that is, each subunit performs completely separate functions. Sequential interdependence occurs when the output of one unit's activity is necessary for the performance by the next subunit, just as in an assembly line. Reciprocal interdependence is similar to sequential interdependence in that the output of one subunit becomes the input of another, but is different from and more complex than sequential interdependence in that the input-output relationship is reciprocal.

Increasing levels of interdependence require closer working relationships and more knowledge transfer, which also increases the amount of knowledge that may leak to transaction partners. Larger amounts of transferred and leaked knowledge increase the risks this knowledge may be acquired by nearby rivals. I therefore expect the incumbent firm's choice of interdependence to be associated with the degree of threat of knowledge acquisition by rivals. Because geographic co-location increases the risks of knowledge leakage by both spillovers and misappropriation, the incumbent firm faces a higher risk of knowledge acquisition by rivals as the technology venture is co-located with more of the incumbent firm's major rivals. Accordingly, I predict that the incumbent firm will need to choose a lower level of task interdependence to curb knowledge transfers and interactions in order to reduce the potential risk as the nearby rivals around the technology venture are more serious competitors to the incumbent firm. Therefore, I posit:

*Hypothesis 2. The greater the degree of rivalry in partner location, the lower the interdependence of the R&D alliance.*

#### 4.2.3 Moderating Effects of Nearby Rivals' Absorptive Capacity

So far, I have argued that when the degree of rivalry in partner location is high, the incumbent firm chooses equity-based governance structures and less interdependent R&D activities for the alliance to reduce the amount of its knowledge at risk of leakage to nearby rivals. However, the potential competitive damage by knowledge leakage to nearby rivals depends not only on the exposure created by geographic co-location with partners, but also on the nearby rivals' capabilities to value, assimilate, and apply the knowledge leaked to them; that is, the rivals' absorptive capacity (Cohen & Levinthal, 1990) magnifies the risk of rivalry in partner locations. Thus, I wish to consider how that relationship between rivalry in partner location and the choice of governance structures and task interdependence is conditioned on the nearby rivals' absorptive capacity.

Firms with higher absorptive capacity are able to benefit more from external knowledge, resulting in higher innovation rates (Tsai, 2001). One such form of external knowledge is the pool of spillovers from co-located firms. As just one example in the context of agglomeration, McCann and Folta (2011) showed that firms with higher absorptive capacity are better able to absorb and benefit from knowledge spillovers in clusters in the U.S. biotechnology industry. Given the important role of absorptive capacity in applying knowledge, I expect that rivalry in partner location will be less of a concern when rival absorptive capacity is low. The risk of incumbent firm knowledge spilling over from its partners is low when rivals have little ability to assimilate and apply that knowledge to compete against the incumbent firm in end markets. By contrast, when rival absorptive capacity is higher, rivalry in partner location will be a more serious concern since the rivals have an ability to assimilate and apply the knowledge to which they have been exposed. Given the heightened risks of rivalry in partner location under these conditions, incumbent firms become even more likely to (1) choose equity-based governance structures to benefit from the monitoring, control, and incentive alignment that equity arrangements provide and (2) further limit knowledge sharing by reducing task interdependence. Therefore, I posit:

*Hypothesis 3. The positive effect of rivalry in partner location on the likelihood of equity-based alliance governance will be more pronounced as the rivals have higher absorptive capacity.*

*Hypothesis 4. The negative effect of rivalry in partner location on interdependence in R&D alliances will be more pronounced as the rivals have higher absorptive capacity.*

## 4.3 Methods

### 4.3.1 Data and Sample

I chose R&D alliances between technology ventures and incumbent firms in the U.S. biopharmaceutical industry as my research setting for several reasons. First, the this industry is characterized by significant agglomeration (Folta et al., 2006). Because I focus on co-location between technology ventures and incumbent firms' rivals as a theoretical factor underlying incumbent firms' knowledge concerns, I need an empirical setting where firms agglomerate. Second, R&D alliances between technology ventures and incumbent firms are regarded as beneficial for both and thus are frequently observed in the industry, just as these collaborations present knowledge leakage and misappropriation concerns (Pisano, 1990). Third, markets are very clearly defined by therapeutic classes in this industry (Anand et al., 2009). In this study, clear market definitions are important because firms defined to be an incumbent firm's major rivals should be actual, meaningful competitors whose products are substitutes for those of the incumbent firm.

For the alliance data, I drew on Thomson Reuters' Recap database, which is known as one of the most robust and representative data sources on alliances in the biopharmaceutical industry (Schilling, 2009) and includes detailed information on alliance governance and design. To define incumbent firm partners' rivals, I relied on the IMS Health database, which provides prescription drug sales by therapeutic class for biopharmaceutical companies around the world. I also used the IMS Health database to ensure that the technology ventures in my sample are R&D-dedicated

firms without presence in product markets. For patent data, I used patent data from the U.S. Patent and Trademark Office (USPTO).

Because of my interest in the location characteristics of the technology venture partner, I focused on R&D alliances involving U.S.-based biotechnology ventures; the incumbent firm partners include both U.S. and foreign firms. Also, because I am interested only in rivals adjacent to U.S.-based biotechnology ventures, incumbent firm partners' rivals are all U.S. firms. In the Recap database, there were 1,242 R&D alliances between U.S. biotechnology ventures and incumbent pharmaceutical firms between 2007 and 2013.

### 4.3.2 Measures

***Dependent variables***. In this paper, I investigate how incumbent firms prevent their knowledge from being acquired by their major rivals located within the same area as their technology venture partners. Because I focus on two defense mechanisms, choice of (1) governance structures and (2) interdependence level, I have two different dependent variables. The first dependent variable, *Equity Alliance*, is a dichotomous variable coded one if a focal R&D alliance between an incumbent firm and a technology venture is equity-based, i.e., either minority equity investment or joint venture, and zero otherwise (Gulati, 1995b; Hagedoorn & Narula, 1996; Li et al., 2012; Osborn & Baughn, 1990; Phene & Tallman, 2012; Pisano, 1989; Robinson & Stuart, 2007). Out of the 1,242 R&D alliances, 84 (6.8%) were equity-based alliances while the remaining 1,158 (93.2%) were non-equity alliances.

My second dependent variable is a binary variable, *Reciprocal Interdependence*, which distinguishes the level of task independence between an incumbent firm and a technology venture. The variable takes the value of one if a focal R&D alliance is coded as “Collaboration” or “Co-Development” in Recap. This database categorizes an R&D agreement in one of these categories when both parties jointly participate in the research and development, and the combined participation of both partners in R&D activities implies reciprocal input-output relationships. Recap codes agreements as “Research” or “Development” if only one of the parties performs research or development, leaving the other downstream activities to the other party. These agreements fall into the category of sequential interdependence because the research output of one party (i.e., technology venture) is the input of an activity in another unit (i.e., incumbent firm). Reciprocal interdependence (the categories of Collaboration and Co-Development) implies stronger interdependence than sequential interdependence (Thompson, 1967) and thus *Reciprocal Interdependence* reflects the level of task interdependence between R&D partners consistent with Thompson’s (1967) definitions.  Because R&D alliances require at least some minimal level of input-output relationship, Thompson’s (1967) third category of pooled interdependence does not apply to my sample of alliances. 47% of the alliances in my sample were classified as involving reciprocal interdependence.

