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The effects of multimarket contact on partner selection for technology cooperation

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Abstract

Research summary**:** We investigate how multimarket contact between prospective partners affects their partner selection for technology cooperation. Drawing on the multimarket competition literature, we argue that multimarket contact generates mutual forbearance from opportunism by enabling broad retaliation across the shared markets against opportunism. As a result, multimarket contact between potential partners makes them prefer each other as partners for technology cooperation. We also claim that this positive effect of multimarket contact on the formation of cooperative agreements is more pronounced when the partners have reciprocal contacts rather than nonreciprocal ones.

Managerial summary**:** This article explains one of the reasons why rival firms can be good partners to each other for technology cooperation. Managers might conjecture that firms tend to avoid partnering with rival firms for R&D because they may be more opportunistic than those without product market overlap. However, our theory suggests a counter-intuitive argument that market overlap between partners rather deters them from engaging in opportunistic behaviors because market overlap enables them to broadly retaliate against such behaviors across the shared product markets. Consistent with this idea, our empirical results show that global top 200 biopharmaceutical companies are more likely to choose each other for technology cooperation as they share more product markets and this tendency is reinforced when their important markets are different.

KEYWORDS
multimarket contact, mutual forbearance, opportunism, partner selection, technology cooperation

1 | INTRODUCTION

Partner selection is a key alliance decision that shapes whether firms achieve their collaborative objectives (Kale & Singh, 2009), and thus the alliance literature has extensively investigated who partners with whom (Gimeno, 2004; Gulati, 1995b; Li, Eden, Hitt, & Ireland, 2008; Reuer & Lahiri, 2014; Rothaermel & Boeker, 2008; Stuart, 1998). In particular, the literature on partner selection and alliance formation has been interested in whether rivalry or market overlap between prospective partners fosters or hinders alliance formation between them (e.g., Ang, 2008; Gulati, 1995b). In this stream of research, the theoretical mechanisms used to link market overlap with partner selection have tended to rely on either market power-based or resource-based perspectives. For instance, some prior research based on the industrial organization economics tradition has maintained that firms with market overlap enter into alliances in general, or R&D partnerships in particular, to better communicate and support market collusion (e.g., Vonortas, 2000). In addition, other research has argued that since potential partners with market overlap can suffer from a lack of resource complementarity, they are unlikely to enter into alliances (e.g., Chung, Singh, & Lee, 2000). However, little attention has been paid to another possible mechanism through which market overlap can affect partner selection: the incentives to cooperate or compete *within* partnerships.

Confidence in partner cooperation, or "a firm's perceived level of certainty that its partner firm will pursue mutually compatible interests in the alliance, rather than act opportunistically," has been regarded as a major criterion for partner selection (Das & Teng, 1998). Confidence in partner cooperation especially takes on importance in technology alliances that are prone to opportunism by partners, including knowledge misappropriation by a partner (Gulati & Singh, 1998; Oxley, 1997; Pisano, 1989). Therefore, if market overlap has a bearing on firms' expectations of potential partners' proclivities toward opportunism, it will also influence partner selection for technology cooperation. That the prior literature has paid little attention to this possible mechanism is an important research gap since market overlap between partners and partner opportunism have both been popular topics in the alliance literature. In order to provide a new perspective on rivalry and partner selection, specifically for technology cooperation, we build upon and extend the previous literature on market overlap and partner selection by joining it with the multimarket competition literature, which has investigated competitive actions and responses between multimarket rivals (Karnani & Wernerfelt, 1985).

The multimarket competition literature has argued and shown that market overlap or multimarket contact[1] in end-product markets between two firms reduces incentives to initiate attacks in the first place by enabling broad retaliation across the two firms' shared markets (Bernheim & Whinston, 1990). Combining this argument with the view that opportunistic behaviors are also a kind of

[1]In this article, for simplicity we will henceforth use the terms multimarket contact and market overlap interchangeably, though the latter can exist without the former.

competitive action that alliance partners can undertake to capture value, we claim that multimarket contact in end-product markets can also deter partners from engaging in opportunistic behaviors and thus facilitate technology cooperation. In addition, because the multimarket competition literature has suggested that reciprocal contacts are more effective than nonreciprocal ones in generating mutual forbearance, we also investigate how the reciprocity of contacts shapes the effect of multimarket contact on partner selection.

To empirically test these arguments, we use a panel of dyads between the global top 200 biopharmaceutical companies and examine who partners with whom by tracing which firms enter into technology cooperation agreements with each other. Our theory and results make several contributions not only to the alliance literature but also to the research stream on multimarket competition. Our main contribution lies in providing a novel view on market overlap and the antecedents of interfirm cooperation. By joining research on partner selection with the multimarket competition literature, on which the alliance research has rarely drawn, we suggest that firms with market overlap can be attractive to each other as partners for technology cooperation because the shared markets can generate mutual forbearance from opportunism. This view complements the prior literature on partner selection, which has paid little explicit attention to the interplay between competition and cooperation for such important decisions in the collaborative strategy domain.

Moreover, we also theoretically and empirically extend previous research on alliances between rivals, or the "competition-oriented cooperation" literature (Chen, 2008). Prior research has argued that partners tend to be more opportunistic in alliances with rivals because opportunistic behaviors can directly undermine the rivals and partners will adopt a zero-sum perspective in these agreements (e.g., Oxley & Sampson, 2004; Park & Russo, 1996). This argument implicitly assumes that firms do not respond to their partners' opportunistic behaviors, in particular outside the scope of their alliance. However, we build upon and extend this argument in the literature by considering the possibility that opportunistic behaviors can provoke partners' retaliation in other product markets. If the costs imposed by retaliation against partner opportunism increase with multimarket contact as our theory suggests, then such market overlap will deter opportunistic behaviors in the first place.

In addition, previous research on market overlap and cooperation risk has tended to conceptualize and operationalize market overlap based on broadly-defined markets, typically at the industry level (e.g., Lin, Yang, & Arya, 2009; Oxley & Sampson, 2004; Wang & Zajac, 2007). Therefore, most of the existing research compares within- and cross-industry alliances, and thus we still know little about how market overlap at the product market level within the same industry influences partner selection for technology cooperation. Since the multimarket competition literature suggests that heterogeneity in breadth of market overlap at the product market level might carry implications for competitive tensions and opportunism between prospective partners, we enrich the existing literature by providing a finer-grained conceptualization and measurement of market overlap to investigate how firms' competitive relationships have an impact on their partner selection decisions for technology cooperation.

Last, we contribute to the multimarket competition literature by linking multimarket competition in product markets with mutual forbearance in R&D collaborations. Prior research in the multimarket competition literature has been interested mainly in investigating how multimarket contact in product markets leads to mutual forbearance from competitive actions taking place in product markets, such as market entry and exit (Baum & Korn, 1996; Fuentelsaz & Gómez, 2006) and pricing (Gimeno & Woo, 1996; Hannan & Prager, 2004). We complement this research by suggesting that multimarket competition in product markets can also affect incentives to cooperate or compete in R&D

collaborations beyond immediate competitive responses in product markets, thereby extending the applicability of the mutual forbearance argument in the strategy and economics literatures.

