Atacking your partners: Strategic alliances and competition between partners in product markets

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Research Summary: This study contributes to the literature on strategic alliances by examining the impact of collaboration on competition between partners in product markets. We integrate the alliance learning and social network perspectives to examine how different combinations of exploratory and exploitative alliances between a firm and its partner influence the firm’s competition against its partner in product markets. Using a longitudinal dataset collected in the U.S. pharmaceutical industry (1984–2003), we find an inverted U-shaped relationship between relative exploration (i.e., the proportion of exploratory alliances in the collaborative portfolio between a firm and its partner) and the firm’s competition against its partner. This relationship is negatively moderated by firms’ relational and structural embeddedness, but positively moderated by their positional embeddedness.

Managerial Summary: This study examines how different combinations of exploratory and exploitative alliances between two firms affect their competition in the product market. Using a 20-year dataset collected in the U.S. pharmaceutical industry, we find that the proportion of exploratory alliances (i.e., joint development of critical innovations) in the alliance portfolio between a firm and its partner increases the firm’s competition against its partner, up to a tipping point at which such competition starts to decline. Given a certain combination of the two types of alliances, such competition is stronger if the firm has more alternative allies than its partner but weaker if the firm and its partner have previously collaborated or share common allies in their networks.

KEYWORDS
alliance, alliance learning, network embeddedness, partner competition, product market
INTRODUCTION

Research on strategic alliances has revealed that prior collaboration often leads to further collaboration between firms (Barden & Mitchell, 2007; Gulati, 1995; Li & Rowley, 2002; Podolny, 1994). However, ample anecdotal evidence indicates that alliances are often followed by aggressive competition between the same firms in product markets. For example, pharmaceutical firm Merck allied with Novartis, Pfizer, Bristol-Myers, and Depomed in the 1990s yet later competed with these firms in product markets. Similar instances appear in the automobile (Hamel, Doz, & Prahalad, 1989), telecommunications (Hille & Taylor, 2011; Ritman, 2006), and other industries. Despite the abundant evidence, however, researchers have not paid adequate attention to the influence of alliances on competition between partners in product markets.

A thorough study of this “collaboration–competition” relationship between partners is of great theoretical importance, contributing to the development of a more comprehensive model of inter-firm behavior rendered by strategic alliances (Kogut, 1989). Prior studies on alliance learning have provided some important insights into the tension between collaboration and competition (Hamel et al., 1989; Katila, Rosenberger, & Eisenhardt, 2008; Khanna, Gulati, & Nohria, 1998). For example, researchers maintain that competition within alliances stems from the misalignment of interests between allies (Gulati & Singh, 1998; Hamel et al., 1989) and have identified important factors that influence allies’ competitive learning within alliances, such as asymmetric learning capabilities (Hamel, 1991; Khanna et al., 1998; Yang, Zheng, & Zaheer, 2015), the ratio between private and common interests (Khanna et al., 1998), and knowledge similarities between allies (Dussauge, Garrette, & Mitchell, 2000). However, three important issues in this sphere of research remain unaddressed.

First, while researchers have examined aggressive learning between allies, whereby allies compete to increase private rather than common benefits (Hamel, 1991; Khanna et al., 1998; Lavie, 2007), prior studies focused on the hazards of misappropriation within alliances; the effect of alliances on competition between partners in the realm of product markets remains poorly understood.

Second, prior studies provide insights into competitive learning between partners by focusing on research-based alliances while overlooking other types of collaboration (e.g., Yang et al., 2015). It is assumed that research-based alliances entail intensive knowledge exchange and therefore create many opportunities for competitive learning between allies, but firms often simultaneously engage in multiple types of alliances (e.g., research-based, marketing, manufacturing) that differ significantly in the incentives they generate for allies to compete with one another (Hamel, 1991; Khanna et al., 1998; Mowery, Oxley, & Silverman, 1996). The extent to which a firm competes with its partner is arguably determined by the composition of all types of alliances binding them, which collectively define the overall orientation of their interactions as well as the costs and benefits of competitive moves against each other (Chen & Miller, 2015). Few studies have yet examined how the composition of the collaborative portfolio between firms affects their competition with one another.

Third, many prior studies have examined the tension between cooperation and competition by focusing on characteristics of the allying firms per se, such as their relative learning capabilities (Yang et al., 2015) and knowledge similarities (Dussauge et al., 2000), while largely overlooking the impact of the broad inter-firm alliance networks within which competitive learning between partners is embedded (Uzzi, 1996). Only a few studies have analyzed the collaboration–competition phenomenon within alliances from the network perspective. For example, Lavie (2007) provides insights into how a firm’s appropriation capacity within alliances is affected by factors such as the availability of alternative alliances and multilateral competition among its partners. Polidoro, Ahuja, and Mitchell (2011) study the impact of network embeddedness on partnering firms’ competitive
incentives and, in turn, on joint venture dissolution.¹ Yet the focus of these studies remains centered either on allies’ market performance or on the survival of joint ventures; the impact of partners’ network embeddedness on the interplay between alliances and competition in the product market has rarely been studied.

Our study addresses these limitations by integrating the alliance learning and network perspectives in order to study the mechanisms through which strategic alliances influence allies’ competition in the product market. We ask, how does the composition of the collaborative portfolio between a firm and its partner affect the firm’s competitive aggressiveness against its partner in the product market, and how does network embeddedness influence this relationship?

We capture the composition of two firms’ collaborative portfolio using the concept of relative exploration, defined as the proportion of exploratory collaborations among all collaborations between a firm and its partner (Uotila, Maula, Keil, & Zahra, 2009; Yang, Lin, & Peng, 2011).² As conceptualized in the alliance learning literature, exploratory collaboration is oriented toward developing critical innovations, which require intensive interactions, tacit knowledge sharing, and relational capital building for long-term benefits (Lavie & Rosenkopf, 2006), whereas exploitative collaboration is oriented toward transacting existing resources for short-term economic benefits (Mowery et al., 1996).

We maintain that increases in the proportion of exploratory alliances within the collaborative portfolio between a firm and its partner facilitate identification of the partner’s vulnerabilities and appropriation of its capacities, increasing the firm’s incentive to launch competitive action against its partner (Yu, Subramaniam, & Cannella, 2009). However, there is a cost/benefit trade-off involved in launching competitive attacks. As the proportion of exploratory alliances increases, the escalating damage to long-term benefits and the risk of “tit-for-tat” retaliatory attacks from the partner may reach a threshold at which the expected cost becomes higher than the expected benefit of launching further competitive attacks. We accordingly propose that relative exploration demonstrates an inverted U-shaped relationship with a firm’s product-market competition with its partner.

We further argue that the cost/benefit trade-off of launching competitive attacks is bounded by firms’ network environments. Firms’ relational embeddedness (i.e., repeated alliance ties), positional embeddedness (i.e., relative network centrality), and structural embeddedness (i.e., common partners) within their alliance networks create important boundary conditions that moderate the effect of relative exploration on their competition in different directions. We test our hypotheses using a longitudinal dataset that integrates data on firms’ alliances and product competition in the U.S. pharmaceutical industry over a period of two decades (1984–2003).

2 | THEORY AND HYPOTHESES

Although strategic alliances are inter-firm partnerships formed to jointly develop, manufacture, and distribute technologies and products (Gulati, 1998), partnering firms often simultaneously collaborate and compete within their alliances (Hamel, 1991). For example, Hamel (1991) observe that firms have a propensity to maximize their own benefits within alliances, even at the cost of common interests. Other researchers suggest that firms race to acquire valuable intellectual properties and

¹Other studies have investigated the impact of embedded relationships on competition in different contexts, such as clique-level rivalries between alliances (Gimeno, 2004) and industry-level competition not specified for a particular target (Andrevski, Brass, & Ferrier, 2016; Gnyawali & Madhavan, 2001).