***Independent variables***. My core independent variable captures the intensity of firm-level product market competition between an incumbent firm partner and its major rivals located in the same geographic area as its technology venture partner. For this purpose, I developed a variable labeled *Rivalry in Partner Location*. For this measure, I first identified the top 10 rivals of a particular incumbent firm, based on total revenues in the product markets in which the incumbent firm is present. In identifying these rivals, I followed the product-market definitions provided by IMS Health, which consists of 338 therapeutic classes. Then, I checked which top 10 rivals of the incumbent firm are located in the same geographic cluster as the technology venture.[10] To define geographic clusters, I used Metropolitan Statistical Areas (MSAs). In the agglomeration literature, different levels of aggregation have been used to identify clusters. My definition of clusters should be aligned with the distance with which the benefits of knowledge spillovers might meaningfully extend. Since Jaffe and colleagues (1993) found that localization of knowledge spillovers was stronger at the MSA level than at the U.S. state level, I elected to use the former. This aggregation level is also consistent with prior studies of agglomeration in the biotechnology industry (DeCarolis & Deeds, 1999; Folta et al., 2006). Focusing on the top 10 rivals located in the same MSA as the technology venture partner, I calculated the weighted average of the aggregate market shares held by the rivals. As a weight for a certain market, I used the importance of the market to the incumbent firm, which is calculated by the ratio of the incumbent firm's revenue from the product market to its total revenue as follows (please see Appendix A for an example):

$$Rivalry\ in\ Partner\ Location_{ij} = \sum_{m} \left( Importance_{m} \times \sum_{r} MS_{rm} \right)$$

$i$: Incumbent Firm

[10] In the few cases in which a focal R&D alliance is a joint venture, I used the location of the joint venture instead of the location of the technology venture. Inclusion or exclusion of joint ventures from the sample did not affect the interpretation of the results.

*j*: Incumbent Firm *i*'s Technology Venture partner
*m*: Product markets in which Incumbent Firm *i* is present
*r*: Incumbent Firm *i*'s top 10 rival located within the same Metropolitan Statistical Area (MSA) as Technology Venture *j*
$MS_{rm}$: The market share of top 10 rival *r* in product market *m*.

I also examine how the nearby rivals' absorptive capacity shapes the effects of the co-location between the incumbent firm's major rivals and its technology venture partner on the governance structure and task interdependence in the R&D alliance. To measure the nearby rivals' absorptive capacity, I used the number of patents that (1) are issued to the nearby rivals, (2) belong to the three-digit, biotechnology-related patent classes, i.e., 424, 435, 436, 514, 530 (Granstrand, Patel, & Pavitt, 1997; Phene, Fladmoe-Lindquist, & Marsh, 2006) and (3) belong to the three-digit patent classes in which the incumbent firm has at least one patent. Some incumbent firms in the biopharmaceutical industry also have their businesses in chemical industries and patent in very diverse areas. However, because I focus on the nearby rivals' absorptive capacity relevant to the incumbent firm's biotechnology-related knowledge, I applied the three criteria above.

***Control variables***. I controlled for a number of additional factors that the previous literature has argued to affect knowledge misappropriation and spillover concerns and therefore could affect alliance governance and design. First, to control for transaction-level attributes that may influence contractual hazards, I included the research stage and scope of the R&D alliance. In the industry, new drug development is typically categorized into discovery, lead molecule, formulation, preclinical, clinical phases I/II/III, and FDA approval phases. *Early Stage* takes the value of one if an R&D alliance belongs to one of the first four phases and zero otherwise. In addition, alliance scope has also been known as a factor influencing the risk of misappropriation (Oxley & Sampson, 2004). Therefore, I also included a dummy variable, *Alliance Scope*, to indicate the breadth of alliance scope. *Alliance Scope* was coded one if an R&D alliance includes downstream activities, i.e., either manufacturing or marketing, and zero otherwise.

The alliance literature has argued that social networks in which alliance partners are embedded provide controls for opportunistic behaviors and thus might also affect the risk of knowledge losses as well as the alliance design choices firms make (Jones et al., 1997). Following Rothaermel and Boeker (2008), I controlled for an alliance dyad's social embeddedness, using variables to capture the partners' prior ties, indirect ties between the two firms in the dyad, and each partner's degree network centrality. To construct *Prior Ties*, I counted the number of prior alliances between the two partners in the past ten years. For *Indirect Ties*, I counted the number of indirect ties between the two partners at degree distance two, using all the alliances reported in Recap to represent the entire network in the biopharmaceutical industry as much as possible (Powell et al., 1996). As a proxy for each partner's positional embeddedness (Ahuja, 2000; Gulati & Gargiulo, 1999), I constructed *Degree Centrality of Incumbent Firm* (*Technology Venture*), using the total number of ties the incumbent firm (technology venture) had entered within the entire industry network in the past ten years. To ensure that the measure of degree centrality is independent from the relational embeddedness between the two partners, I excluded the prior ties between them in measuring each partner's degree centrality.

I also included some other firm-level attributes that may affect my dependent variables and be related to the risk of knowledge losses to rivals. The alliance literature has claimed that when alliance partners are asymmetric in size, they tend to have more conflicts (Li et al., 2012). Therefore, a small technology venture may need better incentive alignment which equity investment can provide when it partners with a larger incumbent firm. Also, a larger incumbent firm may have more resources to buy equity stakes in a technology venture. To control these effects, I included in the model the prescription drug sales of the incumbent firm in a given dyad, i.e., *Size of Incumbent Firm* (Gimeno, 2004). Firms with significant knowledge bases may be more concerned about knowledge leakage and accordingly prefer equity-based R&D alliances to a larger extent to protect their knowledge (Phene & Tallman, 2012). To control for these effects, I constructed *Patent Counts of Incumbent Firm* and *Patent Counts of Technology Venture*.

The agglomeration literature has argued that geographic clusters are characterized by dense interpersonal and interfirm social networks within them (Saxenian, 1996). For this reason, social capital based on dense networks within a cluster may provide control functions. To control this effect, I included *Cluster Size*, which was measured by the number of biopharmaceutical companies in the MSA in which the technology venture in a given dyad is located. Research on geographic distance between alliance partners has also maintained that geographic proximity reduces information asymmetry between alliance partners and can also facilitate monitoring (McCann, Reuer, & Lahiri, 2015; Reuer & Lahiri, 2014). Therefore, I included in the model the distance between an incumbent firm and a technology venture in a given dyad. Since the effect of distance might diminish beyond some level, particularly in international deals, I also used the natural log of the variable as a robustness check and obtained consistent results.

I included three different types of fixed effects to capture other sources of heterogeneity. The risk of knowledge leakage and misappropriation may be influenced by the types of technologies and diseases for a focal R&D project. Therefore, I included technological domain fixed effects and disease fixed effects in the model. Finally, year fixed effects were also included to capture any broader, economy-wide factors affecting the decisions on governance structures and task interdependence made by alliance partners.

### 4.3.3 Statistical Techniques

Since my dependent variables, *Equity Alliance* and *Reciprocal Interdependence*, are binary, I elected to use probit regression as my main model. Because governance structures and task interdependence may be decided jointly and may be correlated I also used bivariate probit models as a robustness check. Lastly, I also tested my hypotheses with Heckman probit models to control for potential selection bias. Because my sample consists of realized alliance deals only, the dyads in my sample may be systematically different from the other possible unrealized dyads and thus selection bias may be a concern. To construct the set of counterfactuals of unrealized alliance deals, I considered all possible dyads for each year (from 2007 to 2013) using all the incumbent firms and technology ventures who formed R&D alliances in each year. In the first-stage model, I used the number of alliances the top 10 rivals of a given incumbent firm had formed in the previous year to predict formation of an alliance. If its rivals were active in forming alliances in the previous year, the incumbent firm is more likely to seek alliances in the following year as a competitive response (Abrahamson & Rosenkopf, 1993) or as an institutional mimetic behavior (Fligstein, 1985). Consistent with these arguments, Garcia-Pont and Nohria (2002) noted that the propensity of firms to form alliances is greatly influenced by the frequency of alliance formation by other firms in the same strategic group in the global automobile industry. However, it is unlikely to be related to its choice of alliance structures and task interdependence, so this variable is likely to be valid in predicting alliance formation in selection models.

## 4.4 Results

Table 4.1 provides descriptive statistics and a correlation matrix of the variables used in the analyses. Although many pairs of variables in Table 1 show significant pairwise correlations, multicollinearity is not a serious issue in my models. *Degree Centrality of Incumbent Firm* had the highest value of variance inflation factor (6.56), but is still below the recommended cutoff level of 10 (Neter et al., 1996).