2 | THEORY AND HYPOTHESES

2.1 | Risk of partner opportunism and partner selection for technology cooperation

Opportunistic behavior, defined as "self-interest seeking with guile" (Williamson, 1975), can be manifested in alliances in many forms—"cheating, shirking, distorting information, misleading partners, providing substandard products/services, and appropriating partners' critical resources" (Das & Teng, 1998). When searching for partners, firms consider potential partners' likelihood of engaging in these behaviors and prefer to collaborate with those judged to be less likely to engage in opportunism (Das & Teng, 1998). Among various types of interfirm collaborations, technology cooperation is known to be particularly prone to the hazard of partner opportunism due to the inherent uncertainty surrounding R&D (Nelson & Winter, 1977). Uncertainty in R&D projects makes it difficult to estimate the ultimate costs and benefits of the projects and specify property rights *ex ante*, thereby making it challenging for collaborators to write complete contracts and enforce them (Pisano, 1989). The contractual gaps in such contacts therefore leave room for future negotiation that is subject to haggling and *ex post* opportunism. Given the inherent challenges in controlling partner opportunism in technology cooperation, firms weigh potential partners' proclivities toward opportunism as an important criterion for partner selection when they search for partners for technology cooperation. Accordingly, if market overlap between prospective R&D partners has a bearing on their incentives to act opportunistically in the collaboration, it will also affect firms' partner selection decisions.

2.2 | Multimarket contact and mutual forbearance from opportunism in technology cooperation

Multimarket contact refers to two firms competing in more than one distinct market (Karnani & Wernerfelt, 1985). The multimarket competition literature has long argued that rivals having multimarket contact between them tend to mutually forbear from attacks, therefore lowering the intensity of rivalry (Bernheim & Whinston, 1990; Edwards, 1955), which has been corroborated by many previous empirical articles (e.g., Baum & Korn, 1996; Gimeno & Woo, 1996; Heggestad & Rhoades, 1978; Parker & Röller, 1997; Shankar, 1999; Yu & Cannella, 2007). 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 focal market in which the attack was initiated, but also in other shared markets. This broad retaliation may eventually result in a larger loss to the attacking firm than the initial gain from the attack in a specific market (Evans & Kessides, 1994; Feinberg, 1985; Haveman & Nonnemaker, 2000; Heggestad & Rhoades, 1978; Phillips & Mason, 1996). Thus, an initiator of an attack will take into account the attacked firm's ability to retaliate and cause serious financial damage, and this shadow of the future functions to deter attacks in the first place. Furthermore, mutual forbearance between two firms increases with the degree of multimarket contact between them because multimarket contact provides a better ability to retaliate against current attacks. The larger number of market contacts means more areas in which to retaliate against current attacks (Jayachandran, Gimeno, & Varadarajan, 1999), and retaliation across more markets can hurt the attacker more seriously (Edwards, 1955).

In the context of technology cooperation, wherein opportunistic behaviors are a kind of competitive action to appropriate value undertaken by an alliance partner, mutual forbearance generated by multimarket contact can curb opportunism by partners due to the shadow of the future (e.g., Parkhe, 1993) that is created by possible broad retaliation. That is, when two partners compete against each other in multiple product markets, one partner can effectively respond to the other's opportunistic behaviors by retaliating in the overlapping product markets outside the partnership. In particular, if market overlap between the two firms is substantial so that retaliation can take place broadly across the multiple shared markets, it can cause the opportunistic partner serious harm (Jayachandran et al., 1999). Therefore, all else equal, as the degree of multimarket contact between two prospective partners increases, they will perceive a lower risk of opportunism and thus are more likely to choose each other as a partner for technology cooperation. We therefore posit:

Hypothesis (H1): *The likelihood of two firms selecting each other as partners for technology cooperation is positively related to the degree of multimarket contact between them.*

2.3 | Reciprocity of market contacts and mutual forbearance from opportunism

The theoretical development thus far has emphasized the costs of engaging in opportunistic behaviors that increase with multimarket contact and the retaliatory opportunities it affords, but the multimarket competition literature would also emphasize that these costs also hinge upon the nature of firms' positions in their overlapping markets. More specifically, the reciprocity of market contacts, in addition to mere contact across multiple markets, increases the costs of an initial attack and thus strengthens deterrence and mutual forbearance. Since initially suggested by Edwards (1955), this "spheres of influence" argument has been theoretically developed by Bernheim and Whinston (1990) and Spagnolo (1999), and it has been empirically corroborated by many studies (e.g., Baum & Korn, 1996; Fuentelsaz & Gómez, 2006; Gimeno, 1999).

The spheres of influence argument suggests that, given that the importance of each shared market is different for each rival, sharing footholds of small market shares in each other's important markets (i.e., reciprocity of market contacts) is an important factor that facilitates mutual forbearance (Gimeno, 1999). In this case, the attacked firm can hurt the attacking firm effectively by retaliating in the shared markets where the retaliating firm has a small market presence while the targeted firm has a large market presence. Given that the retaliation escalates the intensity of competition in the markets, the potential loss caused by the increased level of rivalry (e.g., reduced profits or self-cannibalization) would be far greater for the targeted firm with a sizable market presence than for the retaliating firm having a small market presence. For instance, when the retaliating firm undercuts the targeted firm in a market where the former has a low market share while the latter has a high market share, the cost that the former expects to incur to implement the retaliation tends to be limited due to its small market share. However, a response in kind (i.e., price cutting) by the targeted firm would be very costly to implement due to its large sales. Therefore, reciprocity of market contacts increases the credibility of a retaliation threat and the expected subsequent costs of initial attacks, thereby facilitating deterrence and mutual forbearance. By contrast, if one firm has smaller market shares in all the shared markets than the other (i.e., if the two firms have no reciprocal contacts), the former is likely to incur lower costs of initiating attacks than the latter and therefore the former is less likely to agree upon mutual forbearance than when they have reciprocal market contacts. Hence, in the context of technology cooperation, reciprocal market contacts increase the expected subsequent costs of initiating an opportunistic action (or "attack") to a greater extent than nonreciprocal ones, and consequently has a greater impact on curbing opportunism by the two firms. We therefore posit:

Hypothesis (H2): *The likelihood of two firms selecting each other as partners for technology cooperation is increased to a greater extent by reciprocal market contacts than by nonreciprocal market contacts.*

3 | METHODS

3.1 | Sample and data

To test how multimarket contact and mutual forbearance between two prospective partners affect partner selection for technology cooperation, we use the global biopharmaceutical industry as the empirical context of our study. This industry is ideal for our study for two reasons. First, market definitions in this industry are very clear. In particular, 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 distinct therapeutic classes (e.g., cholesterol regulators, antiulcerants, antipsychotics, and so on) that are widely accepted and used by U.S. government authorities and biopharmaceutical companies. Since 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. For this reason, some prior research in the multimarket competition literature has also used the biopharmaceutical industry as an empirical context (e.g., Anand, Mesquita, & Vassolo, 2009). Second, this industry exhibits high rates of technology cooperation (Hagedoorn, 1993, 2002), and given the amount of research carried out in this industry, our focus on this empirical context is valuable for purposes of drawing comparisons across previous studies on alliances and partner selection.