²Alternatively, we could use the proportion of exploitative alliances among all alliances between a firm and its partner, or relative exploitation. The mechanisms will be the same, except that the predicted relationship will flip.
organization-specific knowledge from each other so that faster learners can reap more private benefits (Khanna et al., 1998).

While competitive learning is an important phenomenon in various types of collaborations, this study focuses on horizontal alliances established between firms operating within the same industry. Firms in horizontal alliances normally have a strong competitive inclination toward each other because of either existing or potential rivalries regarding products or resources (Chen, 1996). The competitive nature of their relationship underpins their alliance interactions, making horizontal collaboration an appropriate setting for studying the mechanisms through which competitive alliance learning leads to competition in the product market.

It is likely that aggressive learning within horizontal alliances can be translated into competition between allies in product markets, for two reasons. First, proprietary technological knowledge obtained from a partner can be applied outside the alliance when contracts do not adequately direct and constrain the use of knowledge-based assets (Khanna et al., 1998). Firms can apply such knowledge to develop or improve their own products, constituting a threat to their partners’ existing products. Second, learning about partners’ organizational systems, behavioral patterns, and intentions can also help firms design calibrated attacks on their partners in the product market in order to maximize their own performance (Yu & Cannella, 2007).

2.1 Relative exploration and product competition between allies

We classify alliances into two categories: exploitative and exploratory (Koza & Lewin, 1998; March, 1991). Exploitative collaborations, such as marketing and licensing alliances, are arm’s-length relationships designed to exchange existing knowledge and resources for short-term economic returns (Mowery et al., 1996). Firms engaged in exploitative collaborations typically do not require close interactions, since they can be guided by contracts to accomplish their respective duties in a relatively stand-alone fashion (Rothaermel & Deeds, 2004). In contrast, exploratory collaborations are designed to synthesize knowledge assets from both parties to develop critical innovations of great strategic importance for a firm’s long-term stakes, and consequently demand more intensive interactions for sharing tacit know-how (Lavie & Rosenkopf, 2006; Rothaermel & Deeds, 2004). Exploratory collaborations cannot be perfectly regulated by contracts, since they consist of non-routinized searches and learning that involves experimentation with new and often unforeseen alternatives and outcomes.

Different compositions of the collaborative portfolio between two firms have different implications for their competition in the product market. When the proportion of exploratory alliances is low, the overlap in the two firms’ long-term stakes is relatively small, so that a short-term horizon and a “transaction-oriented” perspective dominate their interactions. This orientation allows both parties to tolerate self-serving behaviors in their interactions, or even to take them for granted. Their interactions then focus on maximizing immediate profits, so that each firm is motivated to use what it learns from its partner to increase private benefits. In this type of orientation, increases in the proportion of exploratory alliances provide opportunities and incentives to compete in product markets. Specifically, there are two reasons.

First, increases in the proportion of exploratory alliances enhance a firm’s awareness of opportunities to benefit from competition. Exploratory collaborations involve more intensive interactions, which enable the firm to gain a deeper and more comprehensive understanding of its partner’s technologies, organizational operations, leadership, and motives (Davis & Eisenhardt, 2011). This knowledge helps the firm more precisely identify the strengths and weaknesses in its partner’s
organizational systems and innovation schemes (Dussauge et al., 2000; Yang et al., 2011), information that can be used to launch calibrated attacks and provides strong incentives for competitive actions.

Second, exploratory collaboration enhances a firm’s capacity to develop competing products because it requires sharing of proprietary know-how. Exploratory collaboration involves articulating and transferring complex knowledge between allies, which requires intensive hands-on coaching to facilitate joint problem solving. Such coaching often draws on latent knowledge bases, showing the connections between divisional areas of knowledge and organizations (Agrawal, 2006; Uzzi, 1997). This fine-grained knowledge transfer enhances the absorption of tacit know-how (Lane and Lubatkin, 1998) and facilitates the appropriation of fundamental knowledge that spills over during close interactions. Firms’ incentives to apply such technological know-how in designing substitute products is high, since doing so can cause destructive damages to incumbent products and reward the attackers with enhanced private benefits (Chen & Hambrick, 1995; Lichtenberg & Philipson, 2002; Yu & Cannella, 2007).

The above arguments suggest that increasing the proportion of exploratory alliances in the collaborative portfolio enhances the firm’s incentives to compete with its partner when their partnership is transaction oriented. However, as the proportion of exploratory alliances increases, overlap in the firms’ long-term stakes also rises, enlarging their mutual dependence in developing critical innovations (Pfeffer & Salancik, 1978). The risk of retaliation from an attacked partner also increases, as the partner now holds more critical information about the firm. The firms’ interdependence, on the one hand, and the risk of retaliation, on the other, may escalate to a point at which the expected costs exceed the benefits of launching a competitive action, suffocating the firms’ incentives to further intrude into each other’s product market domains.

Specifically, as firms engage more in exploratory collaboration, they become more reliant on one another for developing exploratory innovations. Developing such innovations involves great uncertainty, and thus demands more cooperative efforts (March, 1991). Competition accordingly becomes a growing threat to firms’ common stakes, curbing their incentive to launch attacks. When exploratory alliances dominate the collaboration between two firms, their shared stakes in developing exploratory innovations rise to the point where their partnership becomes strategically important to both parties’ long-term prosperity. A symbiotic relationship featuring a long-term perspective and “relation-oriented” interactions between them is likely to emerge (Davis & Eisenhardt, 2011; McEvily & Marcus, 2005). The damage caused by competition on greater long-term benefits may reach a threshold at which escalating competitive attacks would be too costly to justify. As the marginal cost of competition continues to increase, the likelihood that a firm will compete with its partner is reduced.

Moreover, heavy engagement in exploratory collaboration allows both partners to hold a great deal of high-value information about each other’s operations (Li, Eden, Hitt, & Ireland, 2008). Information about, for example, technological pitfalls and managerial incompetence can be used to design targeted retaliatory attacks (Chen & Hambrick, 1995). The stakes of “betrayal” become substantively higher as the strategic importance of the exploratory partnership increases, so that the tit-for-tat retaliation risk escalates substantially. The consequences of such retaliatory attacks can be tremendously destructive, resulting in significant costs to the attacker (Chen & Hambrick, 1995). An expectation of such retaliation also decreases incentives to undertake competitive actions.

In sum, firms are likely to develop a transaction-oriented partnership when the collaborative portfolio between them is dominated by exploitative alliances (i.e., low relative exploration), and increases in the proportion of exploratory alliances enhance a firm’s incentives to compete with its
partner. However, as the proportion of exploratory alliances increases, the two firms’ long-term stakes become more aligned, so that the damages caused by competition increase. When the collaborative portfolio is dominated by exploratory alliances (i.e., high relative exploration), the partnership becomes strategically important and a relation-oriented interaction pattern is fostered. The escalating damage to long-term benefits and the risk of retaliatory attacks from the partner may reach a level at which the cost of competition outweighs its short-term benefit, and at this level the motivation to compete starts to decline, resulting in an inverted U-shaped relationship between relative exploration and the firm’s competition with its partner; the competition peaks at the medium level of relative exploration (Grant & Schwartz, 2011; Hanns, Pieters, & He, 2016).

**Hypothesis 1 (H1)** There is a curvilinear relationship (taking an inverted U-shape) between relative exploration and the aggressiveness of a firm’s competition against its partner in the product market.

### 2.2 The moderating role of network embeddedness

We further contend that this curvilinear relationship is subject to the influence of the inter-firm alliance networks within which the firm and its partner are embedded. Alliance learning does not take place in a vacuum but is shaped by the broader social context, as firms are not atomistic players but relational entities (Granovetter, 1985; Uzzi, 1996). Polanyi (1957) was the first to use the concept of embeddedness in describing the social structure of modern markets, and many studies have further conceptualized inter-firm embeddedness and examined how it affects economic actions (e.g., Lavie, 2007; Polidoro et al., 2011; Uzzi, 1997).

