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RESEARCH ARTICLE

The invention performance implications of coopetition: How technological, geographical, and product market overlaps shape learning and competitive tension in R&D alliances

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Abstract

Research Summary: We examine how technological, geographical, and product market overlaps between a firm and its alliance partner influence the firm's invention performance by shaping the learning and competitive tension in an R&D alliance. Drawing on research on learning in alliances and competitive dynamics, we argue that the firm's invention performance is influenced positively by technological and geographical overlaps and negatively by product market overlap. We further argue that product market overlap negatively moderates the positive relationships between technological and geographical overlaps and the firm's invention performance. Testing our theory on a dataset of 215 R&D alliances provides support for most of our hypotheses. We discuss how our theory and findings enrich coopetition and alliance research.

Managerial Summary: Prominent R&D alliances, such as between BioNtech and Pfizer or Samsung and Sony, typify coopetition—the collaboration between competing firms. In this context of coopetition, we study how a firm's invention performance is influenced by the technological, geographical, and product market overlaps it has with its R&D alliance partner. Empirical results from a sample of 215 R&D alliances formed between U.S. pharmaceutical firms confirm our theory that product market overlap is distinct from the other types of overlap: it changes the thrust of the alliance from joint value creation toward private value appropriation. This way, product market overlap not only decreases a firm's invention performance, but also weakens the positive impacts of technological and geographical overlaps on a firm's invention performance.

KEYWORDS

competitive dynamics, coopetition, invention performance, learning in R&D alliances, product market overlap

1 | INTRODUCTION

Coopetition refers to firms' simultaneous engagement in cooperation and competition (Brandenburger & Nalebuff, 1996). The phenomenon is gaining traction among practitioners and researchers (e.g., Garrett, 2019; Gnyawali & Charleton, 2018), especially in the context of research and development (R&D) alliances (e.g., Gnyawali & Park, 2011; Ryu, Reuer, & Brush, 2020). An R&D alliance between competing firms can be both rewarding and challenging due to its dual logics (Hoffmann, Lavie, Reuer, & Shipilov, 2018). On the one hand, such an alliance offers learning chances due to the firms' similarities (e.g., in technologies); on the other hand, such an alliance can increase the risk of knowledge misappropriation. This risk may induce competitive tension, which undermines cooperation, a firm's learning, and its subsequent performance (e.g., Gnyawali & Park, 2011; Park & Russo, 1996).

To reconcile how a firm can cope with these dual logics, recent work discusses the role of administrative governance controls (e.g., Devarakonda & Reuer, 2018) and the separation of cooperative and competitive activities using organizational buffers such as firewalls (Hoffmann et al., 2018). As coping with the dual logics also requires knowledge about the salience of learning and competitive tension in an alliance, some studies have begun to examine how market, technological, and geographical overlaps between partners impact a firm's invention performance (Park, Srivastava, & Gnyawali, 2014a, 2014b; Yan, Dong, & Faems, 2020). While most studies claim that market overlap fosters competitive tension within the alliance (e.g., Park et al., 2014a, 2014b), some studies argue that it increases learning owing to shared commercial logics (e.g., Yan et al., 2020). Regarding technological and geographical overlap, most studies claim that they support learning (e.g., Lane & Lubatkin, 1998; Reuer & Lahiri, 2014), while others suggest that these overlaps may lead to competitive tension due to knowledge leakage risks (Devarakonda & Reuer, 2018; Ryu, McCann, & Reuer, 2018; Yan et al., 2020).

Thus, the literature presents diverging arguments on whether the different dimensions of overlap foster learning or create competitive tension in an alliance. To reconcile the diverging arguments, there is a need for theory that untangles how the different dimensions of overlap individually and collectively shape the salience of *both* learning and competitive tension in an alliance. In this regard, it must be noted that there are no prior studies dealing with *product* market overlap although competitive dynamics research considers it a direct predictor of competitive tension (Chen, 1996; Chen, Su, & Tsai, 2007). Instead, prior studies have focused on market overlap in terms of industry relatedness (e.g., Park et al., 2014a, 2014b), which is problematic as industry relatedness also captures business similarity (e.g., Asgari, Tandon, Singh, & Mitchell, 2018; Wang & Zajac, 2007). These deficits may be one reason for the inconclusive empirical findings on the invention performance implications of coopetition (e.g., Dorn, Schweiger, & Albers, 2016; Ritala, 2012).

This study examines how technological, geographical, and product market overlaps between a firm and its partner individually and collectively influence the firm's invention performance by shaping the learning and competitive tension in an R&D alliance. We define invention performance as the extent to which the firm generates novel technological knowledge in terms of the number and technological value of its patented inventions (Ahuja & Katila, 2001; Cirillo, 2019). To untangle how the salience of learning and competitive tension unfolds in an R&D alliance, we draw on insights from research on learning in alliances (Easterby-Smith, Lyles, & Tsang, 2008; Gomes-Casseres, Hagedoorn, & Jaffe, 2006) and competitive dynamics (Chen, 1996; Chen & Miller, 2012). Based on the former, we argue that technological, geographical, and product market overlaps influence the firm's invention performance by shaping its motivation, ability, and opportunity to learn from its partner. Based on the latter, we argue that these overlaps also shape the firm's awareness of its competitive relationship with its partner and its motivation and capability to compete, which determine the salience of competitive tension in the alliance. Consolidating these perspectives, we argue that the firm's invention performance is influenced positively by technological and geographical overlaps and negatively by product market overlap. We also examine how product market overlap, as a moderator, undermines the learning and magnifies the competitive tension mechanisms in the relationships between technological and geographical overlaps and the firm's invention performance. We test our hypotheses on a dataset of 215 R&D alliances formed between 1996 and 2013 by 94 U.S. pharmaceutical firms.

This study offers two main contributions. First, we advance prior coopetition research that examines the invention performance implications of different dimensions of overlap (Park et al., 2014a, 2014b; Yan et al., 2020). We extend this research by developing theory that simultaneously incorporates alliance learning and competitive tension mechanisms. Our theory reveals that product market overlap is the only type of overlap that fosters the firm's awareness of a competitive relationship with its partner, its capability, and motivation to compete. The resulting competitive tension undermines cooperation and learning within the alliance; thus, product market overlap impedes the firm's invention performance. By contrast, technological and geographical overlaps increase the firm's awareness of a competitive relationship with its partner and its capability to compete *without* affecting its motivation to compete. Therefore, technological and geographical overlaps do not induce competitive tension. Instead, they foster learning and, in turn, the firm's invention performance.

Second, we contribute to coopetition (e.g., Park et al., 2014b; Yan et al., 2020) and alliance research (e.g., Devarakonda & Reuer, 2018, 2019; Wehrheim & Palomeras, 2021) by explaining that product market overlap can function as a *master switch* that changes the thrust of the alliance from joint value creation toward private value appropriation. According to our theory, product market overlap introduces a firm's motivation to compete in the relationships between technological and geographical overlaps and the firm's invention performance. This implies that prior research on the role of technological (e.g., Oxley & Sampson, 2004) and geographical (e.g., Gomes-Casseres et al., 2006) overlaps in R&D alliances should be expanded by considering product market overlap as a boundary condition.

2 | THEORY

2.1 | Learning in R&D alliances and invention performance

R&D alliances are formal agreements between firms to cooperate in R&D. Such alliances enable a firm to access and absorb new knowledge from its partner (e.g., Hagedoorn, 2002; Reuer & Lahiri, 2014). The firm can recombine the new knowledge with its existing knowledge, within and beyond the terms of the alliance (Frankort, 2016; Sampson, 2007). This learning increases the firm's likelihood of generating inventions (e.g., Ahuja & Katila, 2001).

Past R&D alliance research highlights that the firm's learning is influenced by its motivation, ability, and opportunity to learn from its partner (e.g., Hamel, 1991; Lane, Koka, & Pathak, 2006). The motivation to learn refers to the extent to which the firm is willing to devote time and resources to learning from its partner (Park et al., 2014b; Szulanski, 1996). The ability to learn refers to the firm's capacity to absorb (i.e., recognize, assimilate, and apply) the partner's knowledge (Cohen & Levinthal, 1990; Lane & Lubatkin, 1998). Finally, the opportunity to learn refers to the extent to which the knowledge of the partner is novel to the firm and offers valuable knowledge recombination opportunities (Ahuja & Katila, 2001; Nooteboom, Vanhaverbeke, Duysters, Gilsing, & van den Oord, 2007). Research highlights that a decline in the motivation, ability, or opportunity to learn increases the likelihood of knowledge transfer frictions (Faems, Bos, Noseleit, & Leten, 2020; Ghosh & Rosenkopf, 2015). These frictions may impede the firm's learning within the R&D alliance and negatively affect its invention performance.