In order to examine firms' activities in different markets, we 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. We draw on the IMS Health data focusing on the top 200 prescription drug sales companies in 2007, which represented more than 90% of total global prescription drug sales reported in the database in the year.[2] For data on technology cooperation, we use Thomson Reuters' Recap database. 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 (e.g., Adegbesan & Higgins, 2011; Lerner, Shane, & Tsai, 2003; Robinson & Stuart, 2007a, 2007b). In addition, we obtain patent data from the U.S. Patent and Trademark Office (USPTO). For the information on the drug development experiences of the sample firms, we also use the IMS R&D Focus data.

The unit of analysis of this study is the dyad between two biopharmaceutical firms in a particular year. Prior studies have often analyzed cooperation and partner selection between firms at the dyad level (e.g., Gimeno, 2004; Gulati, 1995b; Reuer & Lahiri, 2014; Rothaermel & Boeker, 2008). Since the biopharmaceutical industry is not characterized by alliance blocks, the usage of dyads as the unit

[2]Since the number of potential dyads exponentially increases with the number of sample firms, a limit to sample size is needed for practical reasons. Because the top 200 sales firms explain more than 90% of the global sales, competition and cooperation between them could be regarded as the main interfirm interactions in the industry.

of analysis is further justified (Rothaermel & Boeker, 2008). To construct our sample, we form all the possible 19,900 dyads ($={}_{200}C_2$) between the top 200 firms and then track them each year from 2008 to 2013 to check which dyads enter into new technology cooperation agreements. Given the dyad-year structure of the data, it is possible for two firms in a dyad to form multiple agreements in the same year. There were eight such cases in our sample, and we included all of them as separate dyad-year observations, giving us a final sample of 119,408 dyad-year observations. We also investigated whether the results would change if we sampled one of these at random, and we found no change in findings and interpretations.

3.2 | Variables and measurement

3.2.1 | Dependent variable

The dependent variable in this study intends to capture a formation of technology cooperation between two firms in a dyad. For this purpose, we develop a dichotomous variable *Technology Cooperation*$_{ijt}$ coded one if firms i and j in a dyad form a new technology cooperation agreement in year t, and zero otherwise.

Explanatory variables

The key independent variable in this study is multimarket contact between firm i and firm j in a dyad. We calculate *Multimarket Contact*$_{ij,\ t-1}$ as follows:

$$\text{Multimarket Contact}_{ij,t-1} = \frac{\text{The number of the shared markets between firms } i \text{ and } j \text{ in year } t-1}{\text{The number of firm } i\text{'s markets in year } t-1 + \text{the number of firm } j\text{'s markets in year } t-1}$$

if the numerator is greater than 1.

This variable takes the value of zero not only when firm i and firm j in a dyad have no market contact, but also when they have just one market contact because at least two common product markets are needed for two firms to engage in mutual forbearance. This measure has been widely used in the multimarket competition literature due to its parsimony (e.g., Baum & Korn, 1996; Fuentelsaz & Gómez, 2006).

To test the contingent effect of reciprocity of market contacts, we distinguish reciprocal and nonreciprocal contacts in a similar way to Gimeno (1999). First, in the shared markets between firm i and firm j, we compare their market shares to calculate the number of markets where each firm has a larger market share than the other. Then, after we pick the markets where the firm with the smaller number has larger market shares, we pair them with the markets where the other firm (i.e., the firm with the larger number) has larger market shares. Since these paired markets generate reciprocity, they are counted as reciprocal while the remaining shared markets as nonreciprocal. For example, assume that firm i and firm j share 10 product markets and firm i (firm j) has larger market shares than firm j (firm i) in 3 (7) markets. To distinguish reciprocal and nonreciprocal contacts, we first focus on firm i because it occupies larger market shares between the two only in 3 markets while firm j in 7 markets (that is, the number of markets where firm i has a larger market share is smaller than that of firm j). The 3 markets where firm i has larger market shares than firm j generate reciprocity with any 3 markets out of the 7 markets where firm j has larger market shares than firm i. Therefore, among the 10 shared markets, the 6 markets are counted as reciprocal. The remaining 4 markets, by contrast, cannot generate reciprocity because firm j has larger market shares in all the 4 markets, and thus they are counted as nonreciprocal. Meanwhile, as another example, if firm i has larger market shares than firm j in all the 10 shared markets, the number of reciprocal contacts is zero while that of nonreciprocal contacts equals to 10. To be consistent with the structure of the multimarket contact variable, we develop *Reciprocal Contacts*$_{ij,\ t-1}$ and *Nonreciprocal Contacts*$_{ij,\ t-1}$ by dividing the counts of reciprocal and nonreciprocal market contacts by the sum of the each firm's number of markets.

Control variables

Following previous partner selection studies that have modeled the formation of collaboration agreements at the dyad level, we include various controls to account for other factors related to a technology cooperation agreement or partners' interactions more broadly. All the control variables included are measured in year $t-1$. The alliance literature has long argued that social networks in which alliance partners are embedded, and in particular prior ties, provide controls for opportunistic behaviors and thus facilitate interfirm collaborations (Gulati, 1995b). To construct *Prior Ties*, we counted the number of prior alliances between the two partners in the past ten years (Gulati, 1995a).

Firms that are larger or have superior resources tend to be more attractive partners. As proxies for resource endowments that a firm can bring to a partnership, we 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, firms may want to partner with similar firms. 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, we 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 technological resources, we 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 also important since 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 also can shape technology cooperation (Ahuja & Katila, 2001). Firms will have greater absorptive capacity when partnering with other organizations having similar knowledge (Cohen & Levinthal, 1990), so 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). Therefore, we also include in the model cross citation rate and common citation rate measured as follows:

$$\text{Patent cross citation rate}_{ij,t-1} = \left(\frac{\text{Citations to firm } i'\text{s patents in firm } j'\text{s patent}_{t-1}}{\text{Total citations in firm } j'\text{s patents}_{t-1}}\right) + \left(\frac{\text{Citations to firm } j'\text{s patents in firm } i'\text{s patent}_{t-1}}{\text{Total citations in firm } i'\text{s patents}_{t-1}}\right)$$

$$\text{Patent common citation rate}_{ij,t-1} = \left(\frac{\text{Citations to firm } i'\text{s patents to patents cited in firm } j'\text{s patent}_{t-1}}{\text{Total citations in firm } i'\text{s patents}_{t-1}}\right) + \left(\frac{\text{Citations to firm } j'\text{s patents to patents cited in firm } i'\text{s patent}_{t-1}}{\text{Total citations in firm } j'\text{s patents}_{t-1}}\right)$$

where citations are accumulated from year $t-7$ to year $t-2$.