We build a comprehensive model examining the impact of alliance network embeddedness on the relationship between relative exploration and product competition between allies by focusing on all three dimensions of embeddedness: relational, positional, and structural (Gulati & Gargiulo, 1999). **Relational** embeddedness, reflected in repeated alliance ties between two firms, emphasizes cohesive and reliable relationships (Gulati & Gargiulo, 1999). **Positional** embeddedness, reflected in network centrality, manifests a firm’s status and power within the overall network. **Structural** embeddedness, reflected in the common ties shared by the firm and its partner, highlights the information sharing, social monitoring, and reputational effects that regulate inter-firm interactions (Gulati & Gargiulo, 1999; Polidoro et al., 2011).

#### 2.2.1 Relational embeddedness

We argue that repeated collaboration attenuates the inverted U-shaped relationship between relative exploration and the firm’s competition against its partner by (a) lowering the firm’s incentive to act opportunistically when the partnership is more transaction oriented and (b) increasing the cost of aggressive intrusions when the partnership is more relation oriented.

Specifically, at low to medium levels of relative exploration (i.e., more transaction oriented), the effect of relative exploration on a firm’s competition is smaller when the number of repeated collaborations increases, for two reasons. First, repeated ties foster relational capital between allies (Gulati, 1995; Gulati & Singh, 1998; Kale, Singh, & Perlmutter, 2000), stifling a firm’s incentive to compete with its partner. Relational capital, such as trust, aligns the interests of allies as well as promotes cooperation and reciprocity (Kogut, 1989; Uzzi, 1997; Zaheer, McEvily, & Perrone, 1998). Trust encourages firms not to abuse each other’s vulnerabilities and to respect their respective boundary
of resources and proprietary knowledge (Krishnan, Martin, & Noorderhaven, 2006). The incentive to behave opportunistically is therefore reduced as the number of repeated ties increases.

Second, repeated collaborations restrain a firm’s incentive to compete by improving the effectiveness of formal governance mechanisms, such as contracts, in preventing opportunistic learning in exploratory activities. Repeated ties help firms learn how to work together effectively by helping them discover their partners’ self-serving behaviors and patterns, which in turn leads them to anticipate similar behavior in the future (Doz, 1996; Lioukas & Reuer, 2015). Firms normally incorporate such knowledge into improving their contracts and other defensive mechanisms to guard against competitive behaviors from the same partners (Mayer & Argyres, 2004). Repeated collaborations can therefore strengthen these governance mechanisms and reduce a firm’s incentives to compete with its partner.

At medium to high levels of relative exploration (i.e., more relation oriented), too, the effect of relative exploration on competition is reduced by the number of collaborations between allies, as repeated collaboration increases the cost of competition in this type of partnership. First, repeated collaborations further enhance the symbiotic relationship between partners in joint knowledge discovery. Repeated collaboration facilitates the development and refinement of important bilateral systems, such as problem-solving mechanisms, that typically consist of routines of negotiation and mutual adjustments. These mechanisms enable allies to reduce production errors and resolve problems more flexibly (Uzzi, 1997). Repeated collaboration also fosters relational capital, which encourages allies to share proprietary knowledge in a more fine-grained and timely fashion (Krishnan et al., 2006; Uzzi, 1997). These formal or informal mechanisms further enhance the partnership’s synergistic benefits, thus heightening the cost of damaging such a collaboration.

Second, repeated collaborations between firms can help both parties gain more knowledge and intelligence about each other (Gulati, 1995; Podolny, 1994), further escalating the risk of retaliation. Specifically, multiple collaborations help the partner (a) see through superficial phenomena and relationships to identify the firm’s underlying behavior patterns, (b) connect separate units of know-how to detect the firm’s fundamental knowledge bases, and (c) deepen understanding of the firm’s competencies and vulnerabilities (Uzzi, 1997). Such knowledge further increases the risks of destructive retaliation, expanding the cost of aggressive competition.

To summarize, a firm’s incentive to compete with its partner is reduced at low to medium levels of relative exploration, while its competition costs are enlarged at medium to high levels of relative exploration, when the number of repeated ties is higher. The effect of relative exploration on a firm’s competition with its partner is thus attenuated at both sides of the inverted U-shape. The overall slope of the relationship between relative exploration and a firm’s competition with its partner is therefore likely to be flattened, with the peak of the slope becoming lower.

**Hypothesis 2 (H2)** Repeated alliance ties between a firm and its partner negatively moderate the relationship between relative exploration and the firm’s competition against this partner in the product market, such that the inverted U-shape is flattened when the number of repeated alliance ties is higher.

### 2.2.2 Positional embeddedness

A firm’s centrality within the inter-firm network affects the amount of information and resources that it can access (Godart, Shipilov, & Claes, 2014), which represents a significant source of bargaining power (Brass, 1992). Firms’ relative centrality therefore reflects the (im)balance between them in terms of resource flows and power (Gnyawali & Madhavan, 2001; Yang et al., 2011).
argue that a firm’s greater centrality relative to its partner intensifies the inverted U-shaped relationship between relative exploration and the firm’s competition against its partner: it further enhances the firm’s incentive to take advantage of its less central partner when their relationship is more transaction oriented, and also reduces the costs of aggressive intrusions when their partnership is more relation oriented.

At low to medium levels of relative exploration, relatively greater centrality enhances the firm’s incentive to compete with its partner, for two reasons. First, the more central firm has the advantage in terms of information gathering and monitoring, and thus can cast a wider net to capture knowledge leakage from its partner, uncover the partner’s real intentions, and identify weaknesses in its innovation system (Polidoro et al., 2011; Zahra & George, 2002). Second, greater network centrality enhances the firm’s advantage in adapting acquired knowledge to develop substitute products. Situated at the confluence of information flows in the network, a more central firm occupies an advantageous position in terms of identifying opportunities to apply specific knowledge gained from a partnership into broader areas of application. In a more transaction-oriented relationship, these advantages further enhance the firm’s incentive to take action against its partner (Gnyawali & Madhavan, 2001).

At medium to high levels of relative exploration, greater relative centrality reduces a firm’s competition costs, for two reasons. First, when the difference in network centrality between the firm and its partner is large, the firm has more choices of alternative partners than its peripheral partner (Lavie, 2007), while the peripheral partner is more likely to maintain its collaboration with the firm for resource access and institutional endorsement (Ahuja, 2000; Podolny, 1994). The larger the difference in their centrality, the less dependent the firm is on this specific partnership (Brass, 1992). Such asymmetry enhances the firm’s bargaining power in their interactions (Shipilov, 2009), which in turn reduces its cost of competition.

Second, when the firm’s centrality is greater than its partner’s, the risk of retaliation from the peripheral partner is lower. This partner is less likely to respond to aggressive actions of the firm, because (a) due to its lack of information sources, the partner will “find it difficult to interpret the causes and consequences of competitive actions correctly” (Gnyawali & Madhavan, 2001, p. 436), and therefore may not be sufficiently informed to respond; (b) fear of provoking further actions from the more powerful firm may motivate the partner not to respond (Gnyawali & Madhavan, 2001); and (c) the partner may not be capable of mobilizing sufficient assets to orchestrate a response.

To summarize, when a firm’s alliance network centrality is greater than that of its partner, its incentive to compete with that partner is enhanced at low to medium levels of relative exploration, while its costs of competition are reduced at medium to high levels of relative exploration. At both sides of the inverted U-shape, that is, the effect of relative exploration on the firm’s competition is enlarged by the firm’s relative centrality. The slope in the relationship between relative exploration and competition is therefore likely to be steeper, and the peak of the slope is higher.

Hypothesis 3 (H3) A firm’s relative centrality vis-à-vis its partner positively moderates the relationship between relative exploration and the firm’s competition against this partner in the product market, such that the inverted U-shape is steepened when the firm’s relative centrality is higher.