Table 4.2 presents the results of the models analyzing the probability that a particular R&D alliance is equity-based or includes highly interdependent tasks. Model 1 is a base model including control variables only, and Model 2 introduces *Rivalry in Partner Location* to test my first hypothesis. The significant positive coefficient on *Rivalry in Partner Location* ($b$=1.76 and $p$=0.026) supports Hypothesis 1 and indicates that as the intensity of competition between an incumbent firm and its major rivals co-located with its technology venture partner increases, the likelihood increases that the R&D alliance is equity-based rather than a non-equity transaction. To evaluate the economic significance of the effect, I estimated the predicted average probability of equity alliances at various values of *Rivalry in Partner Location*. That is, I calculated the response for each observation and then averaged those responses at the median, top 10%, top 5%, and top 1% quantiles of the variable given its highly skewed distribution (Hoetker, 2007; Train, 1986). The predicted average probabilities were 6.05%, 8.59%, 10.69%, and 18.24% respectively. That is, when the value of *Rivalry in Partner Location* increases from the median to top 10%, top 5%, and top 1%, the predicted average probability increases by 41.77%, 76.47%, and 200.07% respectively. To mitigate a potential concern of outliers driving the effect, I reran Model 2 using the natural log of the variable plus one, and I obtained a consistent interpretation in support of H1 ($b$=2.17 and $p$=0.022).

Models 3 and 4 test my second hypothesis on rivalry in partner location as a determinant of interdependence as a dimension of alliance design. Model 3 includes control variables as a base model and Model 4 adds my core independent variable, *Rivalry in Partner Location*. Since the coefficient of the variable in Model 4 is negative and significant ($b$= -1.55 and $p$=0.011), Hypothesis 2 is also supported since rivalry in partner location reduces the likelihood of designing an alliance with highly interdependent R&D tasks. To assess economic significance, I again estimated the predicted average probability of reciprocal interdependence at the four values of the independent variable as above and obtained 48.78%, 42.43%, 38.24%, and 27.58% respectively. Compared to the predicted value at median, the last three values represent decrease the likelihood of reciprocity by 13.03%, 21.61%, and 43.46% respectively. Given the skewness of the rivalry in partner location variable, I also reran Model 4 using the natural log of the variable plus one and again obtained a consistent result ($b$= -1.87 and $p$=0.009).

Model 5-8 in Table 4.2 show the results related to the moderating effects of rivals' absorptive capacity. Model 6 and 8 include *Rivals' Absorptive Capacity* and its interaction term with *Rivalry in Partner Location* to test Hypotheses 3 and 4, respectively. Although the coefficient estimate for the interaction term in Model 6 was positive as predicted, it was insignificant ($b$= 0.0014 and $p$=0.382) and thus Hypothesis 3 was not supported. However, the interaction term had a negative and significant coefficient in Model 8 ($b$ =-0.003 and $p$=0.038), supporting Hypothesis 4. Therefore, rivals' absorptive capacity does not significantly intensify the positive effect of rivalry in partner location on the likelihood of equity alliance, but it does significantly strengthen the negative effect of rivalry in partner location on the likelihood of reciprocal interdependence. Although the interpretation of the relevant coefficients supports Hypothesis 4, the effect—and even the sign—of an interaction can also change depending on the coefficients of the composite variables and the values of all of the variables in probit models (Hoetker, 2007). In Figure 4.1, therefore, I provide a graphical depiction of the interaction effect. Specifically, I compare the negative slopes between rivalry in partner location and the probability of reciprocal interdependence when the values of *Rivals' Absorptive Capacity* are fixed at the mean, mean plus one standard deviation, and mean plus two standard deviations, respectively. The slope becomes steeper as the value of *Rivals' Absorptive*

*Capacity* increases, supporting the moderation argument in H4. To estimate the economic significance of the moderating effects, I estimated the decreases in the probability of reciprocal interdependence caused by the value increase in *Rivalry in Partner Location* from the median to top 5%, when *Rivals' Absorptive Capacity* is fixed at the mean, the mean plus one standard deviation, and the mean plus two standard deviation. With *Rivals' Absorptive Capacity* fixed at the mean, an increase of *Rivalry in Partner Location* from the median to top 5% decreases the probability of reciprocal interdependence from 49.38% to 43.40% (i.e., decrease by 12.11%). However, the same increase in *Rivalry in Partner Location* decreases the same probability from 52.85% to 41.02% (i.e., decrease by 22.38%) and 56.30% to 38.68% (i.e., decrease by 31.31%) when *Rivals' Absorptive Capacity* is fixed at the mean plus one standard deviation and at the mean plus two standard deviation respectively.

Table 4.1. Descriptive Statistics and Correlation Matrix

| Variables | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) | (15) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| (1) Equity Alliance | 1 | | | | | | | | | | | | | | |
| (2) Reciprocal Interdependence | 0.04 | 1 | | | | | | | | | | | | | |
| (3) Rivalry in Partner Location | **0.06** | -0.05 | 1 | | | | | | | | | | | | |
| (4) Rivals' Absorptive Capacity | 0.03 | **-0.06** | **0.61** | 1 | | | | | | | | | | | |
| (5) Early Stage | 0.03 | **0.28** | 0.04 | -0.03 | 1 | | | | | | | | | | |
| (6) Alliance Scope | 0.00 | -0.05 | 0.02 | -0.01 | **-0.17** | 1 | | | | | | | | | |
| (7) Prior Ties | -0.05 | -0.04 | 0.00 | 0.04 | 0.05 | 0.00 | 1 | | | | | | | | |
| (8) Indirect Ties | -0.04 | 0.00 | **0.10** | 0.08 | 0.03 | -0.03 | **0.32** | 1 | | | | | | | |
| (9) Degree Centrality of Incumbent Firm | 0.00 | **0.06** | 0.00 | 0.05 | **0.12** | **-0.12** | **0.07** | **0.29** | 1 | | | | | | |
| (10) Degree Centrality of Technology Venture | **-0.07** | -0.02 | **0.11** | **0.06** | -0.01 | 0.02 | **0.21** | **0.55** | 0.02 | 1 | | | | | |
| (11) Size of Incumbent Firm | 0.00 | 0.04 | 0.02 | 0.03 | **0.14** | **-0.14** | 0.02 | **0.20** | **0.83** | 0.00 | 1 | | | | |
| (12) Patent Counts of Incumbent Firm | -0.01 | 0.05 | 0.05 | 0.04 | **0.07** | 0.00 | 0.02 | **0.13** | **0.27** | **0.07** | **0.30** | 1 | | | |
| (13) Patent Counts of Technology Venture | -0.02 | 0.03 | -0.01 | -0.02 | -0.03 | -0.01 | **0.07** | 0.04 | 0.03 | **0.07** | 0.00 | 0.02 | 1 | | |
| (14) Cluster Size | 0.01 | -0.04 | **0.63** | **0.69** | 0.00 | 0.04 | 0.04 | 0.05 | -0.04 | **0.11** | -0.05 | 0.02 | -0.03 | 1 | |
| (15) Distance (Ln) | 0.00 | 0.01 | **-0.19** | **-0.23** | -0.05 | 0.00 | 0.01 | 0.01 | **-0.08** | -0.02 | -0.04 | -0.01 | -0.01 | **-0.14** | 1 |
| Mean | 0.07 | 0.47 | 0.03 | 122.4 | 0.38 | 0.16 | 0.11 | 0.74 | 87.30 | 9.96 | 15.50 | 150.5 | 70.41 | 61.37 | 9,160 |
| Standard Deviation | 0.25 | 0.50 | 0.08 | 300.4 | 0.49 | 0.36 | 0.49 | 2.31 | 89.14 | 25.57 | 17.90 | 301.9 | 917.6 | 58.72 | 2,055 |
| Min | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 520.7 |
| Max | 1 | 1 | 0.65 | 1,974 | 1 | 1 | 10 | 38 | 322 | 282 | 61.8 | 5,587 | 31,323 | 214 | 15,491 |

Note: N=1,242. Bolded pairwise correlations are significant at least at 0.05 level.