While prior R&D alliance research acknowledges the benefits of learning in alliances, studies also emphasize that such learning benefits can be undermined by competitive tension between the partners (Das & Teng, 2000; Khanna, Gulati, & Nohria, 1998). Competitive tension can emerge when partners not only cooperate in one domain but also compete in the same or another domain, which may induce them to act opportunistically (Das & Teng, 2000; Hamel, 1991; Khanna et al., 1998). This can evoke suspicion between partners and reduce their openness within the alliance (e.g., Gnyawali & Charleton, 2018; Hamel, 1991). In this way, competitive tension can undermine cooperation and limit the potential for joint value creation (e.g., Park & Russo, 1996). However, the alliance and coopetition literature have paid limited attention to untangling the sources of competitive tension. To examine the emergence of competitive tension in R&D alliances in greater detail, we draw on insights from research on competitive dynamics (Chen, 1996; Chen & Miller, 2012).

2.2 | Sources of competitive tension in R&D alliances

According to competitive dynamics research, competitive tension is a latent strain that a firm experiences owing to the potential for competitive actions (e.g., price cuts, and market entry) by another firm (Chen et al., 2007; Chen & Miller, 2012). The degree of competitive tension between two firms depends on the extent to which they are: *aware* of their competitive relationship, *motivated*, and *capable* to compete (e.g., Chen, 1996; Chen & Miller, 1994). All three mechanisms must be present for competitive tension to manifest (Chen et al., 2007).

Drawing on these insights, we argue that a firm experiences competitive tension in an R&D alliance owing to the potential for competitive actions by its partner. Competitive actions in R&D alliances relate to a firm's opportunistic behavior such as the misappropriation of knowledge from the partner (Das & Teng, 2000; Ryu et al., 2020). A firm's awareness of a competitive relationship refers to the degree to which it is aware of its partner's potential for competitive actions. The motivation to compete refers to a firm's willingness to exert efforts to maximize its own interest at the expense of its partner. Finally, the capability to compete refers to a firm's ability to exploit misappropriated knowledge and to its repertoire to undertake competitive actions against its partner. Next, we examine how technological, geographical, and product market overlaps between a firm and its partner influence the firm's invention performance by shaping the learning and competitive tension mechanisms in an R&D alliance.

2.3 | The direct effects of technological, geographical, and product market overlaps

We argue that technological overlap, defined as the degree of similarity in the technological knowledge domains of a pair of firms (Jaffe, 1986), is positively associated with the firm's invention performance. First, a greater overlap in technological knowledge domains implies that more of the partner's technological knowledge has interlinkages with the firm's existing knowledge, which may increase the firm's motivation to learn from its partner. Second, technological overlap tends to foster the firm's ability to learn, as the firm and its partner increasingly share a common framework, which facilitates interfirm learning and knowledge transfer (e.g., Gomes-Casseres et al., 2006; Lane & Lubatkin, 1998). Such common framework enables the firm to recognize, assimilate, and apply valuable knowledge from its partner, which increases its absorptive capacity (Cohen & Levinthal, 1990; Knoben & Oerlemans, 2006). In addition, more overlapping technological knowledge domains can increase the breadth of knowledge recombination opportunities in an alliance (Lane & Lubatkin, 1998; Nooteboom et al., 2007). Nonetheless, technological overlap may also imply that there is less novel knowledge to be gained from the partner (Nooteboom et al., 2007; Sampson, 2007). However, studies suggest that in industries that are discrete and rich in technological capital (e.g., pharma and chemical industry; Corsino, Mariani, & Torrisi, 2019), valuable learning and recombination opportunities can be found in even a few novel technological components (Ahuja, 2000; Lane & Lubatkin, 1998; Nooteboom et al., 2007).[1] This reasoning is in line with Devarakonda and Reuer (2018), who argue in favor of a positive relationship between technological overlap and knowledge sharing in biopharmaceutical R&D alliances. Thus, greater technological overlap likely promotes the firm's learning of new knowledge by fostering its motivation, ability, and opportunity to learn from its partner. This learning, in turn, increases the firm's likelihood of generating valuable inventions.

[1]This argument is consistent with figs. 2–4 in Nooteboom et al. (2007), which show that firms that are rich in technological capital experience a positive impact of technological overlap on innovation performance.

Technological overlap may also influence the firm's awareness, motivation, and capability to compete. The greater the overlap, the higher the likelihood that the firm and its partner will engage in the same research communities and interest groups (e.g., Lane & Lubatkin, 1998). This engagement may heighten the firm's awareness of its partner's technology-related competitive actions. In addition, technological overlap may increase the potential for contention over scientists and technical equipment (e.g., Markman, Gianiodis, & Buchholtz, 2009). However, such interdependencies in resource markets tend to be less direct and visible, and thus, are unlikely to motivate competitive actions (Barney, 1991; Chen, 1996). Last, technological overlap may foster the firm's capability to compete by increasing its capacity to misappropriate its partner's knowledge (e.g., Devarakonda & Reuer, 2018) and extending its technological repertoire to undertake competitive actions against its partner (e.g., Andrevski & Ferrier, 2019; Ndofor, Sirmon, & He, 2011). Especially when the upstream and downstream activities of the firm and its partner are tightly coupled, technological overlap can imply that the firm has a higher capacity to develop novel products that challenge its partner's market position (Duysters, Lavie, Sabidussi, & Stettner, 2020; Frankort, 2016). Thus, while technological overlap increases the firm's awareness and capability to compete, it is unlikely that the motivation to compete is triggered. However, a motivation to compete must be in place for competitive tension to manifest (Chen et al., 2007). Hence, technological overlap likely fosters knowledge flows between the firm and its partner. This increases the firm's knowledge recombination opportunities and augments its capacity for making novel linkages.[2] Accordingly, technological overlap likely improves the firm's invention performance.

> **Hypothesis 1.** *Technological overlap between a firm and its partner in an R&D alliance is positively related to the firm's invention performance.*

We also argue that geographical overlap, defined as the degree of physical proximity between the headquarters of a pair of firms (Reuer & Lahiri, 2014), is positively associated with the firm's invention performance. Prior research notes that closer physical proximity helps build relational capital between the firm and its partner and increases the probability that they are embedded in the same local communities (e.g., Borgatti & Cross, 2003; Saxenian, 1994). The resulting ease of comparison and the desire to look good in the local community can motivate the firm to learn from its partner and commit to joint R&D activities (Kale, Singh, & Perlmutter, 2000). In addition, closer physical proximity can reduce barriers to interfirm knowledge flows (e.g., Gomes-Casseres et al., 2006; Rosenkopf & Almeida, 2003). For example, prior studies indicate that closer physical proximity increases the likelihood of face-to-face interactions, such as visits to the partner's labs, joint experiments, and personnel exchanges (e.g., Doz, 2017; McCann, Reuer, & Lahiri, 2016). As such face-to-face interactions are information rich (e.g., McCann et al., 2016), geographical overlap likely augments the firm's ability and opportunity to learn. Thus, a greater geographical overlap likely increases the firm's motivation, ability, and opportunity to learn from its partner. This learning, in turn, increases the firm's likelihood of generating valuable inventions.

[2]We acknowledge that greater knowledge flows may imply greater knowledge outflow from a firm to its partner, which can spur new inventions by the partner. In turn, the firm's knowledge recombination space could be restricted, perhaps negatively affecting its invention performance (Yan et al., 2020). Hence, one could argue that less knowledge transfer might benefit a firm's invention performance—an issue we explore in an auxiliary analysis.

Geographical overlap can also influence the firm's awareness, motivation, and capability to compete. Due to an increasing number of overlapping local networks and greater regional employee mobility, closer physical proximity can increase the firm's awareness of its partner's strengths and weaknesses (Chen & Miller, 2012, 2015). In addition, geographical overlap may increase the potential for contention over local aspects such as property, technical infrastructure, and skilled workers (e.g., Baum & Mezias, 1992; Chang & Xu, 2008; Porter, 2000), which could increase the firm's motivation to compete. However, the higher likelihood of a shared local network also implies that acting competitively could damage the firm's reputation in its own network (Granovetter, 1985; Gulati, 1998). Moreover, prior research indicates that frequent personal interactions may reduce the firm's motivation to compete against its partner (Kale et al., 2000). Finally, geographical overlap may foster the firm's capability to compete by increasing the availability of informal (e.g., social gatherings and common stakeholders) and formal (e.g., interfirm mobility of scientists) information channels through which the firm may obtain sensitive knowledge about its partner (Jaffe, Trajtenberg, & Handerson, 1993; Ryu et al., 2018). Thus, geographical overlap increases the firm's awareness and its capability to compete. However, it is unlikely to foster the firm's motivation to compete, which must be in place for competitive tension to manifest (Chen et al., 2007). Hence, geographical overlap tends to foster knowledge flows between the firm and its partner. This increases the firm's knowledge recombination opportunities and augments its capacity for making novel linkages. Therefore, we expect geographical overlap to increase the firm's invention performance.