In this study, it is critical to control for other drivers that have been suggested to affect the formation of partnerships between firms with market overlap. For instance, the effect of market overlap on partner selection might be attributed to market power considerations rather than reduced opportunism as our theory suggests. More specifically, firms may use R&D alliances as a communication channel to facilitate tacit collusion (Vonortas, 2000). To control for this effect, we include the increment of market power that two partners can jointly employ in the shared markets if they behave as one firm. That is, we 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, we calculate a new weighted average of normalized Herfindahl indexes in the shared markets. Finally, we include the difference between the two weighted averages to obtain the increment of market power that the two firms can obtain by collusion.

In addition, some prior research has linked market or niche overlap with the concept of resource complementarity. For example, Yu, Subramaniam, and Cannella (2013) have argued that rivals are likely to have complementary resources because they naturally hold complementary competitive positions (Porter, 1980). On the other hand, drawing on the population ecology literature positing that firms competing in the same organizational niche possess similar resources and capabilities (Hannan & Freeman, 1977), some prior research has interpreted niche overlap as the absence of resource complementarity and thus a factor hindering alliance formation (Chung et al., 2000; Gulati, 1995b; Rothaermel & Boeker, 2008). Therefore, inclusion of a more direct measure of resource complementarity in our models can help disentangle the effect of multimarket contact through resource complementarity from that through reduced opportunism we suggest. For this purpose, given our focus on technology cooperation, we measure resource complementarity based on firms' drug development experiences. Drawing on the IMS R&D Focus data, we count the number of second-level Anatomical Therapeutic Chemical Classification System codes where each sample firm has drug development experiences in the past 5 years before the year of the focal partnership. Then, we calculate the ratio of nonoverlapping codes for each dyad-year observation using the number of nonoverlapping codes over the sum of the each firm's number of codes (e.g., Chung et al., 2000; Gulati, 1995b; Rothaermel & Boeker, 2008).

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 arguments, 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, we include a dummy variable 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 also affect the likelihood of technology cooperation (Rothaermel & Boeker, 2008). We therefore account for these possibilities by using two dummy variables, *Private (bigger firm)* and *Private (smaller firm)*. The former (latter) takes one if the bigger (smaller) firm in a dyad is a private firm and zero otherwise. Last, year fixed effects are included in the model to control for macroeconomic or other factors influencing the propensity of technology cooperation in different years.

3.3 | Statistical methods

Given that the dependent variable, *Technology Cooperation*$_{ijt}$, is a binary variable, we use a probit model for testing our hypotheses. In addition, to avoid any potential effects of nonindependent observations we also use robust estimation of standard errors using the Huber-White sandwich estimator (White, 1980). In analyzing the effect of multimarket contact on technology cooperation, it is critical to address an endogeneity issue and, to be more specific, omitted variable bias. In particular, there can be unobserved heterogeneity that is correlated with both multimarket contact and partner selection for technology cooperation. For example, because two firms having multimarket contact are co-present in multiple end-product markets, they might have similar technological or product market competences as well as common interests in similar technological areas, which can also lead to technology cooperation between them. That is, although we 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 that these unobserved factors can produce potential endogeneity problems caused by omitted variable bias. This potential bias can also suggest an alternative explanation on our main results that two firms sharing many end-product markets tend to form technology cooperation not because of mutual forbearance and reduced risk of partner opportunism but because of the similar technological or product market competences as well as common interests in similar technological areas. To mitigate this endogeneity concern and address this alternative explanation, we use instrumental variable (IV) models that have been widely suggested and used as a solution to omitted variable bias (Wooldridge, 2002, p. 105). We use each partner's (i.e., firms *i*'s and *j*'s) exits from the *non-overlapping* markets as instruments. Since the validity of IV models depends on that of the instruments employed, these instruments are expected to meet the two requirements in our context: (a) the relevance condition that they affect the multimarket competition variable and (b) the exogeneity condition that they do not affect other unobservable factors, in particular, similarity in terms of technological or product market competences as well as technological areas of interest.

Our instrument variables meet these requirements well for several reasons. First, the concern about endogeneity mainly comes from the possibility that presence in the same markets might represent common technological or product market competences as well as common technological interests. However, exits from *nonoverlapping* markets do not affect the common presence itself. That is, when either or both of the two firms exit from the nonoverlapping markets, the similarities based on co-presence in multiple product markets do not change because the shared product markets between the two firms remain the same. By contrast, exits from nonoverlapping markets make mutual forbearance in the shared markets more important because they have more stakes in these markets after the exits. If illustrated using the formula of the multimarket contact variable, the numerator of the multimarket contact variable, which is the number of the *shared* markets between firms *i* and *j*, is not affected by exits from nonoverlapping markets. However, the instrument variables reduce the value of the denominator (i.e., the sum of firms *i*'s and *j*'s number of markets), as a result increasing the value of *Multimarket Contact*$_{ij}$. Second, similarity in terms of technological or product market competences between the two partners at the overall firm level (as well as in the shared markets) also tends to remain the same at least for a while after market exits. Even though a firm quits selling a product in a market segment, the technology and knowledge related to the product does not disappear instantly and entirely. Third, firms *i*'s and *j*'s decisions to exit from nonoverlapping markets tend to be made independently of each other. In other words, the decisions depend on their own firm-level factors rather than on dyad-level factors. Therefore, the market exit decisions might be exogenous to dyad-level unobserved factors such as similar technological or product market competences. In order to calculate each partner's exits from nonoverlapping markets in year t, the information on each partner's market presence in year $t - 1$ is needed, and therefore we lose one-year observations in the first year of our data, which reduces the sample size from 119,408 to 99,506 when the multimarket contact variable is instrumented.