2.2.3 Structural embeddedness

The term structural embeddedness refers to the extent to which two firms are connected by common third parties: the more common ties the partners have, the more structurally embedded they are. We
argue that structural embeddedness can attenuate the inverted U-shaped relationship between relative exploration and a firm’s competition against its partner in the product market by (a) dampening the firm’s incentive to compete when the partnership is more transaction oriented, and (b) heightening the competition costs when the partnership is more relation oriented.

At low to medium levels of relative exploration, the firm’s incentive to take advantage of its partner is reduced when their structural embeddedness is higher. Specifically, a larger number of common ties increases resource symmetry between the firm and its partner. Chen (1996) argues that a firm is more motivated to compete with others when it has superior resources. As the number of common ties increases, the firm and its partner become increasingly similar in resources to which they both have access, which restrains the firm’s incentives to compete with its partner. In addition, if one firm “exploits the vulnerabilities of the other, the occurrence of such behavior can be revealed to common partners and, through them, reach a larger number of firms in the network” (Polidoro et al., 2011: 206). The resulting adverse effects on the firm’s reputation also reduce its incentive to compete.

At medium to high levels of relative exploration, costs of competition are further heightened when structural embeddedness between partnering firms is higher, for two reasons. First, the partnership becomes more symbiotic as structural embeddedness between a firm and its partner increases. Both firms’ success depends increasingly on resource exchanges not only within the dyad but with their common allies, which fosters an ecosystem in which the two firms are more interconnected and their interests more aligned. At a given level of relative exploration, the cost of competition is significantly increased, since any competition between firms may have a multiplicative adverse effect within the system. Second, common partners increase the risk and intensity of revenge for opportunistic behaviors. If the firm acts against its partner within this symbiotic relationship, it is not only likely to be attacked in retaliation by the initial partner but may also experience escalated attacks in revenge from third-party common allies, which also have (in)direct stakes in this partnership (Polidoro et al., 2011).

Taken together, as structural embeddedness between a firm and its partner increases, the firm’s incentive to compete is reduced at low to medium levels of relative exploration, while its competition costs are increased at medium to high levels of relative exploration. Thus, at both sides of the inverted U-shape, the effect of relative exploration on the firm’s competition is reduced as firms’ structural embeddedness increases. The slope in the relationship between relative exploration and the firm’s competition with its partner is likely to be less steep when the number of common ties is higher, and the peak of the slope is likely to be lower.

Hypothesis 4 Structural embeddedness between a firm and its partner negatively moderates the relationship between relative exploration and the firm’s competition against this partner in the product market, such that the inverted U-shape is flattened when the level of structural embeddedness is higher.

3 | METHODS

3.1 | Sample

We chose the U.S. pharmaceutical industry as an appropriate setting for examining our hypotheses because it features both extensive alliance activities and competition for new products (Lichtenberg & Philipson, 2002; Mowery et al., 1996). We first collected data on alliances within this industry from 1984 to 2003, using three data sources—SDC Platinum, MedTrack, and ReCap—
which (a) have very similar standards for reporting information, including the year of alliance establishment, partners’ names, and descriptions of alliance deals, and (b) each normally reports only a fraction of all alliance activities (Schilling, 2009). Although databases that track alliances in the pharmaceutical industry are normally reliable (Schilling, 2009), we found that the SDC database covers more historical data while MedTrack and ReCap include more recent information. We constructed a more comprehensive alliance database by combining these three data sources. For due diligence, we followed Lavie and Rosenkopf (2006), searching for alliance announcements and status reports from LexisNexis News, corporate websites, and Securities and Exchange Commission (SEC) filings accessed via the Edgar database. Most alliance announcements were cross-validated by at least two additional sources. By relying on multiple sources, we minimized the possibility of double-counting alliances and of counting alliances that were announced but not realized.

To measure product competition, we began by selecting all FDA-approved drugs from the FDA’s National Drug Code Directory. We specifically identified drugs approved under clauses 505(b)(2) and 505(j) of the Federal Food, Drug, and Cosmetic Act (FD&C Act) with the aid of the FDA’s Approved Drug Products with Therapeutic Equivalence Evaluations (the “Orange Book”). Clause 505(j) governs generic drug applications, while clause 505(b)(2) governs the modifications of previously approved brand-name drugs. Under the 505(b)(2) and 505(j) pathways of drug application, the timeline for most new drug launches is reduced to approximately 1 year.3 We then collected information on each drug’s ingredients, mechanisms of action, physiologic effect, and chemical structure from four pharmacological databases: Drugs @ FDA, Mosby’s Drug Consult, Drugs-by-Condition on Drugs.com, and AHFS Drug Information from the American Society of Health-System Pharmacists (Toh & Polidoro, 2013). A researcher in the pharmacology discipline who was not part of our team used this information to help classify all listed drugs into competing groups. For example, Zoloft and Celexa are considered direct competitors in the antidepressant market, since they use the same mechanism of action: both are selective serotonin reuptake inhibitors (SSRIs), which boost mood by blocking the re-absorption of the neurotransmitter serotonin within the brain, thus helping brain cells send and receive chemical messages. Both Pristiq and Cymbalta belong to another group of competing antidepressants using serotonin–norepinephrine reuptake inhibitors (SNRIs), which work by inhibiting the reuptake of both serotonin and norepinephrine to boost mood (See Table A in the Appendix S1 for examples of competing antidepressants and their underlying mechanisms). We then linked the competing drugs to their producers and market introduction dates with the aid of the “Orange Book.”

We also collected firm financial information from Compustat, as well as patent data from the U.-S. Patent and Trademark Office (USPTO) and the Thomson Innovation database. We located 126 public firms for which we had complete information on alliances, drugs, patents, and financial reports, and identified 3,752 observations as our sample, with an observation window ranging from 1984 to 2003.

3Drug application is regulated by the FD&C Act, s. 505 of which describes three types of new drug application pathways: (1) Full applications under clause 505(b)(1), which requires full reports of investigations into the safety and effectiveness of a drug conducted by the applicant (what is usually known as the brand-name drug application); under this pathway the new drug development cycle is approximately 10–15 years. (2) Generic drug applications under clause 505(j), which requires information to show that the proposed product is therapeutically identical or equivalent to a previously approved drug. (3) Applications under clause 505(b)(2), which allows pharmaceutical firms to submit new drug applications by referencing the literature or previous agency findings on the safety and efficacy of a drug, even if not developed by the applicant; typical 505(b)(2) applications include modifications of a previously approved brand-name drug such as a new formulation, a change in dosing regimen, a new active ingredient, or a new combination of ingredients. The objective of the 505(b)(2) drug application pathway is to encourage innovation and speed up new drug introductions by eliminating the need for duplicative studies to demonstrate what is already known about a drug.
3.2 | Dependent variable

3.2.1 | Competitive aggressiveness

Following prior studies, we measured the extent of competition in product markets that a firm undertakes against its partner using competitive aggressiveness, describing both the intensity and diversity of the firm’s competitive actions (Yu et al., 2009). This variable contains three items: the number of competitive actions (i.e., market entries) that the firm launched against its partner following the alliance announcement and the width and depth of its competing actions. The width dimension measures the number of different therapeutic areas in which the firm entered that compete against its partner; the depth dimension measures the number of destructive competitions (i.e., modified brand-name drugs) launched by the firm against its partner. The launch of modified brand-name drugs is a more aggressive competitive action than the introduction of generic drugs because of the former’s much longer period of market exclusivity (Lichtenberg & Philipson, 2002).4 We ran a factor analysis of these three items and found that all three loaded high (>0.73) on one latent factor, while the value of Cronbach’s alpha is .81, which suggests that it is a reliable construct. We used the average score for these three items to measure the dependent variable.