> **Hypothesis 2.** *Geographical overlap between a firm and its partner in an R&D alliance is positively related to the firm's invention performance.*

Moreover, we argue that product market overlap, defined as the degree of similarity between the product markets of a pair of firms (Hoberg & Phillips, 2010), negatively influences the firm's invention performance. First, greater overlap in the product market strengthens the firm's motivation to learn from its partner, as internalizing the partner's knowledge increases the chance that the firm can generate inventions that are relevant for its product market (e.g., Hamel, 1991; Lado, Boyd, & Hanlon, 1997). Second, product market overlap suggests that the firm and its partner have more similar commercial logics (e.g., Dussauge, Garrette, & Mitchell, 2000), which increases the firm's ability to learn from the partner (Lane & Lubatkin, 1998; Yan et al., 2020). Third, product market overlap may diminish the novelty of the partner's market knowledge for the firm. This may give the firm fewer opportunities to learn something new about the product market from its partner, and thereby reduce its likelihood of generating inventions from a demand side perspective. Thus, greater product market overlap increases the firm's motivation and ability to learn but decreases its opportunity to learn from its partner. This can impede the firm's learning in the R&D alliance and, in turn, the firm's likelihood of generating valuable inventions.

In addition, the more the firm and its partner overlap in product markets, the higher the likelihood and frequency of market encounters (Chen, 1996). In turn, the firm is likely to monitor its partner more closely and to be more aware of the partner's competitive strengths and weaknesses (e.g., Markman et al., 2009; Peteraf & Bergen, 2003). Product market overlap also implies that acting competitively in the alliance may improve the firm's market position *vis-à-vis* its partner and thereby increase its revenues (e.g., Chen, 1996; Das & Teng, 2000; Frankort, 2016). Hence, product market overlap increases the firm's motivation to compete. Finally, operating in more similar product markets means that the firm and its partner have a better understanding of each other's customers and have more opportunities to undertake competitive actions (e.g., price cuts; Chen, 1996). Thus, product market overlap increases the firm's awareness, motivation, and capability to compete, which leads to competitive tension in the alliance. As a result, the partner tends to be more suspicious of the firm and to reduce its openness (e.g., Gnyawali & Charleton, 2018; Hamel, 1991). This limits the firm's acquisition of its partner's knowledge (e.g., Inkpen, 2000), which impedes the firm's knowledge recombination opportunities and, in turn, its invention performance.

Hypothesis 3. *Product market overlap between a firm and its partner in an R&D alliance is negatively related to the firm's invention performance.*

2.4 | Product market overlap as the master switch

Our theory discerns that product market overlap is the only type of overlap that increases the firm's motivation to compete. Thus, product market overlap can induce the firm to exploit knowledge misappropriation opportunities in the alliance instead of pursuing common objectives. To this end, beyond its direct negative impact on the firm's invention performance, product market overlap may serve as a master switch that changes the thrust of an R&D alliance from joint value creation toward private value appropriation. Based on this idea, we next examine the moderating role of product market overlap in the relationships between technological and geographical overlaps and the firm's invention performance.

We argue that with increasing product market overlap, technological overlap even more increases the firm's motivation to learn because technological knowledge obtained from the partner is more likely to be directly applicable in the market. Given that technological overlap facilitates two-way knowledge flows between the firm and its partner, increases in product market overlap motivate the firm to internalize its partner's technological knowledge as much and as quickly as possible. Thereby, the firm makes sure it gains more knowledge from the partner than it loses and does not end up in a worse market position than it was prior to the alliance. When the partner reacts reciprocally, the alliance partners engage in a "learning race" (Hamel, 1991; Lavie, 2006). The ability to learn is also fostered when the firm and its partner increasingly share technological and commercial logics as the effectiveness of communication between them further improves (e.g., Dussauge et al., 2000; Lane & Lubatkin, 1998). However, increasing product market overlap decreases the firm's learning opportunities owing to technological overlap. A single novel technological knowledge component can offer a broad range of valuable learning and recombination opportunities and thereby spur inventions (e.g., Bresnahan & Trajtenberg, 1995). However, when the firm and its partner also increasingly share commercial logics, the partner more likely already uses its technological components in commercial ways that are similar to the firm's. In turn, product market overlap may reduce the extent to which the firm finds something novel and worth learning from the partner based on technological overlap. Thus, product market overlap likely magnifies the motivation and ability to learn in the relationship between technological overlap and invention performance. However, it also likely decreases the opportunity to learn, which impedes the firm's learning and its likelihood of generating valuable inventions.

Moreover, we argue that, when product market overlap increases, technological overlap additionally fosters the firm's awareness of its partner's technology-related competitive actions, given that such actions ultimately threaten the firm's competitive position in the shared product markets (e.g., Bergen & Peteraf, 2002; Chen, 1996). Further, an increase in product market overlap makes the potential for contention over resource markets associated with technological overlap more visible and direct due to its immediate implications for the firm's competitive position and bottom line. Thus, with an increase in product market overlap, technological overlap fosters the firm's motivation to compete. Finally, product market overlap increases the extent to which technological overlap fosters the firm's capability to compete. With increasing product market and technological overlap, the firm not only has the capability to appropriate technological knowledge but also the market expertise to use this knowledge effectively against its partner. In sum, with increasing product market overlap, technological overlap fosters the firm's awareness, capability, and motivation to compete, which creates competitive tension. As a result, the partner may limit transparency and increase knowledge-protection mechanisms. This undermines cooperation, restricts knowledge exchange, and limits the potential for joint value creation (e.g., Hamel, 1991; Park & Russo, 1996), impeding the firm's knowledge recombination opportunities and invention performance.

Hypothesis 4. *The positive relationship between technological overlap between a firm and its partner in an R&D alliance and the firm's invention performance is negatively moderated by their product market overlap.*

Finally, we consider the moderating role of product market overlap in the relationship between geographical overlap and the firm's invention performance. We argue that, when product market overlap increases, geographical overlap additionally fosters the firm's motivation to learn so that it looks good in the shared local and market community (Porter, 2000). Further, more similar commercial logics between the firm and its partner enhance the firm's ability to learn from face-to-face interactions owing to geographical overlap (e.g., Dussauge et al., 2000; Lane & Lubatkin, 1998). However, increasing product market overlap decreases the firm's learning opportunities owing to geographical overlap. Geographical overlap facilitates more face-to-face interactions, and these offer a broad range of learning opportunities. However, when the firm and its partner also increasingly share commercial logics, the partner will likely already apply knowledge in commercial ways that are similar to the firm's. As a result, product market overlap may reduce the extent to which the firm can gain something novel and worth learning through its face-to-face interactions with the partner. Thus, while product market overlap may foster the firm's motivation and ability to learn in the relationship between geographical overlap and the firm's invention performance, it may decrease the firm's opportunity to learn. This impedes the firm's learning of new knowledge from the partner and, consequently, its likelihood of generating valuable inventions.

Product market overlap may also influence the salience of the firm's awareness, motivation, and capability to compete in the relationship between geographical overlap and invention performance. With increasing product market overlap, geographical overlap causes a firm to become even more aware of the potential competitive actions undertaken by the partner because their local networks are likely to overlap even more. The presence of a larger number of shared local networks can provide the firm with more information on the partner's planned and concurrent actions (e.g., Gnyawali, He, & Madhavan, 2006; Yu & Cannella, 2007). Geographical overlap also increases the likelihood of frequent direct and indirect interactions between the firm and its partner, thereby increasing cooperative behavior. However, we argue that, with increasing product market overlap, those frequent interactions result in head-to-head comparisons between the firm and its partner (e.g., Porter, 2000). Such comparisons can intensify the firm's motivation to compete (e.g., Derfus, Maggitti, Grimm, & Smith, 2008), as the advantages of a competitive action may then outweigh the potential for reputation damage in the local network. Finally, product market overlap may increase the extent to which geographical overlap fosters the firm's capability to compete. That is, product market overlap increases the likelihood that inadvertent knowledge spillovers emerging from interactions or poached employees can be used by the firm against its partner in the shared product market. In sum, with increasing product market overlap, geographical overlap fosters the firm's awareness, capability, and motivation to compete, which creates competitive tension. Consequently, the partner may limit its transparency and establish knowledge-protection mechanisms, which undermines cooperation, restricts knowledge exchange, and limits the potential for joint value creation (e.g., Hamel, 1991; Park & Russo, 1996). This impedes the firm's knowledge recombination opportunities and invention performance.

> **Hypothesis 5.** *The positive relationship between geographical overlap between a firm and its partner in an R&D alliance and the firm's invention performance is negatively moderated by their product market overlap.*

3 | METHODS

3.1 | Data and sample

We tested our hypotheses on a dataset of 215 R&D alliances formed by 94 U.S. pharmaceutical firms (SIC codes 2834, 2836) between 1996 and 2013. The pharmaceutical industry provides an appropriate setting to test our hypotheses because its firms rely extensively on intraindustry R&D alliances and patenting (Kotha, Zheng, & George, 2011; Powell, Koput, & Smith-Doerr, 1996). We took 1996 as the beginning of the observation window and focused on U.S. firms because data regarding the firms' product markets were not available for earlier time periods or outside the U.S. (Hoberg & Phillips, 2016). We took 2013 as the end of the observation window to allow for adequate time after alliance formation for inventions to be patented.