Table 4.2. Probit Model Results

| | Model | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| | H1 | | H2 | |
| Variables | Equity Alliance | | Reciprocal Interdependence | |
| Rivalry in Partner Location | | 1.76** | | -1.55** |
| | | (0.79) | | (0.61) |
| Early Stage | 0.05 | 0.03 | 0.78*** | 0.79*** |
| | (0.13) | (0.13) | (0.09) | (0.09) |
| Alliance Scope | -0.05 | -0.06 | 0.09 | 0.10 |
| | (0.17) | (0.17) | (0.11) | (0.11) |
| Direct Ties | -0.40 | -0.37 | -0.23** | -0.24*** |
| | (0.28) | (0.28) | (0.09) | (0.09) |
| Indirect Ties | 0.04 | 0.03 | 0.01 | 0.01 |
| | (0.04) | (0.04) | (0.02) | (0.02) |
| Degree Centrality of I.F. | 0.00 | 0.00 | 0.00 | 0.00 |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| Degree Centrality of T.V. | -0.03*** | -0.03*** | -0.00 | -0.00 |
| | (0.01) | (0.01) | (0.00) | (0.00) |
| Size of I.F. | -0.00 | -0.00 | -0.00 | -0.00 |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| Patent Counts of I.F. | -0.00 | -0.00 | 0.00 | 0.00 |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| Patent Counts of T.V. | -0.00 | -0.00 | 0.00 | 0.00 |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| Cluster Size | 0.00 | -0.00 | -0.00 | 0.00 |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| Distance | -0.00 | 0.00 | 0.00 | 0.00 |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| Constant | -2.12*** | -2.15*** | -0.47** | -0.45** |
| | (0.39) | (0.39) | (0.22) | (0.22) |
| Year Fixed Effects | Yes | Yes | Yes | Yes |
| Technology Fixed Effects | Yes | Yes | Yes | Yes |
| Disease Fixed Effects | Yes | Yes | Yes | Yes |
| Log Pseudolikelihood | -273.8 | -271.8 | -772.2 | -769.2 |
| Wald Chi-squared | 101.3*** | 107.8*** | 162.1*** | 167.3*** |
| Pseudo $R^2$ | 0.109 | 0.116 | 0.101 | 0.104 |
| Observations | 1,242 | 1,242 | 1,242 | 1,242 |

Note: Robust standard errors in parentheses. *** *p*<0.01, ** *p*<0.05, * *p*<0.1. Two-tailed tests. I.F. refers to incumbenf firm while T.V. technology venture.

Table 4.2. Continued

| | Model | | | |
|---|---|---|---|---|
| | (5) | (6) | (7) | (8) |
| | H3 | | H4 | |
| Variables | Equity Alliance | | Reciprocal Interdependence | |
| Rivalry in Partner Location (1) | 1.69** | 1.25 | -1.50** | -0.52 |
| | (0.81) | (0.96) | (0.65) | (0.78) |
| Rivals' Absorptive Capacity (2) | 0.00 | -0.00 | -0.00 | 0.00 |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| Interaction Term: (1) × (2) | | 0.00 | | -0.003** |
| | | (0.00) | | (0.001) |
| Early Stage | 0.03 | 0.04 | 0.79*** | 0.79*** |
| | (0.13) | (0.13) | (0.09) | (0.09) |
| Alliance Scope | -0.05 | -0.06 | 0.09 | 0.10 |
| | (0.17) | (0.17) | (0.11) | (0.11) |
| Direct Ties | -0.37 | -0.38 | -0.24*** | -0.24*** |
| | (0.28) | (0.28) | (0.09) | (0.09) |
| Indirect Ties | 0.03 | 0.04 | 0.01 | 0.01 |
| | (0.04) | (0.04) | (0.02) | (0.02) |
| Degree Centrality of I.F. | 0.00 | 0.00 | 0.00 | 0.00 |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| Degree Centrality of T.V. | -0.03*** | -0.03*** | -0.00 | -0.00 |
| | (0.01) | (0.01) | (0.00) | (0.00) |
| Size of I.F. | -0.00 | -0.00 | -0.00 | -0.00 |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| Patent Counts of I.F. | -0.00 | -0.00 | 0.00 | 0.00 |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| Patent Counts of T.V. | -0.00 | -0.00 | 0.00 | 0.00 |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| Cluster Size | -0.00 | -0.00 | 0.00 | 0.00 |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| Distance | 0.00 | 0.00 | 0.00 | 0.00 |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| Constant | -2.16*** | -2.12*** | -0.44** | -0.52** |
| | (0.39) | (0.39) | (0.23) | (0.23) |
| Year Fixed Effects | Yes | Yes | Yes | Yes |
| Technology Fixed Effects | Yes | Yes | Yes | Yes |
| Disease Fixed Effects | Yes | Yes | Yes | Yes |
| Log Pseudolikelihood | -271.7 | -271.4 | -769.1 | -767.1 |
| Wald Chi-squared | 107.9*** | 110.6*** | 167.6*** | 169.3*** |
| Pseudo $R^2$ | 0.116 | 0.117 | 0.104 | 0.107 |
| Observations | 1,242 | 1,242 | 1,242 | 1,242 |

Note: Robust standard errors in parentheses. *** *p*<0.01, ** *p*<0.05, * *p*<0.1. Two-tailed tests. I.F. refers to incumbenf firm while T.V. technology venture.

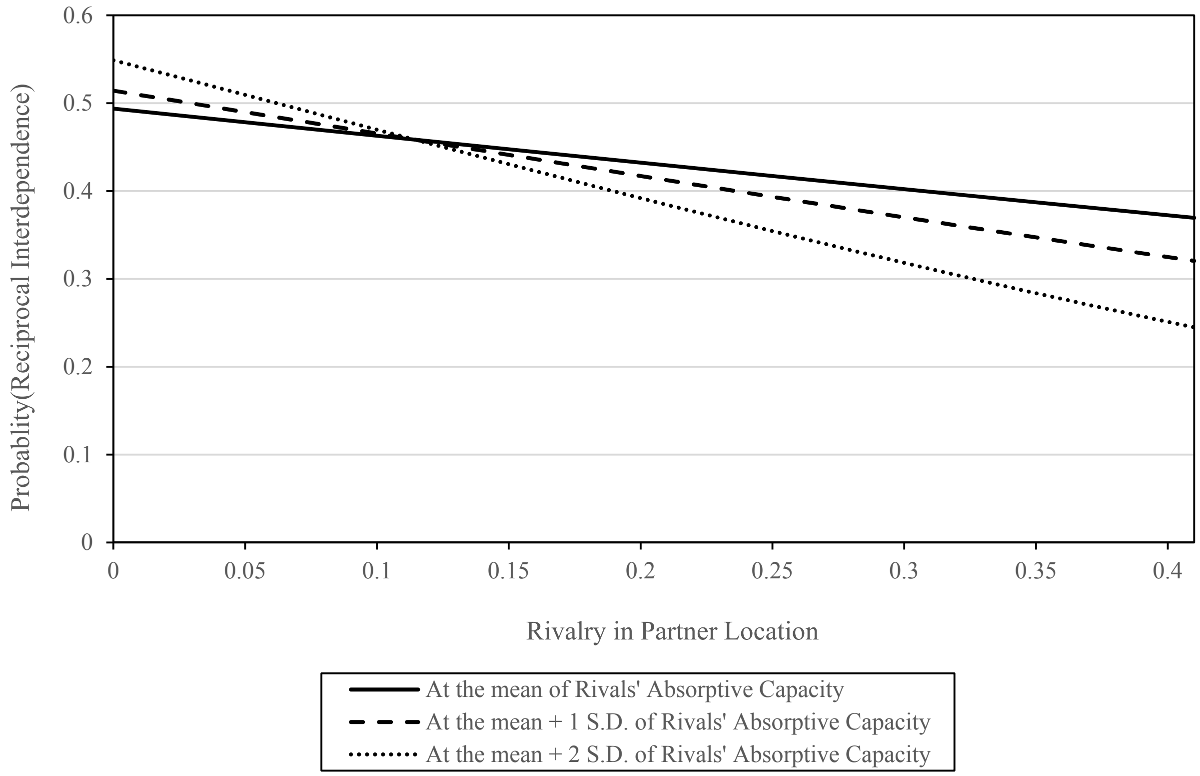


Figure 4.1 Moderating effects of rivals’ absorptive capacity

### 4.4.1 Robustness Checks

Table 4.3 presents the results of robustness analyses using bivariate probit models. The Wald chi-square tests did not reject the null that the correlation in disturbances is zero in all the models, indicating that unobserved factors do not have correlated influences on the two decisions. The results from bivariate probit models, which are known to be more efficient than those from the probit models that are estimated separately, also lead to the same interpretations as those presented above. Table 4 shows the results from Heckman probit models. In the first-stage selection model (Model 1), the coefficient of the number of alliances rival firms had formed in one year prior to a focal year (*Rivals' Num. of Alliances (t-1)*) is positive and significant (*b*=0.01 and *p*=0.000), supporting the appropriateness of the variable as an instrument. Since the Wald chi-square tests did not reject the null that the correlation between the error term in the selection stage and that in the outcome stage is zero, I concluded that selection bias is not significant in my sample. Furthermore, the results from the Heckman probit models again provided consistent results with those from probit models.