3.3 | Independent variable and moderators

Relative exploration is calculated as the ratio of the number of exploratory collaborations to the total number of collaborations between the firm and its partner over a 5-year moving window (Ang, 2008; Yang et al., 2011). We used a 5-year window because alliance databases seldom report the termination dates of alliances, and the life span of an alliance is normally no more than 5 years (Yang et al., 2011). We constructed this variable using a content analysis of the deal summary to identify the nature of alliance learning for each alliance in our sample. Specifically, research and development (R&D) alliances with the objective of exploring and creating critical new knowledge were coded as exploratory collaborations, while alliances such as co-marketing, manufacturing, and licensing, which mainly utilize existing knowledge and resources, were classified as exploitative collaborations (Lavie & Rosenkopf, 2006; Rothaermel, 2001; Rothaermel & Deeds, 2004). Since partners may have different intentions within an alliance, we undertook this coding from the focal firm’s perspective (Lavie & Rosenkopf, 2006). It is important to note that not all R&D collaborations are exploration oriented; within our data set, if two firms formed an R&D alliance for the purpose of making incremental changes to an existing technology, that R&D alliance was coded as exploitative. The value of this variable ranges from 0 to 1.

Repeated alliance ties reflect the relational embeddedness between two firms. We measured this variable by counting the number of repeated alliance ties between the firm and its partner over the previous 5 years (Ahuja, Polidoro, & Mitchell, 2009; Gulati & Gargiulo, 1999).

Relative centrality captures the relative positional embeddedness of two firms. We first constructed yearly alliance matrices within the pharmaceutical industry from 1984 to 2003, using a 5-year moving window. Altogether, we identified 47,862 pairs of alliances, including those started between 1980 and 1983. We constructed a symmetric (non-directional) matrix of these firms for each year using Ucinet 6 (Borgatti, Everett, & Freeman, 2002), then calculated the degree centrality

---

4While a generic drug can be detrimental to the market share of a brand-name drug, Lichtenberg and Philipson (2002) have shown that creative destructions such as new forms or combinations of ingredients can be more detrimental to market share. This is partly because the latter may have better therapeutic effects and are granted longer market exclusivity; while generic drugs are given a maximum 180 days of exclusivity, modifications to brand-name drugs are granted three to seven years of exclusivity.
of each firm within the above alliance network matrices. *Relative centrality* is calculated as the
firm’s degree centrality minus its partner’s degree centrality.

*Common ties* capture the structural embeddedness between the firm and its partner. Following
prior studies, we measured this variable by counting the number of common third-party partners that
the firm and its partner shared during the previous 5 years (Gulati & Gargiulo, 1999; Polidoro
et al., 2011).

3.4 | Control variables

We controlled for sample heterogeneity by including nine variables suggested by prior studies as
influencing the relationship between alliances and competition.

3.4.1 | R&D intensity

A firm’s R&D investment can contribute to its new product development and thus influence its
competition against its partner in the product market. We therefore controlled for the firm’s R&D
investment, measured as its R&D expenditures scaled by sales (Keil, Maula, Schildt, &
Zahra, 2008).

3.4.2 | Return on assets (ROA)

A firm’s financial performance is positively associated with new product development (Rothaermel,
2001); firms that perform better financially may be more prepared to compete in the product market.
We therefore controlled for a firm’s financial performance using its *return on assets*.

3.4.3 | Financial slack

Since researchers have argued that competitive behaviors are dependent on resource availability
(Smith, Grimm, Gannon, & Chen, 1991), we controlled for a firm’s *financial slack*, computed as
current assets divided by current liabilities (Hambrick, Cho, & Chen, 1996).

3.4.4 | Coopetition

If two firms are competing with each other in the market when they establish an alliance, this “coop-
etition” relationship may contribute to the risk of their future competition in the market. We there-
fore controlled for *coopetition* (coded as 1 if two firms were competing in the product market when
they established an alliance and as 0 otherwise).

3.4.5 | Technological overlap

Prior research suggests that resource similarity between firms may influence their competition
(Chen, 1996). We accordingly controlled for dyadic resource similarity by measuring *technological
overlap*, calculated as the percentage of patent cross-citations between a firm and its partner
(Mowery et al., 1996).

3.4.6 | Alliance scope

A wide scope of collaboration increases the likelihood of both information leakage and appropria-
tion within alliances (Oxley & Sampson, 2004), heightening the risk of product competition. How-
ever, collaborations across a wide range of areas may also increase partners’ mutual dependence,
which reduces opportunistic behavior (Pfeffer & Salancik, 1978). Prior studies have not provided a
clear direction for the effect of alliance scope on competition between partners in the product mar-
ket. In our model, we controlled for *alliance scope* using a measure adapted from prior studies
(Oxley & Sampson, 2004), which was coded as 0 if a collaboration does not include R&D activities, as 1 if it includes only R&D activities, and as 2 if it includes both R&D and non-R&D activities.

3.4.7 | Multiparty alliance (“Multiparty”)
In cases where an alliance includes more than two firms, we split the alliance into a set of dyads. Empirically, this may result in a confounding effect with structural embeddedness (i.e., number of common ties). We parcelled out the possible confounding effect caused by multiparty alliances by including a control variable (“Multiparty”) that measures the number of additional parties (>2) to a dyad within an alliance. We also ran the models using a sample excluding multiparty alliances; the results are robust.

3.4.8 | Network density
As Coleman (1988) has noted, a dense alliance network in which a dyad is located can also facilitate information sharing and monitoring within the network, suffocating competition between allies. We therefore controlled for the density of the ego network for each dyad. This ego network includes the two firms within the alliance as well as all other firms that have at least one alliance with at least one of the two firms. We first transformed the firm-by-firm alliance network into an incidence network (i.e., the output is a two-mode firm-by-alliance network) using the command “transform | graph theoretic | incidence” in Ucinet 6. We then transformed the two-mode incidence network into a one-mode alliance-by-alliance square network by using the command “data | affiliations” and selecting column as the unit of interest. Finally, we calculated ego network density within this new network for each alliance in our sample.

3.4.9 | Year dummies
We controlled for unobserved heterogeneity associated with years by including 19 year dummies in our models.

3.5 | Analysis
We tested our hypotheses using fixed-effects models. The unit of analysis is firm–partner–year, and we allowed a 1-year lag between our predictor variables and the dependent variable. A fixed-effects estimator has superior controls for time-invariant variables (Mundlak, 1978) and is an effective way to account for possible endogeneity problems. For example, if unobserved heterogeneities, such as the attractiveness of partners to one another and their tendencies to compete with each other, are constant within firm–partner dyads, then there might be an endogeneity concern. A fixed-effects estimator can rule out such a possibility by eliminating time-invariant heterogeneities. Fixed-effects models also allow us to account for intra-cluster correlations caused by multiple observations of the same dyad over time. We therefore employed dyad fixed-effects and clustered standard errors on dyads in our models.