To identify pharmaceutical firms' R&D alliances, we used the SDC Platinum database on strategic alliances and joint ventures, which Schilling (2009) describes as the most comprehensive source on technology alliances. We validated the alliance information in ambiguous cases using the LexisNexis news database and the U.S. Securities and Exchange Commission's (SEC) 10-K filings. Our search yielded 399 alliances formed by a firm with primary operations in SIC 2834 or 2836 with any other U.S. publicly traded firm during the sampling period. Subsequently, we excluded alliances in which the partner was not a pharmaceutical firm (with primary operations in SIC codes 2834 or 2836). In line with our theory, we considered an alliance twice in the data (i.e., from the perspective of each firm). This yielded 246 alliances.

We supplemented alliance data with information on patents from PATSTAT, a worldwide patent database compiled by the European Patent Office (Devarakonda & Reuer, 2018), and with information on the firms' product markets (Hoberg & Phillips, 2010). Finally, we obtained financial data from Compustat and complemented missing information with data from SEC 10-K filings, Bloomberg, and corporate annual reports. Overall, we collected data on 406,469 patents, 2.6 million citations, and 48,454 kilobytes of text from 246 SEC 10-K filings. Owing to missing data for product market overlap or R&D expenditures in 31 alliances, we applied listwise deletion (e.g., Gulati, Lavie, & Singh, 2009), which yielded 215 alliances formed by 94 firms.

3.2 | Dependent variable

We measured *invention performance* at the firm level using a value-weighted invention count of patents, as they are a key metric of inventions in the pharmaceutical industry (e.g., Aggarwal, 2020; Caner, Cohen, & Pil, 2017). This approach is in line with our theorizing that opportunities to recombine existing knowledge with new knowledge may occur within and beyond the terms of a firm's R&D alliance (Frankort, 2016; Sampson, 2007). We aggregated patent counts to the firm-year level and calculated invention performance as the sum of a firm's value-weighted patents over the alliance's duration. As alliance termination dates are rarely reported, we had to make an assumption about the alliance duration (e.g., Schilling & Phelps, 2007). Consistent with the approach in prior research (e.g., Kang & Zaheer, 2018; Sampson, 2007) and statistics on the average alliance duration (e.g., Lavie, Haunschild, & Khanna, 2014), we used a 4-year window, with a 1-year lag after alliance announcement (i.e., over the years $t+1$ to $t+4$, where t is the alliance announcement year).[3] In order to weigh the patents according to their value, we followed the approach of Cirillo (2019) and used a weighted index of the number of claims awarded to a patent, the forward citations a patent received within 5 years of application, and the backward citations a patent made to prior patents (see Appendix 1 for more details).[4]

Next, we describe the measurement of our independent and control variables, which are all measured in t to ensure a 1-year lag with respect to the dependent variable.

3.3 | Independent variables

To measure *technological overlap*, we assessed the similarity of the firms' technological profiles in year t. Following Jaffe (1986), we measured the technological profile of each firm by considering the distribution of all patents across technology classes applied for until the year of alliance formation (Devarakonda & Reuer, 2018; Schmoch, 2008). Subsequently, we calculated technological overlap as the uncentered correlation coefficient of the firms' technological profiles (Oxley & Sampson, 2004; Sampson, 2007). This measure was bounded between 0 and 1 (with a value of 1 indicating complete technological overlap).

To measure the *geographical overlap* between firms, we used data on the zip code of the firms' headquarters in year t. On the basis of this information, we calculated the latitudes and longitudes of the locations and applied the great circle distance formula (Reuer & Lahiri, 2014):

$$D_{ij} = r \times \arccos\left[\sin(\text{lat}_i) \times \sin(\text{lat}_j) + \cos(\text{lat}_i) \times \cos(\text{lat}_j) \times \cos\left(\text{long}_j - \text{long}_i\right)\right], \tag{1}$$

where D is the distance in miles, i is the firm, j is the partner, and r is the radius of the earth (i.e., $r = 3{,}963$). Latitude (lat) and longitude (long) were converted into radians. We log-

[3]For example, if an alliance was announced in 2000, the invention performance would be the sum of the value-weighted patents applied for in 2001–2004. Our results are robust to using a 3- or 5-year window.

[4]Our results are robust to employing forward citations as a single indicator of patent value.

transformed geographical distance to account for distance decay (Chakrabarti & Mitchell, 2016).[5] Finally, we reverse-coded geographical distance to obtain our measure of geographical overlap, ranging between 0 and 1 (where 1 indicates the highest possible geographical overlap).

To measure the *product market overlap* between the firms, we relied on a measure established by Hoberg and Phillips (2010) that captures the extent to which the firms had overlapping product markets in year *t*. Hoberg and Phillips (2010) used computer-aided text analysis of firms' product descriptions in SEC 10-K filings to determine product similarity between them.[6] The SEC 10-K filings contain a section, in either Item 1 or Item 1A, describing the products a firm offers. A key advantage of these data is that they allow us to dynamically capture the unique degree of product similarity for each pair of firms with high reliability, as the data are legally required to be accurate and updated in the current fiscal year (Shi, Zhang, & Hoskisson, 2017). Furthermore, the data impose no restrictions on firms' product market space and consider firms' corporate product diversification (Chen, Kale, & Hoskisson, 2018). Thus, they also address product and industry changes; this aspect is important, given that firms may introduce and discontinue products over time.

To compute the product similarity between two firms *i* and *j*, Hoberg and Phillips (2010) used the widely accepted basic cosine similarity method (e.g., Angus, 2019). First, they built a main dictionary by creating a list of unique words (e.g., "N" words) used in all the product descriptions in each year. For each firm, they constructed a binary N-vector ("V") to characterize its word usage and normalized the vector to unit length. Subsequently, the product market overlap between firm *i* and firm *j* is measured by taking the multiplicative product of their normalized N-vectors:

$$\text{Product market overlap}_{i,j} = V_i \times V_j \tag{2}$$

The measure is time-variant and continuous (bounded between 0 and 1), with a higher score indicating a higher product market overlap in year *t* (Hoberg & Phillips, 2010, 2016).[7] Compared to conventional industry-based measures (e.g., SIC- or NAICS-based), the product similarity measure better explains, for example, the extent to which managers mention competition in the "Management's Discussion and Analysis" section of the SEC 10-K filings and the extent to which firms are mentioned by managers as being competitors (Hoberg & Phillips, 2016). The measure is established and used in research on strategy (e.g., Chen et al., 2018), marketing (e.g., Kashmiri, Nicol, & Hsu, 2017), innovation (e.g., Li, Qiu, & Wang, 2019), and finance (e.g., Grullon, Larkin, & Michaely, 2019).

3.4 | Control variables

We included various control variables in our analyses. At the firm level, we controlled for *firm size* (the natural logarithm of a firm's total assets), *firm age* (the natural logarithm of a firm's years since

[5]Our empirical results are robust to alternative specifications such as a negative power, an exponential weight distance function (e.g., Faems et al., 2020; Taylor, 1971), or a binary specification of geographical overlap in which two firms are said to be overlapping ("co-located") when they are located within a 50-mile radius (Ryu et al., 2018).

[6]The data were obtained from the Hoberg-Phillips Data Library (http://hobergphillips.tuck.dartmouth.edu).

[7]Our empirical results are robust to considering the average product market overlap between the firms for the 5 years preceding alliance formation (i.e., $t - 4$ to t).

incorporation), and *firm R&D expenditures* (measured in billions of U.S. dollars) (Cohen & Levinthal, 1990; Frankort, 2016). As a firm's accumulated experience in managing alliances may contribute to its ability to extract benefits from an R&D alliance, we also controlled for *firm alliance experience* by counting the number of alliances a firm had formed in the 5 years preceding the alliance (Sampson, 2005; Stuart, 2000). In addition, we counted a firm's total number of prior alliances with the partner (*firm prior ties*)—a greater number of prior alliances may enhance the relational assets in a relationship but it also indicates less novelty of the existing partner's knowledge in the current relationship (e.g., Dyer, Singh, & Hesterly, 2018; Kavusan & Frankort, 2019).

We included additional controls related to potential differences in a firm's awareness, motivation, and capability to compete. Given that a smaller firm will be more aware of and concerned about potential competitive actions initiated by a relatively larger firm (Chen et al., 2007), we controlled for *firm relative scale*, calculated as the firm's assets divided by the partner's assets. Moreover, since firms with poor past performance may be more motivated to compete and firms with greater financial slack may be more capable of competing (Ferrier, 2001), we included *firm past performance* using return on assets and *firm financial slack* using current assets less inventory divided by current liabilities. As market concentration shapes a firm's competitive aggressiveness (e.g., Fosfuri & Giarratana, 2009; Sutton, 1991), we controlled for a firm's *market pressure* using the Herfindahl–Hirschman Index (HHI) of peer firms' revenues (Hoberg & Phillips, 2010, 2016), which we also obtained from the Hoberg–Phillips Data Library. Since a higher HHI score indicates a decrease in market pressure, we reverse-coded the measure. Using the upstream vertical-relatedness measure from Frésard, Hoberg, and Phillips (2019), we controlled for *firm vertical relatedness* with the R&D partner since such relatedness may reduce the partner's willingness to disclose valuable knowledge to the firm owing to the potential for backward integration. Finally, to account for *firm geographical dispersion*, and hence the importance or weight of the geographical overlap for a firm (Baum & Korn, 1996), we used a novel validated measure developed by Chen et al. (2018) to count the number of U.S. states where a firm has business activities using data from SEC 10-K filings.