In addition to the instrumental variable (IV) models, we employ a couple of robustness checks. First, we use random-effects specification (i.e., random-effects probit models) to control for unobserved variables, following prior studies on dyad-level alliance formation (Gimeno, 2004; Reuer & Lahiri, 2014).[3] Second, we also consider the implications of the rareness of any two firms out of sample partnering with one another. Among the 119,408 dyads formed between the top 200 global firms that we use to test our hypotheses, only 129 dyads (about 0.11%) entered into a technology cooperation agreement during the observation window (i.e., 2008–2013). Given that our sample firms were responsible for about 92% of total global prescription drug sales reported in the IMS database in 2007, they could be regarded as major players with resources enough to attract collaboration partners and thus at risk for technology cooperation rather than as dyads where technology cooperation will never arise. However, the usual maximum likelihood estimation, which is used in a standard probit model, can be biased when the number of rare events is small (Cosslett, 1981; Imbens, 1992; Lancaster & Imbens, 1996). Therefore, we use a penalized maximum likelihood estimation method (i.e., Firth's logit model), which is a widely accepted, general approach to reducing small-sample bias (Firth, 1993).[4]

4 | RESULTS

Table 1 presents descriptive statistics and a correlation matrix for the variables used in the analyses. Though there are many significant pairwise correlations, our models do not present multicollinearity concerns. Individual variance inflation factors (VIFs) for the variables are all below the recommended cutoff levels of 10 and the mean value is 1.84 (Neter, Kutner, Nachtsheim, & Wasseman, 1996).

Table 2 reports the main results of this study based on standard and IV probit models examining the effects of multimarket contact between two prospective partners on the likelihood of selecting each other as partners for technology cooperation. The probit estimation in Model 1 contains the control variables only. Some estimation results for several control variables deserve mention. The coefficient of *Prior Ties* is positive ($b = 0.058$ and $p = .000$) as prior research has suggested (Gulati, 1995b), indicating that firms with previous collaboration experiences tend to collaborate repetitively. While the coefficient of *Size (Max)* is positive ($b = 0.110$ and $p = 0.000$), that of *Ratio of Size* (small firm to large firm) is positive but insignificant at conventional levels ($b = 0.022$ and $p = 0.559$), meaning that although larger firms are preferred as partners for technology cooperation, no

[3]Fixed-effects models are not employed to avoid losing the dyads that do not enter into a technology cooperation agreement during the observation window (i.e., 2008–2013).

[4]One thing to note is that what causes rare events bias is not low percentage of ones but the small number of ones. That is, even with an extremely small percentage of ones, rare events bias is not an issue if the total number of observations is very large and thus the number of ones is large enough. Compared to some simulation results that the rare events bias in slope was ignorable with dozens of ones (e.g., King & Zeng, 2001; Leitgöb, 2013), our estimates might not suffer from such bias because we have 129 ones in our sample. Nevertheless, we employ Firth's logit models for robustness checks.

TABLE 1 Descriptive statistics and correlation matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
(1) Technology cooperation	1																			
(2) Multimarket contact	**0.019**	1																		
(3) Reciprocal contacts	**0.020**	**0.877**	1																	
(4) Nonreciprocal contacts	**0.006**	**0.627**	**0.180**	1																
(5) Prior ties	**0.076**	**0.052**	**0.054**	**0.019**	1															
(6) Size (Max)	**0.042**	**0.176**	**0.029**	**0.310**	**0.176**	1														
(7) Ratio of size	**−0.007**	**−0.036**	**0.099**	**−0.229**	**−0.037**	**−0.479**	1													
(8) Patent count (Max)	**0.024**	**0.071**	0.003	**0.139**	**0.110**	**0.542**	**−0.271**	1												
(9) Ratio of patent count	−0.002	**0.028**	**0.058**	**−0.035**	**−0.026**	**−0.210**	**0.201**	**−0.245**	1											
(10) Class count (Max)	**0.022**	**0.461**	**0.317**	**0.416**	**0.089**	**0.466**	**−0.253**	**0.229**	**−0.055**	1										
(11) Ratio of class count	**0.006**	**0.652**	**0.622**	**0.340**	−0.004	**−0.034**	**0.071**	**−0.014**	**0.029**	**−0.165**	1									
(12) Common citation rate	**0.021**	**0.025**	**0.011**	**0.033**	**0.037**	**0.081**	**−0.025**	**0.094**	**−0.015**	**0.043**	0.000	1								
(13) Cross-citation rate	**0.019**	0.004	−0.001	**0.008**	**0.024**	**0.029**	**−0.008**	**0.036**	−0.002	**0.017**	−0.005	**0.184**	1							
(14) Increment of H-index	**0.064**	**0.126**	**0.111**	**0.080**	**0.182**	**0.305**	0.005	**0.190**	**−0.009**	**0.167**	**0.042**	**0.071**	**0.023**	1						
(15) Resource complementarity	**0.017**	**0.040**	**0.029**	**0.034**	**0.050**	**0.150**	**−0.076**	**0.107**	**−0.087**	**0.130**	−0.005	**0.024**	0.003	**0.057**	1					
(16) International deal	**−0.018**	**0.056**	**0.051**	**0.028**	**−0.030**	**−0.010**	0.003	**−0.024**	**0.023**	**0.094**	−0.002	**−0.014**	−0.001	**−0.042**	**−0.034**	1				
(17) Private (bigger firm)	**−0.013**	**0.015**	**0.045**	**−0.043**	**−0.058**	**−0.269**	**0.250**	**−0.222**	**0.214**	**−0.108**	**0.044**	**−0.033**	**−0.012**	**−0.073**	**−0.057**	**0.055**	1			
(18) private (smaller firm)	**−0.021**	**0.015**	**−0.007**	**0.041**	**−0.062**	**−0.062**	**−0.050**	**−0.071**	**0.043**	**−0.040**	**0.034**	**−0.033**	−0.003	**−0.071**	**−0.016**	**0.046**	**0.023**	1		
(19) Exit from nonoverlapping markets (bigger firm)	**0.015**	**0.245**	**0.218**	**0.144**	**0.068**	**0.235**	**−0.215**	**0.211**	**−0.040**	**0.283**	**0.069**	**0.020**	0.006	**0.062**	**0.034**	**0.031**	−0.003	**−0.026**	1	
(20) Exit from nonoverlapping markets (smaller firm)	**0.011**	**0.336**	**0.290**	**0.217**	**0.037**	**0.072**	**0.023**	**0.046**	−0.004	**0.201**	**0.214**	**0.012**	−0.001	**0.080**	−0.000	**0.063**	**−0.032**	−0.006	**0.029**	1
Mean	0.001	0.141	0.094	0.048	0.020	0.006	0.373	46.11	0.310	117.17	0.433	0.001	0	0.000	0.416	0.911	0.31	0.47	2.744	1.952
S.D.	0.033	0.106	0.082	0.051	0.169	0.011	0.291	104.52	0.423	60.11	0.280	0.009	0.002	0.000	0.459	0.285	0.462	0.499	2.434	2.136
Min	0	0.000	0.000	0.000	0	0	0	0	0	1	0.004	0	0	0.000	0	0	0	0	0	0
Max	1	0.471	0.434	0.411	6	0.060	1	913	1	279	1	1	0.408	0.012	1	1	1	1	15	15

Note: $N = 119{,}408$ except (19) Exit from Nonoverlapping Markets (bigger firm) and (20) Exit from Nonoverlapping Markets (smaller firm). For the two variables, $N = 99{,}506$ because they have data for 2008–2013 while all the other variables for 2007–2013. Bolded pairwise correlations have p-values less than .05.