Table 4.3. Bivariate Probit Model Results

| | Model | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| | H1 & H2 | | | |
| Variables | Equity Alliance | Reciprocal Interdep-endence | Equity Alliance | Reciprocal Interdep-endence |
| Rivalry in Partner Location | | | 1.76** | -1.55** |
| | | | (0.79) | (0.61) |
| Early Stage | 0.05 | 0.78*** | 0.03 | 0.79*** |
| | (0.13) | (0.09) | (0.13) | (0.09) |
| Alliance Scope | -0.05 | 0.09 | -0.06 | 0.10 |
| | (0.17) | (0.11) | (0.17) | (0.11) |
| Direct Ties | -0.40 | -0.23** | -0.38 | -0.24*** |
| | (0.29) | (0.09) | (0.28) | (0.09) |
| Indirect Ties | 0.04 | 0.01 | 0.04 | 0.01 |
| | (0.04) | (0.02) | (0.04) | (0.02) |
| Degree Centrality of I.F. | 0.00 | 0.00 | 0.00 | 0.00 |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| Degree Centrality of T.V. | -0.03*** | -0.00 | -0.03*** | -0.00 |
| | (0.01) | (0.00) | (0.01) | (0.00) |
| Size of I.F. | -0.00 | -0.00 | -0.00 | -0.00 |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| Patent Counts of I.F. | -0.00 | 0.00 | -0.00 | 0.00 |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| Patent Counts of T.V. | -0.00 | 0.00 | -0.00 | 0.00 |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| Cluster Size | 0.00 | -0.00 | -0.00 | 0.00 |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| Distance | 0.00 | 0.00 | 0.00 | 0.00 |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| Constant | -2.11*** | -0.47** | -2.14*** | -0.45** |
| | (0.38) | (0.22) | (0.38) | (0.22) |
| Year Fixed Effects | Yes | Yes | Yes | Yes |
| Technology Fixed Effects | Yes | Yes | Yes | Yes |
| Disease Fixed Effects | Yes | Yes | Yes | Yes |
| Log Pseudolikelihood | -1045.4 | | -1040.2 | |
| Wald Chi-squared | 279.8*** | | 287.2*** | |
| Wald Test of Rho = 0: $\chi^2(1)$ | 1.42 | | 1.79 | |
| (p-value) | (p=0.23) | | (p=0.18) | |
| Observations | 1,242 | | 1,242 | |

Note: Robust standard errors in parentheses. *** *p*<0.01, ** *p*<0.05, * *p*<0.1. Two-tailed tests. I.F. refers to incumbenf firm while T.V. technology venture.

Table 4.3. Continued

| | Model | | | |
|---|---|---|---|---|
| | (5) | (6) | (7) | (8) |
| | H3 & H4 | | | |
| Variables | Equity Alliance | Reciprocal Interdep-endence | Equity Alliance | Reciprocal Interdep-endence |
| Rivalry in Partner Location (1) | 1.68** | -1.49** | 1.23 | -0.51 |
| | (0.81) | (0.65) | (0.96) | (0.78) |
| Rivals' Absorptive Capacity (2) | 0.00 | -0.00 | -0.00 | 0.00 |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| Interaction Term: (1) × (2) | | | 0.00 | -0.003** |
| | | | (0.00) | (0.001) |
| Early Stage | 0.03 | 0.79*** | 0.04 | 0.79*** |
| | (0.13) | (0.09) | (0.13) | (0.09) |
| Alliance Scope | -0.05 | 0.09 | -0.06 | 0.10 |
| | (0.17) | (0.11) | (0.17) | (0.11) |
| Direct Ties | -0.38 | -0.24*** | -0.38 | -0.24*** |
| | (0.28) | (0.09) | (0.29) | (0.09) |
| Indirect Ties | 0.04 | 0.01 | 0.04 | 0.01 |
| | (0.04) | (0.02) | (0.04) | (0.02) |
| Degree Centrality of I.F. | 0.00 | 0.00 | 0.00 | 0.00 |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| Degree Centrality of T.V. | -0.03*** | -0.00 | -0.03*** | -0.00 |
| | (0.01) | (0.00) | (0.01) | (0.00) |
| Size of I.F. | -0.00 | -0.00 | -0.00 | -0.00 |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| Patent Counts of I.F. | -0.00 | 0.00 | -0.00 | 0.00 |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| Patent Counts of T.V. | -0.00 | 0.00 | -0.00 | 0.00 |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| Cluster Size | -0.00 | 0.00 | -0.00 | 0.00 |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| Distance | 0.00 | 0.00 | 0.00 | 0.00 |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| Constant | -2.15*** | -0.44** | -2.10*** | -0.52** |
| | (0.38) | (0.23) | (0.39) | (0.23) |
| Year Fixed Effects | Yes | Yes | Yes | Yes |
| Technology Fixed Effects | Yes | Yes | Yes | Yes |
| Disease Fixed Effects | Yes | Yes | Yes | Yes |
| Log Pseudolikelihood | -1040.0 | | -1037.7 | |
| Wald Chi-squared | 288.1*** | | 289.3*** | |
| Wald Test of Rho = 0: $\chi^2(1)$ | 1.81 | | 2.03 | |
| (p-value) | (p=0.18) | | (p=0.15) | |
| Observations | 1,242 | | 1,242 | |

Note: Robust standard errors in parentheses. *** *p*<0.01, ** *p*<0.05, * *p*<0.1. Two-tailed tests. I.F. refers to incumbenf firm while T.V. technology venture.