We also controlled for alliance-level characteristics by accounting for whether the *alliance scope* is broad, that is, includes manufacturing and/or marketing in addition to R&D (coded as 1; otherwise 0), which may influence knowledge misappropriation hazards and knowledge sharing in an alliance (e.g., Lioukas & Reuer, 2020; Oxley & Sampson, 2004). We also controlled for *alliance partner geographical dispersion* (Chen et al., 2018) and for whether the alliance is organized as an *equity joint venture* (coded as 1; otherwise 0).

Finally, in line with prior research (e.g., Hess & Rothaermel, 2011), we took several steps to minimize unobserved heterogeneity and a potential bias due to endogeneity. First, to reduce the risk of omitted variable bias and rule out alternative explanations, we collected extensive data on control variables (as outlined above). Second, to address the risk of additional unobserved endogeneity in the cross-section dimension, we employed *firm fixed effects* (Bloom, Schankerman, & Van Reenen, 2013; Blundell, Griffith, & Windmeijer, 2002), as explained in more detail in the next section. Third, to account for potential remaining heterogeneity in firms' *business similarity* (Gulati et al., 2009; Koh & Venkatraman, 1991; Wang & Zajac, 2007), we used the information on the firms' four-digit SIC code and included a set of four dummy variables capturing all possible combinations of business similarity in terms of the industry and industry overlap in our sample (i.e., Biotech-Biotech, Pharma-Pharma, Biotech-Pharma, and Pharma-Biotech alliance; e.g., Devarakonda & Reuer, 2018).[8] Fourth, we employed *year fixed effects* by including dummy variables corresponding to each year of alliance formation

[8]Employing separate variables for a firm's and its partner's industry and their overlap yields identical results.

(1996–2013) in order to control for temporal differences in macroeconomic conditions and unobserved factors systematically associated with the years (Stuart, 2000). Finally, in line with Hess and Rothaermel (2011), we reduced the risk of potential simultaneity bias, by lagging the independent and control variables by 1 year with respect to the dependent variable.

3.5 | Estimation method

In line with our conceptualization of a firm's invention performance in an R&D alliance, our unit of analysis is each focal firm alliance. As our dependent variable is a count variable (the number of a firm's value-weighted patents), and as we found significant evidence of over-dispersion ($\alpha = 1.073$; $p <.00$), we chose the negative binomial regression model to obtain consistent and unbiased estimates (Long & Freese, 2014). However, employing firm fixed effects is more complex in negative binomial regression models than in standard regression models (Hilbe, 2011). We followed prior research (e.g., Bloom et al., 2013; Boone, Lokshin, Guenter, & Belderbos, 2019; Li et al., 2019) and employed the presample mean estimator introduced by Blundell et al. (2002), which relies on presample means as an initial condition to proxy for unobserved heterogeneity (Bloom et al., 2013).[9] The advantage of employing this fixed effects estimator for count data (Bloom et al., 2013; Li et al., 2019) is its explicit suitability for the analysis of patents (Blundell et al., 2002). Monte Carlo evidence from Blundell et al. (2002) indicates that this estimator outperforms alternative econometric estimators in such analyses, for which reason it was suggested for the inclusion of fixed effects in empirical models that do not allow for standard approaches (Bettis, Gambardella, Helfat, & Mitchell, 2014).

We standardized independent variables to perform the regression at meaningful values of the covariates and to reduce multicollinearity when constructing interaction terms (Aiken & West, 1993; Dawson, 2014). All models employ robust standard errors (clustered at the firm level).

4 | RESULTS

Table 1 shows the descriptive statistics and pairwise correlations. The correlations between technological, geographical, and product market overlap and all other variables are below .32, which is far below the common threshold of 0.7 (Anderson, Sweeney, Williams, Camm, & Cochran, 2016). Among the control variables, we observe comparably high correlations for *firm age* and *firm size*.[10] To further inspect the issue of potential multicollinearity, we calculated all the variables' inflation factor (VIF). The VIFs did not exceed the frequently suggested threshold of 10 and condition numbers stayed below the threshold of 30. This finding indicates that multicollinearity does not pose a serious concern (Aguinis, Edwards, & Bradley, 2017; Cohen et al., 2003).

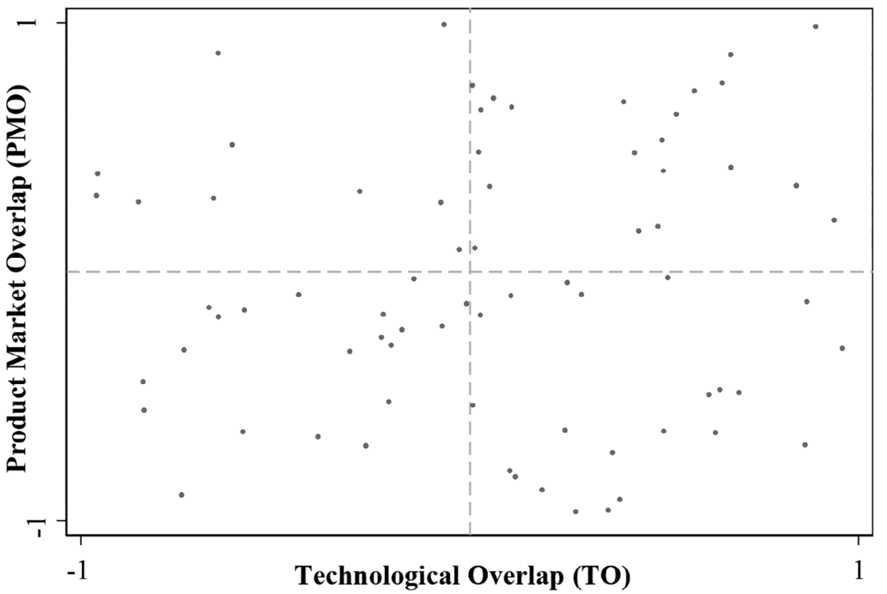
[9]Following Li et al. (2019), we used 10 years of presample patent data (i.e., from 1985 to 1995, inclusive) to construct the presample average of a firm's invention performance.

[10]Re-running our regression models and excluding firm age yielded robust results, while excluding firm size yielded lower p-values for the moderating impact of product market overlap on the relationship between technological overlap and invention performance. As firm size naturally represents a significant predictor of our dependent variable (e.g., Cohen & Klepper, 1996), and as dropping an important variable to resolve a multicollinearity concern should be avoided owing to potential omitted variables bias (Cohen, Cohen, West, & Aiken, 2003), we chose to keep firm size as a standard control variable.

TABLE 1 Descriptive statistics and pairwise correlations

Variable	Mean	*SD*	Min.	Max.	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.	16.	17.	18.
1. Invention performance	464.58	568.35	0.00	2050.87	1																	
2. Firm size (log)	7.13	2.80	2.01	12.13	0.59	1																
3. Firm age (log)	3.77	0.87	1.39	5.11	0.64	0.82	1															
4. Firm R&D expenditures	1.39	2.29	0.00	12.18	0.25	0.77	0.69	1														
5. Firm alliance experience	10.87	15.26	0.00	65.00	0.61	0.60	0.71	0.37	1													
6. Firm prior ties	0.08	0.29	0.00	2.00	0.07	0.08	0.14	0.04	0.19	1												
7. Firm relative scale	1.34	0.84	0.23	4.34	0.58	0.78	0.67	0.48	0.53	0.04	1											
8. Firm past performance	−0.12	0.32	−1.95	0.24	0.48	0.69	0.53	0.40	0.45	0.12	0.60	1										
9. Firm financial slack	4.33	7.07	0.68	91.72	−0.24	−0.34	−0.34	−0.25	−0.26	−0.07	−0.27	−0.13	1									
10. Firm market pressure	0.85	0.11	0.00	0.96	−0.32	−0.15	−0.24	0.06	−0.32	−0.05	−0.26	−0.22	0.13	1								
11. Firm vertical relatedness	0.25	0.10	0.02	0.50	0.12	0.08	0.10	−0.07	0.15	0.19	0.05	0.19	−0.07	−0.12	1							
12. Firm geographical dispersion	3.86	3.08	1.00	15.00	0.21	0.39	0.34	0.30	0.27	0.11	0.39	0.25	−0.19	0.03	0.05	1						
13. Alliance scope	0.33	0.47	0.00	1.00	0.01	0.12	0.02	0.09	0.01	−0.02	0.01	0.05	−0.08	0.07	−0.23	0.11	1					
14. Alliance partner geographical dispersion	3.63	2.97	1.00	15.00	−0.09	−0.22	−0.19	−0.15	−0.10	0.06	−0.31	−0.13	0.08	−0.02	0.09	−0.11	0.05	1				
15. Equity joint venture	0.05	0.21	0.00	1.00	0.00	−0.07	−0.04	−0.10	0.00	0.02	−0.01	0.04	0.03	−0.05	0.12	−0.06	−0.02	−0.05	1			
16. Technological overlap	0.45	0.22	0.00	0.93	0.05	0.08	0.05	0.02	0.03	−0.01	−0.09	−0.02	0.01	0.02	0.15	−0.07	0.05	−0.01	0.02	1		
17. Geographical overlap	0.20	0.24	0.00	0.97	−0.07	0.01	0.02	0.08	−0.03	0.04	−0.04	0.03	−0.03	0.05	0.15	−0.03	0.09	−0.03	0.16	0.14	1	
18. Product market overlap	0.16	0.10	0.02	0.94	−0.25	−0.04	−0.20	0.05	−0.13	0.16	−0.17	−0.10	0.07	0.31	0.07	−0.03	−0.06	−0.01	0.09	0.15	0.27	1