4 | RESULTS
Table 1 reports descriptive statistics and correlations for all variables, including the quadratic and interaction terms. We mean-centered the variables before creating quadratic and interaction terms in order to reduce non-essential ill-conditioning between independent variables and their higher-order
<table>
<thead>
<tr>
<th>Variables</th>
<th>Mean</th>
<th>S.D.</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>11</th>
<th>12</th>
</tr>
</thead>
<tbody>
<tr>
<td>1  Competitive aggressiveness</td>
<td>0.141</td>
<td>0.921</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2  R&amp;D intensity</td>
<td>0.897</td>
<td>5.874</td>
<td>−0.020</td>
<td></td>
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</tr>
<tr>
<td>3  ROA</td>
<td>0.027</td>
<td>0.242</td>
<td>0.058</td>
<td>−0.385</td>
<td></td>
<td></td>
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</tr>
<tr>
<td>4  Financial slack</td>
<td>3.201</td>
<td>3.650</td>
<td>0.081</td>
<td>0.170</td>
<td>−0.169</td>
<td></td>
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<td></td>
</tr>
<tr>
<td>5  Coopetition</td>
<td>0.058</td>
<td>0.233</td>
<td>0.620</td>
<td>−0.011</td>
<td>0.086</td>
<td>0.001</td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>6  Technological overlap</td>
<td>0.000</td>
<td>0.012</td>
<td>−0.004</td>
<td>−0.003</td>
<td>−0.003</td>
<td>0.017</td>
<td>−0.006</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>7  Alliance scope</td>
<td>0.914</td>
<td>0.696</td>
<td>−0.013</td>
<td>0.041</td>
<td>−0.108</td>
<td>0.056</td>
<td>−0.111</td>
<td>−0.029</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>8  Repeated alliance ties</td>
<td>0.343</td>
<td>0.702</td>
<td>−0.008</td>
<td>−0.038</td>
<td>0.067</td>
<td>−0.104</td>
<td>0.034</td>
<td>−0.102</td>
<td>−0.010</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>9  Relative centrality</td>
<td>−0.191</td>
<td>5.365</td>
<td>0.019</td>
<td>−0.133</td>
<td>0.364</td>
<td>−0.309</td>
<td>0.012</td>
<td>−0.028</td>
<td>−0.079</td>
<td>0.080</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>10 Common ties</td>
<td>14.892</td>
<td>16.240</td>
<td>0.011</td>
<td>−0.084</td>
<td>0.241</td>
<td>−0.244</td>
<td>0.146</td>
<td>−0.018</td>
<td>0.022</td>
<td>0.321</td>
<td>0.067</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>11 Multiparty</td>
<td>0.039</td>
<td>0.193</td>
<td>0.021</td>
<td>−0.019</td>
<td>−0.001</td>
<td>0.006</td>
<td>0.027</td>
<td>−0.005</td>
<td>0.075</td>
<td>−0.032</td>
<td>0.03</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>12 Network density</td>
<td>0.642</td>
<td>0.090</td>
<td>−0.103</td>
<td>0.041</td>
<td>−0.156</td>
<td>0.097</td>
<td>−0.078</td>
<td>0.005</td>
<td>0.028</td>
<td>−0.083</td>
<td>−0.135</td>
<td>−0.224</td>
<td>−0.007</td>
<td></td>
</tr>
<tr>
<td>13 Relative exploration</td>
<td>0.320</td>
<td>0.366</td>
<td>0.014</td>
<td>0.021</td>
<td>−0.104</td>
<td>0.052</td>
<td>0.004</td>
<td>−0.020</td>
<td>0.403</td>
<td>0.095</td>
<td>−0.100</td>
<td>0.117</td>
<td>0.080</td>
<td>0.047</td>
</tr>
<tr>
<td>14 Relative exploration squ</td>
<td>0.236</td>
<td>0.338</td>
<td>−0.065</td>
<td>0.037</td>
<td>−0.113</td>
<td>0.055</td>
<td>−0.058</td>
<td>−0.006</td>
<td>0.073</td>
<td>−0.129</td>
<td>−0.074</td>
<td>−0.004</td>
<td>0.007</td>
<td>0.069</td>
</tr>
<tr>
<td>15 Relative exploration × Repeated alliance ties</td>
<td>0.134</td>
<td>0.364</td>
<td>−0.014</td>
<td>0.004</td>
<td>0.011</td>
<td>−0.050</td>
<td>0.012</td>
<td>0.009</td>
<td>−0.088</td>
<td>0.195</td>
<td>0.031</td>
<td>0.124</td>
<td>0.013</td>
<td>−0.087</td>
</tr>
<tr>
<td>16 Relative exploration squared × Repeated alliance ties</td>
<td>0.084</td>
<td>0.266</td>
<td>0.023</td>
<td>−0.02</td>
<td>0.036</td>
<td>−0.106</td>
<td>0.064</td>
<td>−0.006</td>
<td>0.006</td>
<td>0.671</td>
<td>0.076</td>
<td>0.230</td>
<td>0.023</td>
<td>−0.096</td>
</tr>
<tr>
<td>17 Relative exploration × Relative centrality</td>
<td>−0.257</td>
<td>2.714</td>
<td>0.020</td>
<td>−0.033</td>
<td>0.167</td>
<td>−0.079</td>
<td>0.019</td>
<td>0.023</td>
<td>−0.010</td>
<td>0.026</td>
<td>0.047</td>
<td>0.070</td>
<td>−0.016</td>
<td>−0.105</td>
</tr>
<tr>
<td>18 Relative exploration squared × Relative centrality</td>
<td>−0.224</td>
<td>2.358</td>
<td>0.012</td>
<td>−0.122</td>
<td>0.365</td>
<td>−0.250</td>
<td>0.022</td>
<td>−0.014</td>
<td>−0.032</td>
<td>0.056</td>
<td>0.698</td>
<td>0.081</td>
<td>−0.024</td>
<td>−0.139</td>
</tr>
<tr>
<td>19 Relative exploration × Common ties</td>
<td>5.461</td>
<td>10.400</td>
<td>0.012</td>
<td>−0.023</td>
<td>0.119</td>
<td>−0.075</td>
<td>0.064</td>
<td>0.013</td>
<td>−0.024</td>
<td>0.111</td>
<td>0.073</td>
<td>0.204</td>
<td>−0.023</td>
<td>−0.077</td>
</tr>
<tr>
<td>20 Relative exploration squared × Common ties</td>
<td>3.951</td>
<td>8.563</td>
<td>0.044</td>
<td>−0.082</td>
<td>0.243</td>
<td>−0.210</td>
<td>0.137</td>
<td>−0.01</td>
<td>0.029</td>
<td>0.193</td>
<td>0.092</td>
<td>0.708</td>
<td>−0.016</td>
<td>−0.199</td>
</tr>
</tbody>
</table>