Table 4.4. Heckman Probit Model Results

| | Model | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| | Selection | Outcome | | | |
| | | H1 | | H2 | |
| Variables | | Equity Alliance | | Reciprocal Interdependence | |
| Rivalry in Partner Location | | | 1.59** | | -1.49** |
| | | | (0.72) | | (0.59) |
| Early Stage | | 0.04 | 0.02 | 0.74*** | 0.76*** |
| | | (0.11) | (0.12) | (0.10) | (0.10) |
| Alliance Scope | | -0.05 | -0.05 | 0.08 | 0.09 |
| | | (0.15) | (0.16) | (0.10) | (0.10) |
| Direct Ties | 0.41*** | -0.51* | -0.49* | -0.32*** | -0.33*** |
| | (0.04) | (0.26) | (0.26) | (0.10) | (0.10) |
| Indirect Ties | 0.01 | 0.03 | 0.03 | 0.00 | 0.01 |
| | (0.01) | (0.04) | (0.04) | (0.02) | (0.02) |
| Degree Centrality of I.F. | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| Degree Centrality of T.V. | -0.00 | -0.03*** | -0.03*** | -0.00 | -0.00 |
| | (0.00) | (0.01) | (0.01) | (0.00) | (0.00) |
| Size of I.F. | 0.00 | -0.00 | -0.00 | -0.00** | -0.00* |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| Patent Counts of I.F. | 0.00 | -0.00 | -0.00* | 0.00 | 0.00 |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| Patent Counts of T.V. | -0.00 | -0.00 | -0.00 | 0.00 | 0.00* |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| Cluster Size | 0.00 | 0.00 | -0.00 | -0.00 | 0.00 |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| Distance | -0.00 | -0.00 | 0.00 | 0.00 | 0.00 |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| Constant | -2.39*** | -0.74 | -0.83 | 0.40 | 0.42 |
| | (0.06) | (0.99) | (1.00) | (0.62) | (0.62) |
| Rivals' Num. of Alliances (t-1) | 0.01*** | | | | |
| | (0.00) | | | | |
| Inverse Mills Ratio | | -0.48 | -0.46 | -0.32 | -0.33 |
| | | (0.32) | (0.32) | (0.23) | (0.23) |
| Year Fixed Effects | Yes | Yes | Yes | Yes | Yes |
| Technology Fixed Effects | No | Yes | Yes | Yes | Yes |
| Disease Fixed Effects | No | Yes | Yes | Yes | Yes |
| Log Pseudolikelihood | -6,100.7 | -6,373.6 | -6,371.7 | -6,871.9 | -6,868.9 |
| Wald Chi-squared | 1187.6*** | 110.1*** | 114.5*** | 156.6*** | 159.4*** |
| Wald Test of Rho = 0: $\chi^2(1)$ | | 2.24 | 2.05 | 1.98 | 1.97 |
| (p-value) | | (p=0.13) | (p=0.15) | (p=0.16) | (p=0.16) |
| Observations | 90,659 | 90,659 | 90,659 | 90,659 | 90,659 |

Note: Robust standard errors in parentheses. *** $p$<0.01, ** $p$<0.05, * $p$<0.1. Two-tailed tests. Selection model for the realized alliance deals are the same for all the outcome models. I.F. refers to incumbenf firm while T.V. technology venture.

Table 4.4. Continued

| | Model | | | |
|---|---|---|---|---|
| | (6) | (7) | (8) | (9) |
| | Outcome | | | |
| | H3 | | H4 | |
| Variables | Equity Alliance | | Reciprocal Interdependence | |
| Rivalry in Partner Location (1) | 1.53** | 1.12 | -1.43** | -0.49 |
| | (0.74) | (0.87) | (0.63) | (0.74) |
| Rivals' Absorptive Capacity (2) | 0.00 | -0.00 | -0.00 | 0.00 |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| Interaction Term: (1) × (2) | | 0.00 | | -0.003** |
| | | (0.00) | | (0.001) |
| Early Stage | 0.02 | 0.03 | 0.75*** | 0.75*** |
| | (0.12) | (0.12) | (0.10) | (0.10) |
| Alliance Scope | -0.05 | -0.05 | 0.09 | 0.10 |
| | (0.16) | (0.16) | (0.10) | (0.10) |
| Direct Ties | -0.49* | -0.49* | -0.33*** | -0.33*** |
| | (0.26) | (0.26) | (0.10) | (0.10) |
| Indirect Ties | 0.03 | 0.03 | 0.01 | 0.01 |
| | (0.04) | (0.04) | (0.02) | (0.02) |
| Degree Centrality of I.F. | 0.00 | 0.00 | 0.00 | 0.00 |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| Degree Centrality of T.V. | -0.03*** | -0.03*** | -0.00 | -0.00 |
| | (0.01) | (0.01) | (0.00) | (0.00) |
| Size of I.F. | -0.00 | -0.00 | -0.00* | -0.00* |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| Patent Counts of I.F. | -0.00* | -0.00* | 0.00 | 0.00 |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| Patent Counts of T.V. | -0.00 | -0.00 | 0.00* | 0.00* |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| Cluster Size | -0.00 | -0.00 | 0.00 | 0.00 |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| Distance | 0.00 | 0.00 | 0.00 | 0.00 |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| Constant | -0.85 | -0.80 | 0.43 | 0.37 |
| | (1.00) | (1.00) | (0.62) | (0.63) |
| Inverse Mills Ratio | -0.46 | -0.46 | -0.33 | -0.33 |
| | (0.32) | (0.32) | (0.23) | (0.23) |
| Year Fixed Effects | Yes | Yes | Yes | Yes |
| Technology Fixed Effects | Yes | Yes | Yes | Yes |
| Disease Fixed Effects | Yes | Yes | Yes | Yes |
| Log Pseudolikelihood | -6,371.6 | -6,371.3 | -6,868.8 | -6,866.8 |
| Wald Chi-squared | 114.8*** | 117.6*** | 159.5*** | 160.4*** |
| Wald Test of Rho = 0: $\chi^2(1)$ | 2.01 | 2.06 | 1.98 | 2.04 |
| (p-value) | (p=0.16) | (p=0.15) | (p=0.16) | (p=0.15) |
| Observations | 90,659 | 90,659 | 90,659 | 90,659 |

Note: Robust standard errors in parentheses. *** $p$<0.01, ** $p$<0.05, * $p$<0.1. Two-tailed tests. Selection model for the realized alliance deals are the same for all the outcome models.

## 4.5 Discussion

In this paper, I theorize and corroborate that the governance structure and task interdependence of an R&D alliance between an incumbent firm and a technology venture is influenced by the characteristics of the technology venture's location. More specifically, I argue that when the technology venture is co-located with major rivals of the incumbent firm, the incumbent firm faces a higher risk of knowledge leakage to rivals by unintentional knowledge spillovers from the technology venture to the nearby rivals as well as joint misappropriation by the technology venture and the nearby rivals. This higher risk increases the need for knowledge protection and thus makes the incumbent firm more likely to respond by using an equity governance structure and reducing task interdependence. Furthermore, I also claim that the absorptive capacity of the nearby rivals aggravates the risk of the nearby rivals' gaining access to the incumbent firm knowledge, intensifying the effect of rivalry in partner location on the incumbent firm's protective alliance design decisions. Empirical analyses based on 1,242 R&D alliances between technology ventures and incumbent firms in the biopharmaceutical industry broadly support my arguments.

### 4.5.1 Contributions and Implications

My theory and evidence make several contributions to the alliance literature as well as to the agglomeration literature. My most immediate contribution to the alliance literature lies in building upon and extending the competition-oriented cooperation literature that investigates the competitive aspects of collaborations and potential downsides of partnering with rivals (Hamel et al., 1989; Khanna et al., 1998; Oxley & Sampson, 2004; Park & Russo, 1996). This literature that had paid attention to dyadic competitive relationships, and related research has just recently begun to consider the threats of knowledge leakage to rivals via indirect links such as through common suppliers, shared intermediary organizations, and board interlocks (Hernandez et al., 2015; Mesquita et al., 2008; Pahnke et al., 2015). I complement this emerging literature that has paid attention to formal, established ties by suggesting that geographic co-location between an allying firm's partner and its rivals is an overlooked but important factor that can present risks of knowledge losses, and incumbent firms respond to these risks through their alliance design choices.

I also contribute to the literature on R&D alliances between incumbent firms and technology ventures. The literature has typically focused on misappropriation by incumbent firms of the knowledge possessed by technology ventures. Since technology ventures have greater difficulty in learning partner knowledge, controlling knowledge flows, and reacting to misappropriation by partners (Alvarez & Barney, 2001), it makes sense that the previous literature has mainly focused on the technology venture viewpoint. However, this exclusive focus on one side of the partnership overlooks the fact that the counterpart (i.e., incumbent firms) might also be concerned about knowledge loss. That is, I suggest that despite their superior resources and bargaining power, incumbent firms are also prone to the risk of knowledge loss in R&D alliances with technology ventures. In cases where this risk is particularly salient, incumbent firms need to devise appropriate defensive mechanisms. In this paper, I showed that incumbent firms' choices of governance and task interdependence vary based on the degree to which their technology venture counterparts are in geographic proximity to their major rivals.