Note: Pearson correlation, $n = 215$.



Note: The plot displays combinations of values between one standard deviation below and one standard deviation above the mean. The dashed line displays the respective mean values.

FIGURE 1 Heterogeneity of alliance partners across technological and product market overlap

Table 1 shows that firms have, on average, a value-weighted patent count of about 465, a technological overlap of 0.45, a geographical overlap of 0.20, and a product market overlap of 0.16 with their R&D alliance partners. Figure 1 shows the heterogeneity of combinations of technological and product market overlap between the alliance partners in our dataset.

4.1 | Hypotheses tests

Table 2 shows the results of the negative binomial regressions. Model 1 includes only the control variables, while Model 2 introduces the main effects of the technological, geographical, and product market overlaps. Models 3 and 4 add the interaction terms between technological and product market overlaps and between geographical and product market overlaps, respectively. Model 5 depicts a three-way interaction post-hoc test.

The results of Model 1 show a significant impact of firm size, R&D expenditures, market pressure, and vertical relatedness on a firm's invention performance. Larger firms and those with greater market pressure have, on average, a higher invention performance, while a higher degree of vertical relatedness with the partner is negatively associated with a firm's invention performance. R&D expenditures are negatively associated with a firm's invention performance. This may be attributed to the fact that firms that were less successful in generating inventions in the past make large investments in R&D to improve in the future, while it takes time to reap these benefits (e.g., Greve, 2003; Hess & Rothaermel, 2011).

Model 2 shows that the relationship between technological overlap and a firm's invention performance is positive and significant (β = .183, *SE* = 0.089, *p* = .039, 95% CI: 0.009–0.357), lending support to Hypothesis 1. The effect size of technological overlap can be interpreted by

TABLE 2 Results of negative binomial regression analyses for firm invention performance

				Hypotheses 1, 2, 3			Hypothesis 4			Hypothesis 5			Post-hoc analysis: three-way interaction		
	Model 1			Model 2			Model 3			Model 4			Model 5		
Variables	Coef.	*SE*	*p* >|*z*|	Coef.	*SE*	*p* >|*z*|	Coef.	*SE*	*p* >|*z*|	Coef.	*SE*	*p* >|*z*|	Coef.	*SE*	*p* >|*z*|
Firm fixed effects	Included			Included			Included			Included			Included		
Year fixed effects	Included			Included			Included			Included			Included		
Business similarity fixed effects	Included			Included			Included			Included			Included		
Firm size (log)	0.491	0.087	.000	0.431	0.089	.000	0.455	0.092	.000	0.443	0.086	.000	0.496	0.093	.000
Firm age (log)	0.540	0.281	.054	0.424	0.284	.135	0.467	0.286	.102	0.430	0.269	.110	0.490	0.260	.059
Firm R&D expenditures	−0.241	0.060	.000	−0.203	0.053	.000	−0.213	0.055	.000	−0.224	0.052	.000	−0.232	0.050	.000
Firm alliance experience	0.009	0.006	.131	0.014	0.006	.019	0.014	0.006	.025	0.014	0.006	.016	0.013	0.006	.027
Firm prior ties	−0.404	0.277	.145	−0.369	0.256	.150	−0.359	0.237	.129	−0.293	0.226	.195	−0.308	0.210	.143
Firm relative scale	−0.029	0.131	.822	0.103	0.140	.460	0.055	0.145	.706	0.075	0.142	.594	−0.026	0.161	.871
Firm past performance	0.045	0.217	.837	0.069	0.233	.766	0.075	0.238	.753	0.068	0.218	.754	0.015	0.231	.947
Firm financial slack	0.019	0.018	.298	0.014	0.017	.431	0.017	0.018	.354	0.019	0.017	.272	0.018	0.017	.278
Firm market pressure	1.760	0.840	.040	2.180	0.810	.010	2.260	0.760	.000	1.570	0.760	.040	1.580	0.810	.050
Firm vertical relatedness	−2.747	0.889	.002	−2.961	0.883	.001	−3.392	0.974	.000	−3.193	0.852	.000	−3.281	0.907	.000
Firm geographical dispersion	−0.056	0.031	.067	−0.061	0.030	.041	−0.063	0.032	.046	−0.049	0.032	.125	−0.048	0.034	.168
Alliance scope	−0.126	0.156	.417	−0.138	0.144	.336	−0.191	0.151	.205	−0.166	0.138	.230	−0.195	0.139	.161
Alliance partner geographical dispersion	0.057	0.033	.088	0.049	0.032	.132	0.048	0.034	.153	0.056	0.031	.077	0.057	0.031	.064
Equity joint venture	0.267	0.346	.442	0.276	0.346	.424	0.253	0.336	.452	0.364	0.351	.300	0.340	0.337	.314
Technological Overlap (TO)				0.183	0.089	.039	0.175	0.091	.054	0.187	0.089	.036	0.212	0.085	.013
Geographical Overlap (GO)				0.044	0.077	.568	0.042	0.075	.577	0.131	0.074	.077	0.112	0.082	.170
Product Market Overlap (PMO)				−0.268	0.085	.002	−0.160	0.072	.025	−0.035	0.101	.728	0.060	0.107	.574
TO × PMO							−0.197	0.098	.044				−0.023	0.099	.816
GO × PMO										−0.263	0.092	.004	−0.137	0.121	.261
TO × GO													−0.013	0.074	.856
TO × PMO × GO													−0.212	0.099	.032
Constant	1.509	1.122	.179	2.112	1.213	.082	2.165	1.236	.080	1.880	1.115	.092	1.697	1.119	.129
Lnalpha	0.070	0.187	.706	0.039	0.184	.833	0.027	0.184	.883	0.017	0.189	.929	−0.002	0.191	.990
Log likelihood	1,399.167			1,395.168			1,393.692			1,392.358			1,390.002		
Likelihood ratio test				$\chi^2(3) = 153.914$			$\chi^2(4) = 90.284$			$\chi^2(4) = 53.529$			$\chi^2(7) = 356.808$		
Wald chi-square (*d.f.*), improved fit relative to baseline model															
AIC	2,868.333			2,866.336			2,865.384			2,862.715			2,864.004		

Note: Dependent variable: Firm invention performance (4-year postalliance commencement window). Independent variables are lagged by 1 year with respect to the dependent variable. $n = 215$, *SE* robust standard errors (clustered on the focal-firm).
Abbreviations: AIC, Akaike information criterion; *d.f.*, degrees of freedom.

examining the exponentiated coefficients, which can be interpreted as multipliers of the outcome in a negative binomial regression model (Long & Freese, 2014). We find that, on average, a one-unit increase in technological overlap results in an *exp*(0.183) -1 = 20.08% (48.44 value-weighted patents) increase in a firm's expected invention performance. Regarding geographical overlap, we observe a positive but statistically insignificant impact on a firm's invention performance (β = .044, *SE* = 0.077, *p* = .568, 95% CI: −0.107–0.195), giving no support to Hypothesis 2. This result indicates that the learning mechanisms underlying geographical overlap are less impactful in shaping a firm's invention performance than expected—an issue that we further explore in Section 5. In addition, we observe a negative and significant effect of product market overlap on a firm's invention performance (β = −.268, SE = 0.085, *p* = .002, 95% CI: −0.433 to −0.102), supporting Hypothesis 3. The result implies that a one-unit increase in product market overlap leads to an *exp*(−0.268) −1 = 23.51% (56.63 value-weighted patents) decrease in a firm's invention performance.