preference for partners of similar size is evident (cf., Gimeno, 2004). Also, consistent with prior research (e.g., Rothaermel & Boeker, 2008), positive coefficients are estimated for both *common citation rate* (b = 0.015 and p = .034) and *cross-citation rate* (b = 0.014 and p = .010), which supports the idea that similarity in knowledge bases promotes partnerships. The coefficient of *Increment of H-index* is also positive (b = 0.021 and p = .007), suggesting that two firms who can achieve a greater increment of market power by coordinating as one firm are more likely to partner each other, which is consistent with the prior work based on a collusive motivation of alliance formation (e.g., Vonortas, 2000). *Resource Complementarity* also has a positive coefficient (b = 0.125 and p = .000), which means that two firms are more likely to partner each other for technology cooperation as their drug development experiences are less overlapping. This result supports the previous research that has argued that resource complementarity facilitates the formation of partnerships (Chung et al., 2000; Gulati, 1995b; Rothaermel & Boeker, 2008). A negative coefficient is estimated for *International Deal* (b = −0.320 and p = .000), 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 (bigger firm)* and *Private (smaller firm)* both are negative (b = −0.133 and p = .122; b = −0.390 and p = .000), indicating that firms tend to avoid partnering with private firms smaller than them.

Model 2 in Table 2 augments the first model with *Multimarket Contact* to test H1. The coefficient of *Multimarket Contact* is positive (b = 0.168 and p = 0.003), implying that as two potential partners have a greater level of multimarket contact, they are more likely to select each other as partners for technology cooperation. To estimate economic significance, we calculated the marginal effects of each observation and averaged the responses (Hoetker, 2007). As the value of *Multimarket Contact* moves from the mean to one and two standard deviations above the mean, the predicted value of *Technology Cooperation* increases by 65.2% and 168.1%, respectively.

In Models 3 and 4, H1 is re-tested by an IV model to address the endogeneity concern that an omitted variable such as similarity in technological or product market competences is potentially correlated with both multimarket contact and partner selection. The IV models still support H1 because in Model 4 the coefficient of *Multimarket Contact* is positive (b = 0.820 and p = .028). Regarding the validity of the instruments, in the first-stage model (Model 3) the coefficient of *Exits from Non-overlapping Markets* is positive and significant for both bigger and smaller firms (b = 0.021 and p = .000; b = 0.030 and p = .000, respectively), which preliminarily supports the relevance of the instrument variables. As a formal test, we compare the first-stage F-statistic with the critical values suggested by Stock and Yogo (2004), tables 2–4), which is known as the most robust and conservative test (Bascle, 2008). The value of the first-stage F-statistic is 1,199.92, but the critical values for one endogenous regressor and two instruments are all below 20 though they vary depending on the different definitions of weak instruments Stock and Yogo (2004) suggest. Therefore, the relevance of our instruments is strongly supported. For instrument exogeneity, the Amemiya–Lee–Newey (ALN) test supports the exogeneity of the instrument variables (i.e., the ALN minimum distance chi-square statistic is .772 and the p-value is .3797).

Model 5 tests H2 that the likelihood of two firms selecting each other as partners for technology cooperation is increased more by reciprocal market contacts than by nonreciprocal market contacts. The coefficients for *Reciprocal Contacts* and *Nonreciprocal Contacts* are both positive (b = 0.191, b = 0.014). However, while the former is strongly significant (p = .000), the latter is not (p = .710). In addition, the coefficient of *Reciprocal Contacts* is significantly larger than that of *Nonreciprocal Contacts*, as the Wald test rejects the equality of the two coefficients (Chi-square (1) = 19.14 and p = .000), supporting H2. When the value for *Reciprocal Contacts* increases from the mean to one

TABLE 2 Determinants of technology cooperation

	Model				
	(1)	(2)	(3)	(4)	(5)
Model specification	**Probit**	**Probit**	**IV Probit**	**IV Probit**	**Probit**
Dependent variable	**Tech. cooperation**	**Tech. cooperation**	**Multimarket contact (first-stage)**	**Tech. cooperation (second-stage)**	**Tech. cooperation**
Hypothesis	**H1**	**H1**	**H1**	**H1**	**H2**
Multimarket contact		0.168		0.820	
		(0.057)		(0.373)	
Reciprocal contacts					0.191
					(0.047)
Nonreciprocal contacts					0.014
					(0.037)
Prior ties	0.058	0.057	0.012	0.050	0.053
	(0.008)	(0.008)	(0.002)	(0.010)	(0.008)
Size (max)	0.110	0.119	−0.059	0.132	0.132
	(0.028)	(0.029)	(0.002)	(0.039)	(0.029)
Ratio of size	0.022	0.020	0.031	−0.031	0.000
	(0.038)	(0.038)	(0.002)	(0.042)	(0.040)
Patent count (max)	0.013	0.015	−0.036	0.029	0.011
	(0.029)	(0.029)	(0.003)	(0.041)	(0.029)
Ratio of patent count	0.033	0.032	0.013	0.017	0.028
	(0.030)	(0.030)	(0.002)	(0.038)	(0.030)
Class count (max)	0.057	−0.042	0.599	−0.458	−0.035
	(0.030)	(0.047)	(0.002)	(0.233)	(0.046)
Ratio of class count	0.068	−0.075	0.730	−0.576	−0.096
	(0.030)	(0.052)	(0.002)	(0.284)	(0.054)
Common citation rate	0.015	0.015	0.005	0.013	0.015
	(0.007)	(0.007)	(0.002)	(0.009)	(0.007)
Cross-citation rate	0.014	0.014	−0.003	0.021	0.014
	(0.005)	(0.005)	(0.002)	(0.008)	(0.005)
Increment of H-index	0.021	0.020	0.011	0.023	0.018
	(0.008)	(0.008)	(0.002)	(0.011)	(0.008)
Resource complementarity	0.125	0.128	−0.017	0.146	0.125
	(0.030)	(0.031)	(0.002)	(0.037)	(0.031)
International deal	−0.320	−0.322	−0.027	−0.348	−0.322
	(0.073)	(0.073)	(0.005)	(0.078)	(0.073)
Private (bigger firm)	−0.133	−0.142	0.040	−0.193	−0.139

TABLE 2 (Continued)