My results using equity alliance and reciprocal interdependence as dependent variables also make an interesting comparison with the previous literature that has focused on partner selection as a means for technology ventures to deal with knowledge misappropriation concerns (Diestre & Rajagopalan, 2012; Katila et al., 2008). When taking the technology venture perspective, focusing on partner selection is sensible because technology ventures normally lack the bargaining power to attain other safeguards they might desire. Therefore, a realistic option to them might be to avoid partnering with a certain incumbent firm when it entails a high risk of misappropriation. By contrast, an incumbent firm may still enter into rather than avoid an R&D alliance with a technology venture entailing a high risk of knowledge loss because the incumbent firms' superior bargaining power allows it to protect itself by negotiating appropriate governance structures and level of task interdependence.

One related secondary contribution I make to the alliance literature is that I further extend the important but relatively sparse literature treating task interdependence as a decision variable (Oxley & Sampson, 2004) with finer measures and results. Unlike alliance research that regards task interdependence as an exogenously given condition mainly affecting alliance decisions by increasing coordination costs (Gulati & Singh, 1998), this alternative view highlights that alliance partners endogenously choose the level of task interdependence depending on the level of misappropriation risk they face. The literature has typically used alliance scope, i.e., whether a given R&D alliance includes downstream activities such as manufacturing and/or marketing, as a proxy for the level of interdependence. Despite many benefits such as its alignment with theory and data availability, it does not consider the heterogeneity in task interdependence among different R&D tasks. That is, when an R&D alliance includes marketing activities but its R&D tasks are just sequential, it is not clear that the R&D alliance with wide scope is always more interdependent than a pure R&D alliance of which tasks are highly reciprocal. Furthermore, since R&D-dedicated technology ventures might not be interested in the knowledge related to manufacturing and marketing, the broader scope of R&D plus manufacturing or marketing might not add substantially additional risk of knowledge loss. Because my models explain the variation in the level of R&D task interdependence controlling alliance scope, my results support based on a finer measure that a level of task interdependence is a decision made by alliance partners depending on the need for knowledge protection rather than an exogenously given condition.

Lastly, I also contribute to the agglomeration literature by adding new insights and findings to the research on the downsides of agglomeration. The predominant emphasis in the agglomeration literature has been the benefits of geographic clustering, particularly because geographic co-location fosters access to a pool of knowledge spillovers. A small subset of the literature has raised the concern that firms not only draw from but also contribute to that pool. This concern has led some scholars to predict that firms with superior resources may be less likely to choose clustered locations (Shaver & Flyer, 2000). If a firm believes the costs of rivals' having access to knowledge spillovers from the firm outweighs the benefits of accessing the pool of spillovers generated by the co-located rivals, firms will avoid entering clusters. I raise a similar concern in the context of allying with clustered firms. Forming alliances with firms in clusters has been suggested as a way for isolated firms to access the benefits of clusters (McCann & Folta, 2008), and empirical research indicates that clustered firms are more likely to attract partners (Rothaermel, 2002). While I agree that this represents an opportunity to indirectly tap into the cluster's pool of knowledge spillovers, my work emphasizes that the risk of contributing to the pool and losing relative advantages still exists in these relationships. Important incumbent firm knowledge may spill over via the technology venture into the cluster where it is potentially accessible to rival firms. In cases where a significant number of incumbent firms' rivals are co-located with the technology venture, the incumbent firm should take steps to reduce the potential for knowledge losses.

### 4.5.2 Limitations and Future Research

This study has some limitations that provide fruitful opportunities for extensions to address. In this paper, I focused only on the increasing risk of knowledge spillovers and misappropriation when a technology venture is co-located with the major rivals of its incumbent firm partner. In an R&D alliance between an incumbent firm and a technology venture, knowledge shared with or newly created with the technology venture inevitably resides within the technology venture and thus the risk of knowledge spillovers and misappropriation obviously exists. As noted above, however, geographic proximity between the technology venture and the nearby rivals might also increase the benefit of knowledge spill-ins from the rivals to the incumbent firm through the technology venture. Although this benefit of potential knowledge spill-ins exists, it is relatively less certain because it depends on (1) whether the technology venture has absorbed the knowledge of interest to the incumbent firm (which is difficult to assess prior to a transaction with the technology venture) and (2) the ability and willingness of the technology venture to transfer that knowledge to the incumbent firm. For this reason, the risk of knowledge spillovers and misappropriation is more obvious than the benefit of knowledge spill-ins in my case and thus I focused on the former. However, future research could explore situations where potential benefits of knowledge spill-ins plays a larger role than potential risk of knowledge spillovers and misappropriation. For instance, when an incumbent firm invests in the ownership of a technology venture through corporate venture capital, knowledge transfers from the incumbent firm to the technology venture do not necessarily take place, but the incumbent firm possesses property rights on the knowledge of the technology venture. Therefore, while potential benefit of knowledge spill-ins remains, potential risk of knowledge spillovers and misappropriation might be relatively lower in this case.

In this paper, I highlighted co-location or geographic proximity between an allying firm and its partner's major rivals as a factor increasing the risk of knowledge spillovers and misappropriation. However, there are other interesting relationships between an allying firm and its partner's major rivals that might influence the risk of knowledge loss. Examples include, but are not limited to, prior ties, spin-offs, and labor mobility between them. Since co-location or geographic proximity increases the likelihood of all these relationships and events, I focused on agglomeration and the proximity of an incumbent firm's rivals in this paper. However, each factor would be meaningful and may potentially have different implications individually and independently from geographic proximity per se. Future studies might examine how each of these factors affects firms' external corporate development activities in terms of partner/target selection, governance choice, and the design of collaborative agreements.

## 4.6 Conclusion

To the best of knowledge, this is the first empirical study that explicitly examines how co-location between an allying technology venture and its incumbent partner's major rivals affect the design and governance of R&D alliances. I theorize that co-location increases the risk of rivals' gaining access to an incumbent firm's knowledge and, therefore, the incumbent firm mitigates this concern by (1) opting for equity governance structures to provide greater incentive alignment, control, and monitoring and (2) choosing less interdependent R&D projects to reduce knowledge sharing. I further claim that the effects of rivalry in partner location on the usage of these defense mechanisms strengthen with the absorptive capacity of nearby rivals. My results largely support these theoretical arguments, and I hope this paper more broadly stimulates future research that considers the implications of the competitive context of collaboration, including potential dark sides of agglomeration.

# CHAPTER 5. CONCLUSION

In this dissertation, I attempt to advance our understanding on the interplay between competition and cooperation by examining how R&D collaborations are affected by (1) direct competition between partner firms and (2) the geographic co-location between an allying firm's partner and rivals.

More specifically, drawing on the multimarket competition literature, I argue that the mutual forbearance that market overlap between R&D alliance partners generates can curb opportunism and thus reduce the exchange hazards in their collaborations. Based on this argument, in Essay 1 (Chapter 2), I claim and show that as two firms share more markets, they estimate the partner's inclination toward opportunism as lower and are thus more likely to enter into a technology cooperation. Essay 1 (Chapter 2) also supports that this effect is intensified for technology cooperation with high technological uncertainty, as well as with a broad vertical scope, because both cases entail a greater risk of opportunism, rendering partners' proclivity toward opportunism more important as a criterion for partner selection. Consistently, Essay 2 (Chapter 3) shows that multimarket rivals are less likely to employ hierarchical governance structures for their collaborations due to the reduced risk of opportunism between them. The competition-oriented cooperation literature has argued that competition undermines cooperation by increasing the benefits realized by opportunistic behaviors. However, my findings suggest the nature and number of market contacts might affect the possibility of partners' retaliatory responses to opportunism and the costs caused by the retaliation and therefore, these factors should be considered to anticipate the effect of competition between alliance partners on their cooperation.

In addition, by combining the multimarket competition literature and the literature on relational embeddedness, Essay 2 (Chapter 3) also shows that different dyadic relationships in which alliance partners are embedded jointly influence the partners' proclivity toward opportunism. That is, factor market rivalry intensifies the mutual forbearance from opportunism that multimarket contact in end-product markets generates, while previous cooperative experience (i.e., prior ties) dampens the relative value of mutual forbearance due to market overlap as a remedy for exchange hazards. These results also propose that it is important to consider the broad economic—competitive or cooperative—context in which alliance partners are embedded in predicting the level of cooperation hazards that the alliance partners encounter and the consequential decisions concerning the collaboration.