**Note.** (a) \( N=3,752 \). (b) Means were calculated using un-centered variable values.
<table>
<thead>
<tr>
<th></th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>39.286</td>
<td>37.947</td>
<td>38.294</td>
<td>36.838</td>
<td>39.115</td>
<td>38.105</td>
</tr>
<tr>
<td>R&amp;D intensity</td>
<td>−0.001</td>
<td>−0.002</td>
<td>−0.002</td>
<td>−0.001</td>
<td>−0.002</td>
<td>−0.001</td>
</tr>
<tr>
<td>ROA</td>
<td>0.024</td>
<td>−0.003</td>
<td>−0.005</td>
<td>−0.004</td>
<td>−0.013</td>
<td>−0.010</td>
</tr>
<tr>
<td>Financial slack</td>
<td>0.041</td>
<td>0.040</td>
<td>0.040</td>
<td>0.040</td>
<td>0.040</td>
<td>0.040</td>
</tr>
<tr>
<td>Coopetition</td>
<td>2.382</td>
<td>2.786</td>
<td>2.776</td>
<td>2.785</td>
<td>2.775</td>
<td>2.769</td>
</tr>
<tr>
<td>Technological overlap</td>
<td>−0.113</td>
<td>−0.145</td>
<td>−0.129</td>
<td>−0.207</td>
<td>−0.089</td>
<td>−0.150</td>
</tr>
<tr>
<td>Alliance scope</td>
<td>0.015</td>
<td>−0.139</td>
<td>−0.156</td>
<td>−0.138</td>
<td>−0.142</td>
<td>−0.155</td>
</tr>
<tr>
<td>Repeated alliance ties</td>
<td>0.017</td>
<td>−0.054</td>
<td>0.032</td>
<td>−0.053</td>
<td>−0.045</td>
<td>0.027</td>
</tr>
<tr>
<td>Relative centrality</td>
<td>0.010</td>
<td>0.010</td>
<td>0.009</td>
<td>0.005</td>
<td>0.010</td>
<td>0.005</td>
</tr>
<tr>
<td>Common ties</td>
<td>−0.001</td>
<td>−0.001</td>
<td>−0.001</td>
<td>−0.000</td>
<td>0.001</td>
<td>0.001</td>
</tr>
<tr>
<td>Multiparty</td>
<td>−0.048</td>
<td>−0.047</td>
<td>−0.029</td>
<td>−0.044</td>
<td>−0.042</td>
<td>−0.021</td>
</tr>
<tr>
<td>Network density</td>
<td>−1.001</td>
<td>−1.005</td>
<td>−1.015</td>
<td>−0.997</td>
<td>−0.933</td>
<td>−0.984</td>
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<tr>
<td>Relative exploration</td>
<td>1.508</td>
<td>1.803</td>
<td>1.492</td>
<td>1.880</td>
<td>2.011</td>
<td></td>
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<tr>
<td>Relative exploration sq.</td>
<td>−1.439</td>
<td>−1.735</td>
<td>−1.430</td>
<td>−1.831</td>
<td>−1.970</td>
<td></td>
</tr>
<tr>
<td>Relative exploration × Repeated alliance ties</td>
<td>−0.670</td>
<td></td>
<td></td>
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<tr>
<td>Relative exploration sq. × Repeated alliance ties</td>
<td>0.692</td>
<td></td>
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<tr>
<td>Relative exploration × Relative centrality</td>
<td>0.056</td>
<td></td>
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<tr>
<td>Relative exploration sq. × Relative centrality</td>
<td>−0.054</td>
<td></td>
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</tr>
<tr>
<td>Relative exploration × Common ties</td>
<td>−0.023</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Relative exploration sq. × Common ties</td>
<td>0.024</td>
<td></td>
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</tr>
<tr>
<td>R²</td>
<td>0.423</td>
<td>0.434</td>
<td>0.436</td>
<td>0.434</td>
<td>0.435</td>
<td>0.437</td>
</tr>
<tr>
<td>χ² (2) (compared with the baseline)</td>
<td>67</td>
<td>79</td>
<td>72</td>
<td>75</td>
<td>88</td>
<td></td>
</tr>
<tr>
<td>Prob &gt; χ²</td>
<td>2.236e−15</td>
<td>5.655e−18</td>
<td>2.914e−16</td>
<td>4.396e−17</td>
<td>9.878e−20</td>
<td></td>
</tr>
</tbody>
</table>

*Note.* (a) N = 3,752. (b) Robust standard errors in parentheses. (c) Year dummies included in regressions but not reported. (d) “sq.”: squared.
terms (Aiken & West, 1991). The dependent and independent variables show considerable variance, and the correlation coefficients are consistent with our expectations.

We ran fixed-effects models following a hierarchical approach: Model 1 includes only the control variables, while Models 2 through 5 add the independent and interaction variables. Model 6 is the full model, including all independent and interaction variables. Variance inflation factor (VIF) scores were calculated for all models; none of the maximum VIFs exceed the value of 2.5, which is substantially lower than the rule-of-thumb cut-off of 10 (Ryan, 1997). We then used the “coldiag” procedure in Stata to conduct the Belsley, Kuh, and Welsch (1980) multicollinearity diagnostic test, which showed that the condition number for our complete model is 7.53, well below the threshold of 30. We also ran the fixed-effects models using non-centered data; the results are consistent. Since centered estimations can make interpretation of the results less straightforward (Echambadi & Hess, 2007), we report estimations using the original variable values in Table 2.

In Model 2 of Table 2, we tested Hypothesis 1 by introducing both the linear and quadratic terms of relative exploration. The result shows that competitive aggressiveness first increases significantly with relative exploration ($b = 1.508, p = 8E-08$), then decreases significantly as relative exploration continues to increase ($b = -1.439, p = 1E-07$). This result indicates a curvilinear relationship (inverted U-shape) between relative exploration and competitive aggressiveness, with a medium effect size (Cohen’s $d = 0.428$). We examined the marginal effects of this relationship.

![FIGURE 1](image1.png) The relationship between relative exploration and competitive aggressiveness

![FIGURE 2](image2.png) The moderation effect of repeated alliance ties
following the three steps suggested by Lind and Mehlum (2010). First, we examined whether or not the second-order term is significant and of the expected sign; this is confirmed by the result. Second, we tested whether the slope is indeed sufficiently steep at both ends of the data range of relative exploration. Using the “margins” command in Stata 12, we confirmed that when relative exploration = 0, the slope $dy/dx = 1.701 (p = 4E-05)$, and when relative exploration = 1, the slope $dy/dx = -1.561 (p = 3E-05)$. Third, we tested whether or not the turning point is located within the data range of relative exploration. We confirmed this using the “nlcom” command in Stata 12 by showing that the inverted U-shape turns when relative exploration = 0.522 and that the 95% confidence interval for the turning point [0.504, 0.539] is within the value range of relative exploration. We provide additional support by plotting this relationship in Figure 1. These findings suggest that Hypothesis 1 is supported.

In Model 3, the interaction terms between repeated alliance ties (relational embeddedness) and both the linear and quadratic terms of relative exploration are introduced in order to test Hypothesis 2: whether repeated alliance ties negatively moderates the inverted U-shaped relationship. This moderation effect is supported if the second-order interaction term is significantly positive (Hanns et al., 2016). As confirmed by our results, the second-order interaction term is indeed positive ($b = 0.692, p = 6E-06$), with a small-to-medium effect size (Cohen’s $d = 0.364$). Figure 2 illustrates this moderation effect, showing that the inverted U-shape is flattened when the value of repeated alliance ties is higher, supporting Hypothesis 2.
Model 4 introduces the interaction terms between relative centrality (positional embeddedness) and both the linear and quadratic terms of relative exploration in order to test Hypothesis 3: whether the firm’s relative centrality positively moderates the inverted U-shaped relationship. This moderation effect is supported if the second-order interaction term is significantly negative (Hanns et al., 2016). We found that indeed the second-order interaction term is negative \((b = -0.054, p = 0.019)\), with a small-to-medium effect size (Cohen’s \(d = 0.226\)). Figure 3 illustrates this moderation effect, indicating that the inverted U-shape is steepened when the firm’s relative centrality is higher, supporting Hypothesis 3.

Model 5 introduces the interaction terms between common ties (structural embeddedness) and both the linear and quadratic terms of relative exploration in order to test Hypothesis 4: whether common ties negatively moderates the inverted U-shape. As indicated in our results, the second-order interaction term is positive \((b = 0.024, p = .009)\), with a small-to-medium effect size (Cohen’s \(d = 0.318\)). Figure 4 illustrates this moderation effect, showing that the inverted U-shape is flattened when the value of common ties is higher, supporting Hypothesis 4. Model 6 is the full model, including all control, independent, and interaction variables; all results from Models 2–5 hold.

4.1 | Post-hoc analyses

We conducted six additional analyses, either as robustness checks or to gain additional insights into the primary relationships. These analyses investigated (a) whether the results are robust to alternative measures for relative exploration; (b) which firm in a dyad is more likely to initiate competitive actions; (c) what factors determine a firm’s response to its partner’s actions; (d) the extent to which the technological know-how acquired in one area and knowledge of a partner’s managerial system can be applied to competition against the same partner in different technological areas; (e) whether the results are robust to different paradigms of competition; and (f) the potential moderating effects of network density and multiparty. Details of these analyses are available in the Appendix S1.

5 | DISCUSSION

This study contributes to a core research area in strategic alliances: the influence of collaboration on inter-partner dynamics (Gulati, 1995; Kogut, 1989). While previous studies provide important insights into how prior collaboration can promote further collaboration between partners (Gulati, 1995; Gulati & Singh, 1998), we add to this line of research by investigating whether collaboration can lead to intense product market competition between partners. We approach this question by analyzing the composition of the collaborative relationships between two firms as well as by studying the impact of their interconnectedness in the context of alliance networks. We find that in addition to the path-dependent paradigm of partners’ interactions whereby prior collaboration leads to future collaboration (Gulati, 1995), certain compositions of collaborative relationships between two firms can lead to a new path of interaction—a transition from collaboration to competition in product markets. Furthermore, the firms’ network embeddedness can modify this transition process.