	Model				
	(1)	(2)	(3)	(4)	(5)
Model specification	**Probit**	**Probit**	**IV Probit**	**IV Probit**	**Probit**
Dependent variable	**Tech. cooperation**	**Tech. cooperation**	**Multimarket contact (first-stage)**	**Tech. cooperation (second-stage)**	**Tech. cooperation**
Hypothesis	**H1**	**H1**	**H1**	**H1**	**H2**
	(0.086)	(0.086)	(0.004)	(0.096)	(0.086)
Private (smaller firm)	−0.390	−0.395	0.024	−0.445	−0.382
	(0.074)	(0.075)	(0.003)	(0.084)	(0.074)
Exit from nonoverlapping markets (bigger firm)			0.021 (0.001)		
Exit from nonoverlapping markets (smaller firm)			0.030 (0.001)		
Constant	−2.851	−2.853	−0.122	−2.803	−2.869
	(0.076)	(0.077)	(0.007)	(0.106)	(0.078)
Year fixed effects	Included	Included	Included	Included	Included
Wald chi-square (d.f.)	423.11 (18)	423.36 (19)		289.10 (19)	426.27 (20)
F-statistic: Joint significance of IVs coefficients			1,199.92		
Wald test of exogeneity: chi-square (p-value)			3.20 (0.0737)		
Amemyia–Lee–Newey test: Chi-square (p-value)			0.772 (0.3797)		
(pseudo) R-square	0.1454	0.1486			0.1531
Log pseudolikelihood	−869.03	−865.76			−861.22
Observations	119,408	119,408	99,506		119,408

Note: Robust standard errors in parentheses but Models 3 and 4. Standard error specification is used in Models 3 and 4 because Stock and Yogo's (2004) test assumes independently and identically distributed (i.i.d) errors. Though not reported here, however, the results from IV probit models with robust error specification are also consistent with those reported here. All the continuous variables above are standardized for better presentation. Two-tailed tests.

standard deviation above the mean, the likelihood of a focal dyad forming a technology cooperation agreement increases by 76.4%. Meanwhile, the same change in *Nonreciprocal Contacts* is estimated to increase the same likelihood by 4.1%.

Our result that the likelihood of technology cooperation between two firms is increased more by reciprocal market contacts than by nonreciprocal market contacts also helps rule out the alternative

TABLE 3 Robustness analyses

	(1)	(2)	(3)	(4)
Model specification	**Random-effects probit**	**Random-effects probit**	**Firth logit**	**Firth logit**
Dependent variable	**Tech. Cooperation**	**Tech. Cooperation**	**Tech. Cooperation**	**Tech. Cooperation**
Hypothesis	**H1**	**H2**	**H1**	**H2**
Multimarket contact	0.155		0.518	
	(0.068)		(0.213)	
Reciprocal contacts		0.194		0.569
		(0.057)		(0.179)
Nonreciprocal contacts		−0.010		0.077
		(0.045)		(0.125)
Prior ties	0.061	0.056	0.124	0.112
	(0.011)	(0.011)	(0.017)	(0.018)
Size (max)	0.131	0.147	0.373	0.404
	(0.036)	(0.036)	(0.086)	(0.087)
Ratio of size	0.036	0.014	0.062	0.004
	(0.047)	(0.050)	(0.116)	(0.119)
Patent count (max)	0.029	0.024	0.033	0.024
	(0.033)	(0.032)	(0.079)	(0.079)
Ratio of patent count	0.040	0.036	0.126	0.114
	(0.037)	(0.037)	(0.109)	(0.109)
Class count (max)	−0.019	−0.011	−0.137	−0.123
	(0.056)	(0.055)	(0.161)	(0.159)
Ratio of class count	−0.065	−0.090	−0.216	−0.290
	(0.063)	(0.065)	(0.204)	(0.211)
Common citation rate	0.018	0.019	0.037	0.038
	(0.008)	(0.008)	(0.013)	(0.013)
Cross-citation rate	0.014	0.014	0.041	0.041
	(0.007)	(0.008)	(0.009)	(0.009)
Increment of H-index	0.025	0.023	0.037	0.032
	(0.010)	(0.010)	(0.021)	(0.022)
Resource complementarity	0.134	0.130	0.407	0.399
	(0.038)	(0.038)	(0.106)	(0.106)
International deal	−0.397	−0.399	−1.017	−1.000
	(0.090)	(0.090)	(0.212)	(0.211)
Private (bigger firm)	−0.201	−0.196	−0.500	−0.481
	(0.110)	(0.111)	(0.286)	(0.286)

TABLE 3 (Continued)

Model specification	(1) Random-effects probit	(2) Random-effects probit	(3) Firth logit	(4) Firth logit
Dependent variable	**Tech. Cooperation**	**Tech. Cooperation**	**Tech. Cooperation**	**Tech. Cooperation**
Hypothesis	**H1**	**H2**	**H1**	**H2**
Private (smaller firm)	−0.425	−0.410	−1.305	−1.275
	(0.093)	(0.093)	(0.251)	(0.252)
Constant	−3.322	−3.345	−6.056	−6.106
	(0.171)	(0.172)	(0.250)	(0.252)
Year fixed effects	Included	Included	Included	Included
Rho (s.e.)	0.257 (0.063)	0.259 (0.629)		
Wald chi-square (d.f.)	291.22 (19)	284.92 (20)	416.24 (19)	424.54 (20)
Observations	119,400	119,400	119,408	119,408

Note: Robust standard errors in parentheses in all the models. All the continuous variables above are standardized for better presentation. Two-tailed tests. 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 119,408 to 119,400.

explanation that similarity in terms of technological or product market competences drives the main effect. The multimarket competition literature has long argued and corroborated that reciprocity reinforces mutual forbearance (e.g., Baum & Korn, 1996; Bernheim & Whinston, 1990; Fuentelsaz & Gómez, 2006; Gimeno, 1999; Spagnolo, 1999). Meanwhile, reciprocity weakens similarity in terms of technological or product market competences because multimarket contacts are reciprocal when firm i is weak (i.e., has small market share) in the markets where firm j is strong (i.e., has large market share) and vice versa. The fact that the effect of reciprocal contacts is greater than that of nonreciprocal contacts in our results is more consistent with the mutual forbearance argument rather than the resource similarity perspective.

4.1 | Supplemental analyses

Table 3 shows the results from our robustness analyses. First, in order to address unobserved heterogeneity, random-effects probit models (Models 1 and 2) are employed. Models 1 and 2 support H1 and H2, respectively, although random-effects are significant in both models. In particular, the coefficient of *Multimarket Contact* is positive ($b = 0.155$ and $p = .023$) in Model 1 and *Reciprocal Contacts* has a significantly greater coefficient ($b = 0.194$ and $p = .001$) than *Nonreciprocal Contacts* ($b = -0.010$ and $p = .826$) (chi-square (1) = 16.26 and $p = .000$).

In Models 3 and 4, logit models using penalized likelihood estimation (so-called Firth logit models) are estimated to re-test H1 and H2 while addressing potential rare events bias (Firth, 1993). As shown in Model 3, the positive effect of multimarket contact (i.e., H1) is still supported ($b = 0.518$ and $p = .015$). Model 4 also still supports H2: the Wald test shows that the coefficient of *Reciprocal Contacts* ($b = 0.569$ and $p = .001$) is significantly larger than that of *Nonreciprocal Contacts* ($b = 0.077$ and $p = .536$; Chi-square (1) = 12.19 and $p = .0005$). As an additional robustness check, we also employed the rare events logit models suggested by King and Zeng (2001) and obtained qualitatively similar results.