The findings from Essay 1 (Chapter 2) and Essay 2 (Chapter 3) that market overlap can enhance transaction efficiency by generating mutual forbearance from opportunism provide a critical implication to the multimarket competition literature, as well. The multimarket competition literature has entirely interpreted mutual forbearance as tacit collusion that takes place across markets to earn monopolistic rent and has paid exclusive attention to the benefit from multimarket contact via rivalry restraint (Jayachandran et al., 1999; Yu & Cannella Jr., 2013). However, the mechanism through which I claim market overlap benefits alliance partners is efficiency enhancement in transactions, and it has nothing to do with monopolistic rent seeking. Therefore, my dissertation sheds new light on multimarket contact and mutual forbearance in terms of efficiency considerations, calling for more future research linking the multimarket competition literature with research on cooperative strategy.

In Essay 3 (Chapter 4), I combine the agglomeration literature with the alliance literature to argue that the geographic co-location between an allying technology venture and its incumbent partner's major rivals creates indirect paths of knowledge leakage to the nearby rivals, influencing the design of the R&D alliance as a result. I maintain that when co-location aggravates the risk of rivals' acquiring an incumbent firm's knowledge, the incumbent firm is more likely to (1) choose equity-based governance modes to enhance monitoring, control, and incentive alignment and (2) reduce the level of task interdependence to limit knowledge sharing. Considering nearby rivals' ability to leverage external knowledge, as well as the exposure created by geographic co-location between partners and rivals, I further argue that the effects of rivalry in partner location on the usage of these defense mechanisms is intensified by the absorptive capacity of nearby rivals. Based on these findings, I contribute not only to the emerging literature on indirect knowledge leakage to rivals, but also to the agglomeration literature.

Unlike the conventional competition-oriented cooperation literature that has been mainly interested in knowledge leakage via direct interaction between alliance partners (Dussauge, Garrette, & Mitchell, 2000; Hamel, Doz, & Prahalad, 1989; Khanna, Gulati, & Nohria, 1998; Oxley & Sampson, 2004), some recent research has suggested that knowledge leakages to rivals can take place via indirect linkages, as well (Hernandez et al., 2015; Mesquita et al., 2008; Pahnke et al., 2015). However, this stream of research has been interested only in *formal* inter-firm relationships as an indirect channel of knowledge leakage to rivals. In Essay 3 (Chapter 4), I contribute to this emerging literature by suggesting geographic co-location between partners and rivals as an interesting but understudied path that might aggravate knowledge protection concerns.

The results from Essay 3 also extend the literature on the downsides of agglomeration to the alliance context. The agglomeration literature has highlighted knowledge spillovers in geographic clusters as the main benefit that incentivizes firms to agglomerate, and only a small subset of the literature has suggested the possible costs that firms with superior resources might incur by joining a pool of knowledge spillovers (Shaver & Flyer, 2000). However, the literature has paid attention to this concern in the context of location choice, but not in the context of collaborating with clustered firms. Therefore, the findings in Essay 3 (Chapter 4) contribute to this literature by providing evidence that the risk of contributing to the pool and losing relative advantages also exists in partnerships with clustered firms, particularly those who are co-located with rivals.

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APPENDIX

# APPENDIX

This section is to illustrate how *Rivalry in Partner Location* is calculated. For this purpose, assume the followings:

1) Incumbent Firm *i* and Technology Venture *j* enter into an R&D alliance.

2) Technology Venture *j* is located in $MSA_c$

3) Three top 10 rivals of Incumbent Firm *i*, $Rival_{i1}$, $Rival_{i2}$, and $Rival_{i3}$, are also located in $MSA_c$ while other top 10 rivals, i.e., $Rival_{i4}$—$Rival_{i10}$ are located elsewhere.

4) In the industry, there are five distinct markets ($M_1$~$M_5$) and the market sizes are all $100.

5) Incumbent Firm *i* is present in three markets, $M_1$, $M_2$, and $M_3$ and earns $50, $30, and $20 from $M_1$, $M_2$, and $M_3$ respectively.

6) $Rival_{i1}$ is present in $M_1$, $M_2$, $M_3$, and $M_4$ and earns $20, $30, $50, and $10 from $M_1$, $M_2$, $M_3$, and $M_4$ respectively.

7) $Rival_{i2}$ is present in $M_1$, $M_2$, and $M_5$ and earns $30, $30, and $10 from $M_1$, $M_2$, and $M_5$ respectively.

8) $Rival_{i3}$ is present in $M_2$, $M_3$, and $M_4$ and earns $10, $20, and $30 from $M_2$, $M_3$, and $M_4$ respectively.

The following table summarizes the relevant firms' revenues from each market.

| | $M_1$ | $M_2$ | $M_3$ | $M_4$ | $M_5$ | Total Revenue |
|---|---|---|---|---|---|---|
| Incumbent Firm *i* | $50 | $30 | $20 | $0 | $0 | $100 |
| $Rival_{i1}$ | $20 | $30 | $50 | $10 | $0 | $110 |
| $Rival_{i2}$ | $30 | $30 | $0 | $0 | $10 | $70 |
| $Rival_{i3}$ | $0 | $10 | $20 | $30 | $0 | $60 |

Then, $\text{Rivalry in Partner Location}_{ij} = \sum_m (\text{Importance}_m \times \sum_r \text{MS}_{rm}) =$

$\text{Importance}_1 (= \frac{50}{100}) \times \sum_r \text{MS}_{r1} \left(= \frac{20}{100} + \frac{30}{100} + \frac{0}{100}\right) + \text{Importance}_2 (= \frac{30}{100}) \times$

$\sum_r \text{MS}_{r2} \left(= \frac{30}{100} + \frac{30}{100} + \frac{10}{100}\right) + \text{Importance}_3 (= \frac{20}{100}) \times \sum_r \text{MS}_{r3} \left(= \frac{50}{100} + \frac{0}{100} + \frac{20}{100}\right) =$

$0.6$

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**PUBLICATIONS & WORKING PAPERS**

Ruth, D., Brush, T.H., & Ryu, W. 2015. The Use of Information Technology in the Provision of HR Compensation Services and its Effect on Outsourcing and Centralization," ***Journal of Purchasing and Supply Management*** 21(1): 25—37.

Ryu, W. & Reuer, J.J. Effects of Multimarket Contact on the Governance of R&D Alliances.

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Ryu, W., Brush, T.H., & Reuer, J.J. How Competition Fosters Cooperation: The Effect of Market Overlap on Partner Selection for Technology Cooperation, Working paper.

- The earlier version of the paper was a ***2014 SMS Best Conference PhD Paper Prize Finalist***

Ryu, W., MacCann, B.T., & Reuer, J.J. Geographic Locations of Partners and Rivals: Implications for the Design of R&D Alliances

- To be submitted to ***Academy of Management Journal***

## PRESENTATIONS

"Effects of Multimarket Contact on the Governance of R&D Alliances," with Jeffrey Reuer.

- Strategic Management Society Annual Conference, Denver, 2015
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"How Multimarket Competition Fosters Collaboration: Mutual Forbearance and Market Power Effects," with Jeffrey Reuer and Thomas Brush.

- Academy of Management Annual Meeting, Vancouver, Canada, 2015

"The Effect of Multimarket Contact on Alliance Partner Selection" with Thomas Brush.

- Strategic Management Society Annual Conference, Madrid, Spain, 2014
- ***2014 SMS Best Conference PhD Paper Prize Finalist***

"Cluster Size: Determinant of Network Strategy and Innovation Performance," with Thomas Brush.

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- International Conference on Management, Leadership, and Governance, Boston, 2014
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## TEACHING EXPERIENCE

### Instructor

- MGMT 451 Strategic Management, Krannert School of Management, Purdue University, Spring 2013
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LG Electronics, Independent Management Consultant, Seoul, Korea (2011)

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