Model 3 reveals that the interaction between technological and product market overlaps is negative and significant (β = −.197, *SE* = 0.098, *p* = .044, 95% CI: −0.390 to −0.005), which supports Hypothesis 4. Similarly, Model 4 shows that the interaction term between geographical and product market overlaps is negative and significant (β = −.263, *SE* = 0.092, *p* = .004, 95% CI: −0.444 to −0.083), which supports Hypothesis 5.

To improve our understanding of the moderating relationships, we plotted them within the feasible range of observed values (e.g., Cohen et al., 2003; Lioukas & Reuer, 2015). Specifically, we inspected the relationships at different values of the predictor variables, ranging from one standard deviation below the mean to one standard deviation above the mean, holding all remaining variables at their mean values. If this yielded a value outside the observed range, we used the minimum/maximum value instead. Figure 2 displays the predicted values of a firm's invention performance across combinations of technological and product market overlaps. We observe that the positive relationship between technological overlap and firm invention performance decreases with an increase in product market overlap. For example, for firms with a product market overlap corresponding to one standard deviation below the mean, a one-unit increase in technological overlap increases a firm's invention performance by around 45.15%

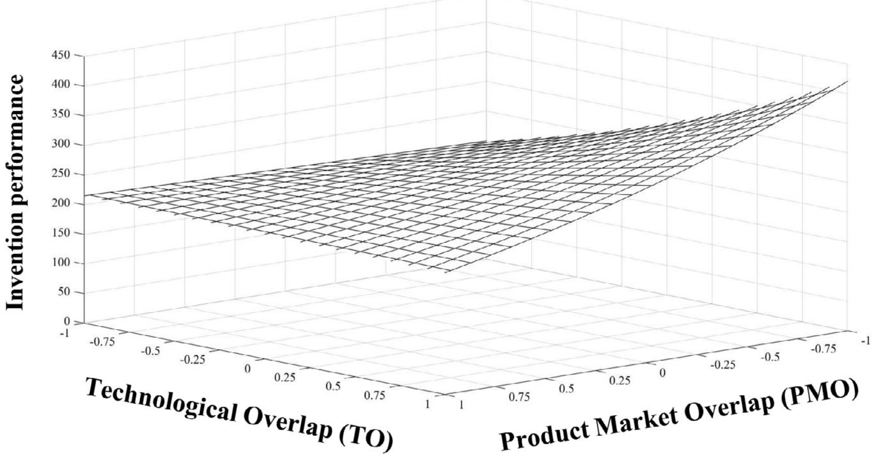


FIGURE 2 The relationship between technological overlap and invention performance for different degrees of product market overlap

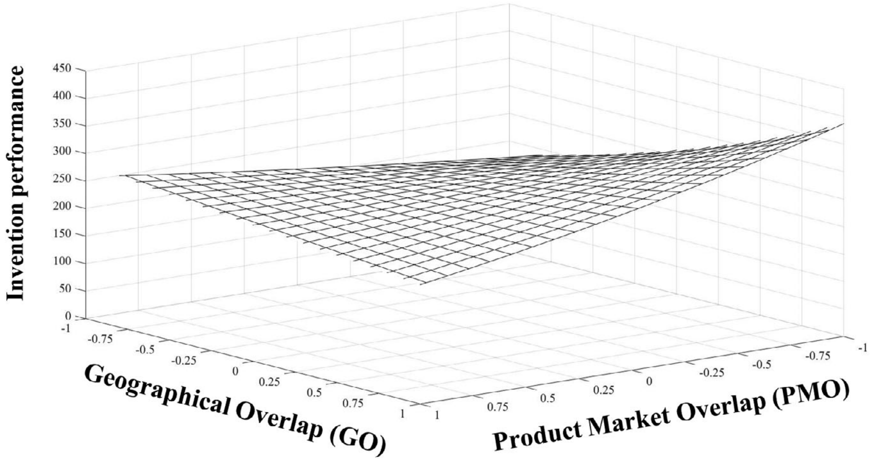


FIGURE 3 The relationship between geographical overlap and invention performance for different degrees of product market overlap

(130.77 value-weighted patents). In comparison, when the product market overlap is half a standard deviation higher (i.e., PMO = −.50), a one-unit increase in technological overlap results only in an increase of around 31.50% (84.23 value-weighted patents), which is about one-third less.

Figure 3 displays the predicted values of a firm's invention performance across combinations of geographical and product market overlaps. Again, we observe that the positive relationship between geographical overlap and firm invention performance decreases with an increase in product market overlap. For example, for firms with a product market overlap corresponding to one standard deviation below the mean, a one-unit increase in geographical overlap increases a firm's invention performance by around 48.31% (127.70 value-weighted patents). In comparison, when product market overlap is half a standard deviation higher (i.e., PMO = −.50), a one-unit increase in geographical overlap results only in an increase of around 30.02% (77.98 value-weighted patents), which is more than one-third less.

We further analyzed these interaction effects by inspecting how the average marginal effects of the technological and geographical overlaps on the firm's invention performance change with product market overlap. Consistent with our theory, the plotted results show that the average marginal effects of the technological (Figure A in Appendix 2) and geographical (Figure B in Appendix 2) overlaps on a firm's invention performance decrease with increasing product market overlap. The average marginal effects are positive and statistically significant for values of product market overlap around the mean and below, while they become statistically indistinguishable from zero for higher values of product market overlap. These results additionally corroborate our theory regarding the negative moderating effect of product market overlap on the relationships between technological and geographical overlaps and the firm's invention performance.

4.2 | Robustness checks

In addition to the robustness checks reported in footnotes 3–10, we ran additional tests to examine the stability of our results (results are available upon request). First, we inspected the sensitivity of our findings to alternative measures of patent value. To this end, we linked our data on each firm's patents from PATSTAT to information from the OECD Patent Quality Indicators database (Squicciarini, Dernis, & Criscuolo, 2013). We were able to link OECD patent data (which only contain information for a subset of EPO and USPTO patents) for 158,480 (~40%) patents and found a strong positive correlation (r >.95, p <.001) between our measure and alternative measures based on the OECD computed patent quality statistics. Additionally, we re-ran the regression models with value-weighted patent counts based on OECD patent quality indices, which produced robust findings.

Second, while several studies point toward a linear effect of technological overlap on interfirm knowledge flows (e.g., Devarakonda & Reuer, 2018; Gomes-Casseres et al., 2006; Rosenkopf & Almeida, 2003) and innovative performance (e.g., Ahuja, 2000; Frankort, 2016), others reveal an inverted U-shaped effect (e.g., Sampson, 2007). However, using the utest procedure in Stata (Haans, Pieters, & He, 2016; Lind & Mehlum, 2010), we did not find support for an inverted U-shaped association (p = .463 t = −0.094). Similarly, we found no support for an inverted U-shaped association between product market overlap and invention performance (p = 0.175 t = .940).

Third, in response to recent discussions regarding mean-centering in the strategy literature (Aguinis et al., 2017), we re-ran the regression analyses using uncentered measures of our independent variables, which provided stable results.

Fourth, we examined whether our findings are sensitive to outliers. We used a combination of visual tools (i.e., scatterplot and boxplot) and quantitative techniques (i.e., percentage analysis) to identify outliers (Aguinis, Gottfredson, & Joo, 2013). We identified 12 outliers by using the recommended cutoff of observations in the top and bottom 2.5% (Aguinis et al., 2013). Re-running our analyses showed that our findings are insensitive to the exclusion of these outliers.

Fifth, for completeness, we also tested the interaction effect between technological and geographical overlaps on a firm's invention performance, which revealed a negative, but statistically insignificant effect (β = −.088, SE = 0.061, p = .145).

Sixth, as we acknowledged in our theory, it may be argued that technological overlap may lower a firm's invention performance owing to an increase in knowledge outflows. To probe deeper into this issue, we performed different tests. We followed Yan et al. (2020) and considered the impact of technological overlap on knowledge outflows using the cross-citations made by the partner to the firm's patents as the dependent variable (Corsino et al., 2019; Oxley & Wada, 2009). We found that technological overlap has a significant positive impact on knowledge outflows (β = .952, SE = 0.208, p = .000). Additionally, as knowledge outflows may limit a firm's knowledge recombination space in its own knowledge domain, we tested whether technological overlap negatively influences the firm's invention performance in its own knowledge domain (i.e., excluding patents in the partner's knowledge domain). Our findings revealed a barely significant but positive effect (β = .156, SE = 0.081, p = .055). This finding is consistent with Bresnahan and Trajtenberg (1995), who argue that inventions often may have spillover benefits even beyond the original inventor. Moreover, we tested the impact of technological overlap on knowledge inflows using the firm's cross citations to the partner's patents as the dependent variable, which revealed a statistically significant positive effect (β = .545, SE = .195, p = .005). The results suggest that technological overlap helps a firm benefit from the increased knowledge transfer in an R&D alliance, despite knowledge outflows.