5 | DISCUSSION

5.1 | Contributions and implications

This article makes several theoretical contributions to the alliance literature, in particular to the stream of research on partner selection, and this article also advances the multimarket competition literature. To begin with, our theory and results suggest a novel view of how market overlap between two prospective partners affects cooperation hazards and, as a result, partner selection for technology cooperation. Indeed, prior research has already paid attention to the effects of rivalry or market overlap between potential partners on their formation of an alliance. However, unlike previous work that has emphasized the pursuit for resource complementarity or market power as the underlying mechanism (Chung et al., 2000; Gulati, 1995b; Rothaermel & Boeker, 2008; Yu et al., 2013), we focus on partners' incentives for opportunism given the competitive tensions inherent in cooperation with rivals. Therefore, this article complements the stream of research on partner selection and alliance formation by illuminating that market overlap or multimarket contact between prospective partners might influence the formation of their collaborations by affecting the partners' incentives for opportunism. We therefore offer a new mechanism behind the influence of market overlap and rivalry on technology collaboration.

In addition to the stream of research on partner selection, we also contribute to the broader alliance literature on alliances between competing firms. The literature has mainly argued that competitive relationships in end-product markets aggravate hazards of cooperation by increasing the private benefits that partners can reap from engaging in opportunistic behaviors (Oxley & Sampson, 2004; Park & Russo, 1996). However, we extend this conventional view that focuses on the immediate pay-off from opportunistic behavior by suggesting that it is also valuable to consider the possible responses by the counterpart in the overlapping product markets outside the partnership and thereby attend to the expected subsequent costs of acting opportunistically. That is, we suggest that the effects of competition between partners outside an alliance on behavior within an alliance is considerably more complicated than contemplated in the current alliance literature.

In addition, we contribute to the previous research on market overlap and cooperation risk by providing a finer-grained conceptualization and measurement of market overlap. Existing alliance research has typically conceptualized and operationalized market overlap in broad terms such as firms' co-presence in the same industry using industrial codes such as those provided by the North American Industrial Classification System (NAICS) or similar systems (e.g., Lin et al., 2009; Oxley & Sampson, 2004; Park & Russo, 1996; Wang & Zajac, 2007). Therefore, the results from prior work using the industry-level market definition imply comparisons between cross-industry and within-industry alliances. In this case, even if some research indicates an adverse effect of market overlap on partnerships, it actually does not necessarily contradict our findings. The former results just imply that firms prefer cross-industry alliances to within-industry ones and do not explain how market overlap at the product market level in the same industry affects partner selection. Drawing on the multimarket competition literature, which suggests that the degree of mutual forbearance between two firms can vary depending on their breadth of market overlap at the product market level, we conceptualize and operationalize market overlap at the product market level in the same industry. Therefore, our results build upon and extends the prior literature on cooperation and market overlap by showing how product market overlap between rivals in the same industry affects their interfirm collaborations.

Finally, our theory and results contribute to the multimarket competition literature by extending prior research on multimarket contact and R&D activities. Previous research on multimarket competition has tended to focus on linking mutual forbearance generated by product market overlap with competitive actions taking place in product markets, for example, market entry and exit (Baum & Korn, 1996; Fuentelsaz & Gómez, 2006) and pricing decisions (Gimeno & Woo, 1996; Hannan & Prager, 2004). However, in high-technology industries where R&D is a key basis for competition and firms often collaborate with rivals for R&D activities, mutual forbearance generated by product market overlap might also affect competitive and cooperative actions in their R&D efforts. Indeed, recently there has been some research in the multimarket competition literature that has broadened the scope of multimarket competition research to R&D domains. For instance, Markman, Gianiodis, and Buchholtz (2009) distinguished multimarket contact in factor markets (e.g., R&D markets in high-technology industries) from that in end-product markets and investigated how these two different kinds of contact can collectively generate mutual forbearance. Anand et al. (2009) have also examined the effects of multi-point contact in R&D domains on entry into and exit from rivals' R&D areas. While these prior studies extended the scope of multimarket competition research to R&D domains beyond product markets, research has not yet investigated the possibility that the two different domains affect each other. Therefore, this article builds upon and extends the emerging literature on multi-point competition in both product and R&D domains by suggesting that multimarket competition in product markets can also cause mutual forbearance from competitive actions in R&D collaborations. We believe that the linkage between multimarket competition in product markets and R&D activities deserves further research, and we hope our article will encourage such research in the future.

5.2 | Limitations and future research directions

This study also has some specific limitations that extensions to this research might address. It is important to note that due to data limitations this article considers the product market dimension of competition, and the results might be weakened if the firms are also not overlapping in their geographic market domains. The multimarket competition literature defines markets in a way to ensure that firms defined as present in the same market actually compete with each other or, in other words, produce goods or services that serve similar functions and compete for similar customers (Abell, 1980; Jayachandran et al., 1999). Thus, if two firms competing in the same end-product markets serve completely distinct geographical markets, they might not consider each other as direct, meaningful competitors and cannot effectively attack and retaliate against each other, which means they have no reason to enact mutual forbearance. Thus, it would be ideal if the matrix of product and geographical markets is defined and multimarket contact is measured at the product-geographical market level. However, since revenue breakdowns were only available by product markets but not by geographical markets in our data, we could not define markets at the product-geographical market level. Thus, in order to mitigate this concern, we took as our sample the top 200 global firms in biopharmaceuticals that were responsible for about 92% of total global prescription drug sales reported in the IMS database in 2007. Given the high share taken by our sample firms in the global market, they are likely to be overlapping and meaningful competitors to each other in major geographical markets. Our interviews with industry experts also confirmed that these firms typically sell their products in major global markets. Nevertheless, it would be valuable to investigate heterogeneity in firms' geographic markets to consider this potential boundary condition for mutual forbearance in promoting technology cooperation.

Given that in the current study we only consider partner selection, it would be natural and interesting extension of this study to investigate how the mutual forbearance from opportunism between prospective partners affects other collaboration-related decisions and outcomes. There are many opportunities to apply the implications from the multimarket competition literature to different streams of research on alliances. For instance, future studies might examine how mutual forbearance affects alliance design as well as the outcomes of 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 by multimarket competition. Also, inasmuch as mutual forbearance has the potential to stabilize relationships, it would be valuable to examine whether market overlap and reciprocal contacts in particular might be related to the on-going existence of interfirm ties and their consequences (e.g., Mitchell & Singh, 1996; Singh & Mitchell, 1996). Moreover, 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 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 together these two important literatures in strategic management (Hoffmann, Lavie, Reuer, & Shipilov, 2018).

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