Our research contributes to this line of investigation on three fronts. First, our research extends the literature on the tension between collaboration and competition within alliances. Prior studies have long argued that firms race to appropriate knowledge from each other within alliances (Hamel, 1991; Khanna et al., 1998). We extend this literature by identifying (a) the composition of collaborative portfolios and (b) network embeddedness between allies as important mechanisms through
which learning within alliances is translated into competitive interactions in the product market. Our study thus bridges two streams of research: learning races within alliances and competitive dynamics in the product market.

Second, we extend prior studies on learning races, which tend to focus on competition within research-based alliances. We examine the roles played by all types of alliance between two firms, in terms of their combinations, in determining a firm’s competition with its partner. Our findings suggest that a firm’s product market competition with its partner is not necessarily high in research-intensive collaborations; in fact, the firm is more likely to adopt a long-term outlook that encourages relationship building and cooperation when the collaboration portfolio is dominated by exploratory alliances, reducing its motivation to compete with its partner. Our finding of a curvilinear relationship between relative exploration and competitive aggressiveness highlights the role that the overall collaborative portfolio between partners plays in determining their competitive interactions.

Third, this research contributes to the literature by studying the moderating role of allies’ network embeddedness in the “collaboration–competition” relationship. We demonstrate that network embeddedness—namely relational, positional, and structural embeddedness—affects the relationship between relative exploration and product market competition. Our research speaks directly to the importance of looking beyond dyadic interactions when examining dyadic competition, representing a valuable addition to the growing body of studies exploring how allies’ network characteristics influence their interaction patterns and performance (Lavie, 2007; Polidoro et al., 2011).

Our post hoc analyses (see Appendix S1) make further contributions to the research on collaboration and competition by unpacking the competitive dynamics (i.e., actions and responses) between allies. For example, post hoc analysis 2 found an asymmetry between allies with respect to who will be more likely to “defect” from collaboration: in addition to firms with relatively great network centrality, those with more experience competing with other allies are also more likely to compete with their current partners. This suggests that the likelihood that allies will compete against each other is not evenly distributed within a dyad: the firm with either more advantageous network positioning or richer experience in managing the transition from collaboration to competition is more likely to do so.

Post hoc analysis 3 revealed an interesting relationship with respect to responses to competitive actions: more aggressive actions tend to provoke more acts of retaliation. This finding seems to be different from suggestions by traditional studies on competitive dynamics that aggressive competition (e.g., irreversible actions) tends to suffocate reactions (Chen & MacMillan, 1992). This is likely because those studies assume that competitors have no knowledge of each other ex ante, and thus compete as if they were strangers each time they encounter one another (Ketchen, Snow, & Hoover, 2004). As recent research indicates, traditional competitive dynamics studies assume a Markov or memory-less process of competition, in which only the current state matters in predicting subsequent states (Kilduff, Elfenbein, & Staw, 2010). Prior studies on competitive dynamics have overlooked the role of inter-firm learning (Nelson & Winter, 1982) in determining firms’ competitive interactions. Our finding suggests that when firms are alliance partners, the attacked firm is likely to respond to the aggressor’s actions, having developed the capacity to do so through alliance learning. This observation is echoed by two additional findings: first, that the attacked firm is more likely to respond if the number of repeated ties with the aggressor is high, because these ties can provide the attacked firm with ample knowledge regarding the aggressor, and therefore enable it to take effective retaliatory action; and, second, that the attacked firm is less likely to respond if it is either less centrally located within the alliance network or less experienced in managing the transition from collaboration to competition than the aggressor—situations in which the attacked firm is less informed.
and/or less capable of retaliating. Our findings thus complement the classic literature on competitive dynamics.

Our findings provide strong support for the recent conceptualization of competition as “relational” (Chen & Miller, 2015). Different from the traditional “rivalrous view” of competitive dynamics, which highlights a firm-centric perspective (Chen & Miller, 2015), the “relational” view emphasizes the necessity of understanding others’ needs and preferences, as well the interdependencies between self and others, before deciding on competitive moves. Our research extends this line of argument by suggesting that firms can increase their “relational” savvy through learning in various forms of interactions, including alliances (Lioukas & Reuer, 2015), competitions (Tsai, Su, & Chen, 2011), and the transition between the two; all of these relationships may inform subsequent competitive encounters.

5.1 Limitations and directions for future research

The findings of our study should be interpreted in light of its limitations, which suggest opportunities for future research. First, we examined our hypotheses only in the context of horizontal alliances in the U.S. pharmaceutical industry. Although the findings are strongly supportive of our hypotheses, we must be cautious about generalizing them to other collaboration types (e.g., vertical alliances) and other industries. Researchers may further advance this emerging research paradigm by considering the roles of alliance- and industry-specific conditions in the relationship between collaboration and competition.

Second, while the alliance learning perspective has provided important insights for the development of our theoretical framework, we are also aware that alliances are complex partnerships. This learning approach can be well complemented by other relevant theories, such as transaction-cost economics and the resource-based view. For example, researchers might explore how firms structure their alliances by taking governance and resources into consideration in order to prevent competition from allies.

Third, while we studied an important dimension of inter-firm competition (i.e., competitive aggressiveness) that has been extensively examined in the competitive dynamics literature, there are other dimensions of competition that are currently not included in our research. For example, we did not study competitive actions using such variables as action execution speed, action visibility, and competitor’s acumen (Chen & Hambrick, 1995; Tsai et al., 2011). There are also ample opportunities to study how alliance learning may affect different paradigms of product competition, such as the “racing” and “incumbent” types of competition (see Appendix S1 for descriptions of these paradigms). While our preliminary analysis suggests that the relationship between collaboration and competitive aggressiveness does not differ between these two scenarios, it may prove fruitful to examine whether and how the relationship between collaboration and the other dimensions of competition (e.g., speed, visibility, and acumen) may differ in these two scenarios or in other competitive paradigms. Studying these characteristics of competition will enrich our understanding of the competitive consequences of alliances.

Finally, while we compiled a comprehensive longitudinal dataset depicting alliances and competitions, the use of second-hand data constrained our ability to interpret the micro-level processes through which information and knowledge are leaked or appropriated through interactions among individuals, as well as the mechanisms through which decisions regarding new product introductions are made. For example, we were not able to measure tacit technological and managerial know-how in our data because of its low codifiability and visibility. Nor were we able to investigate the extent to which such tacit knowledge travels across technological and organizational boundaries. Despite
our modest attempts to address this issue in a post hoc analysis, we acknowledge that this is an important limitation of our study. Field research, such as intensive case studies and interviews, might uncover some of the latent and important processes that cannot be completely revealed by our present work. Future studies in this direction will be warranted.

6 | CONCLUSION

This study investigates an important yet overlooked relationship in the alliance literature: the impact of alliances on partners’ competition in the product market. Integrating alliance learning and network perspectives, we argue that the composition of the collaborative relationship between a firm and its partner affects the firm’s competition against this partner. We found an inverted U-shaped relationship between the firm’s relative exploration and its competitive aggressiveness against its partner in the market. This curvilinear relationship is flattened by their relational embeddedness (i.e., repeated ties) and structural embeddedness (i.e., common ties), but steepened by their positional embeddedness (i.e., relatively great centrality of the firm) within the alliance network. This study contributes to the literature on inter-firm dynamics between collaboration and competition, calling for more studies to investigate this intriguing area.

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REFERENCES


SUPPORTING INFORMATION

Additional Supporting Information may be found online in the supporting information tab for this article.

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