Finally, we tested for a possible three-way interaction effect of technological, geographical, and product market overlaps on the firm's invention performance (Yan et al., 2020). Model 5 (Table 2) reveals a negative and significant three-way interaction of all three dimensions of overlap ($\beta = -.212$, $SE = 0.099$, $p = .032$, 95% CI: −0.407 to −0.018). To facilitate the interpretation of the interaction, we followed the recommendations of Cohen et al. (2003) and plotted interactions between technological and geographical overlaps for lower and higher degrees of product market overlap between a firm and its partner. We observed that, for firms with a product market overlap below the sample median (Figure 4a), the positive effect of technological overlap on a firm's invention performance is fostered by an increase in geographical overlap. For firms with a product market overlap above the sample median (Figure 4b), the positive effect of technological overlap on a firm's invention performance diminishes with an increase in geographical overlap. Thus, product market overlap appears to determine how the interplay between technological and geographical overlaps shapes a firm's invention performance.

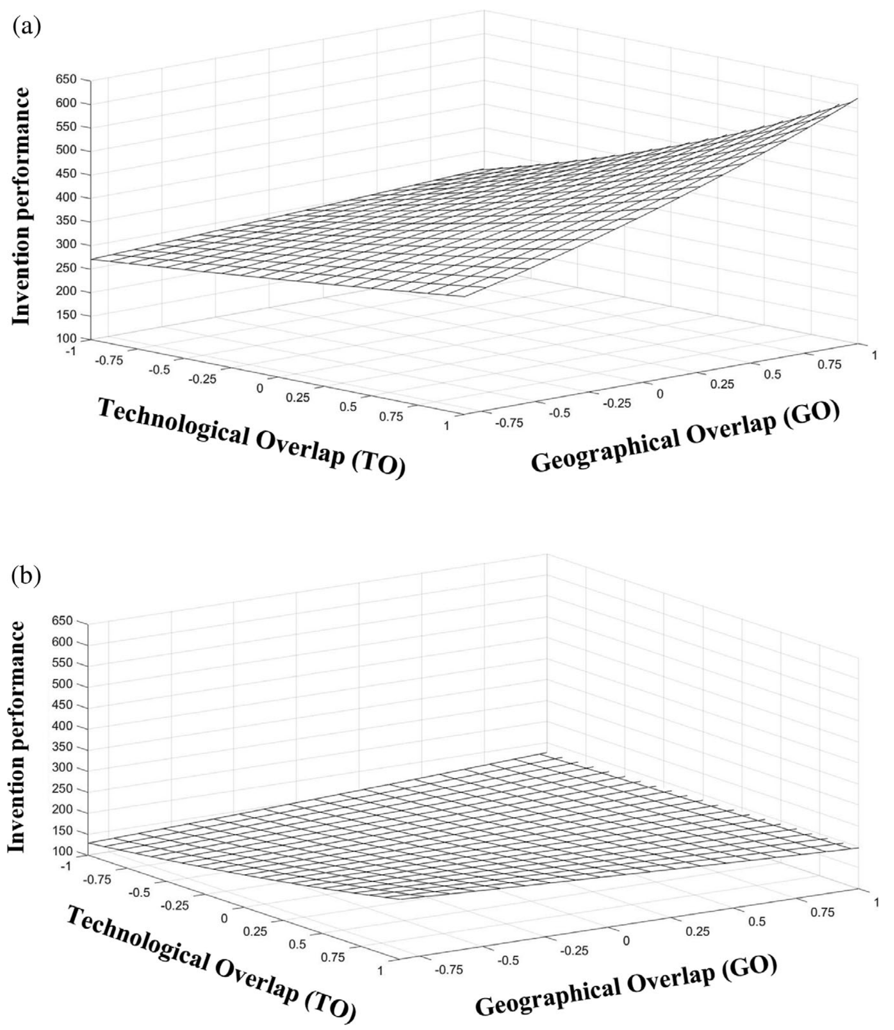


FIGURE 4 (a) The three-way interaction for lower degrees of product market overlap. (b) The three-way interaction for higher degrees of product market overlap

5 | DISCUSSION

We developed and tested theory of how the technological, geographical, and product market overlaps between a firm and its partner influence a firm's invention performance by shaping the learning and competitive tension in an R&D alliance. Combining insights from research on learning in alliances and competitive dynamics, we theorized that technological and geographical overlaps between a firm and its partner enhance the firm's invention performance, while product market overlap decreases the firm's invention performance. We also theorized that product market overlap serves as a master switch that negatively moderates the positive relationships between technological and geographical overlaps and the firm's invention performance. Testing our hypotheses on a dataset of R&D alliances, we found wide support for our theory, but also some unexpected findings.

5.1 | Contributions to theory

Our study contributes to the extant coopetition research on the heterogeneity of R&D alliance partners along different dimensions of overlap (Park et al., 2014a, 2014b; Yan et al., 2020). Our theory discerns that the awareness and capability to compete are fostered by all three overlap dimensions; however, the motivation to compete is fostered only by product market overlap. Therefore, product market overlap critically determines the salience of competitive tension and learning in an alliance, and thus, a firm's invention performance. To this end, we encourage future research to consider *product* market overlap instead of (market overlap captured by) industry relatedness. This is because the latter does not allow for discerning the detrimental impact of competition from the beneficial impact of possessing similar (e.g., technological) knowledge (Asgari et al., 2018; Reuer & Lahiri, 2014). The finding that alliance partners in our sample differ in terms of their overlap in product markets and technologies *within* the same industry (Figure 1) corroborates the need for a differentiated examination. Since the overlaps are unique for each pair of firms, earlier studies' neglect of this heterogeneity (e.g., Dussauge et al., 2000; Oxley & Sampson, 2004; Park et al., 2014b; Wehrheim & Palomeras, 2021) may be one reason for the mixed findings on the merits of coopetition (e.g., Dorn et al., 2016; Ritala, 2012).

By untangling the sources of competitive tension underlying the different dimensions of overlap in R&D alliances, we also inform the broader alliance literature that discusses governance mechanisms (e.g., equity-, administrative-, relational-based controls) as a means to manage knowledge leakage risk in alliances (e.g., Devarakonda & Reuer, 2018; Kale et al., 2000; Oxley & Sampson, 2004). We extend this research by revealing that the knowledge leakage risks underlying technological and geographical overlaps can differ in the extent to which they are threatening, regardless of alliance governance, and do not per se undermine learning in (only) contractually governed alliances. By assessing how competitive tension among alliance partners emerges through partners' awareness, motivation, and capability to compete, our study helps future research examine how other types of partner- and alliance-related characteristics can increase competitive tension and undermine learning between partners and how differences in governance can influence these complexities.

While the significant empirical findings regarding the direct effects of technological and product market overlaps corroborate our theory, the insignificant direct effect of geographical overlap warrants a more detailed discussion. One possible explanation for this unexpected finding is that, in global and technology-intensive industries, geographical overlap may matter less for communication and personal interactions nowadays. This can be attributed to technological advancements and internationalization, which have increased the prevalence of virtual communication and knowledge sharing in many larger organizations (Raghuram, Hill, Gibbs, & Maruping, 2019). As related research suggests that the type of virtual communication also affects the effectiveness of knowledge sharing (Klitmøller & Lauring, 2013), future research may examine to what extent geographical overlap in combination with new means of communication fosters or undermines learning in R&D alliances.

We also contribute to recent coopetition (e.g., Park et al., 2014b; Yan et al., 2020) and alliance research (e.g., Devarakonda & Reuer, 2018, 2019; Wehrheim & Palomeras, 2021) by explaining that product market overlap serves as a master switch that changes the thrust of the alliance from joint value creation toward private value appropriation. Our novel theory can inform a broad array of studies on the role of technological and geographical overlaps for various strategic decisions in the alliance context. For example, Devarakonda and Reuer (2019) argue that because of concerns about knowledge misappropriation, technological overlap decreases the likelihood of granting a partner with a minority share a seat on the board of an equity alliance. Transferring insights from our theory to this context, it may be argued that the concerns about knowledge misappropriation underlying technological overlap are justified at higher degrees of product market overlap. However, technological overlap also indicates that the partner possesses knowledge valuable to the board. Given this, a reverse argument could be that if product market overlap (and thus, the motivation to compete) is at lower degrees, technological overlap may *increase* the likelihood that a minor partner will be granted a seat on the board. In line with this example, our theory on the role of product market overlap may help provide more detailed explanations on the role of technological and geographical overlaps in alliance formation (Reuer & Lahiri, 2014), the choice of scope and governance mode (Oxley & Sampson, 2004; Reuer & Devarakonda, 2016), R&D staffing decisions (Wehrheim & Palomeras, 2021), knowledge sharing and learning (Devarakonda & Reuer, 2018; Gomes-Casseres et al., 2006; Subramanian, Bo, & Kah-Hin, 2018), and new product development (Frankort, 2016).

5.2 | Limitations and implications

Despite the many steps taken to ensure the robustness of our findings, our study has several limitations. First, testing our hypotheses on a sample of public pharmaceutical firms has potential limitations in terms of generalizability. For instance, our results may not extend to private firms, which tend to be younger, smaller, and face greater financial resource constraints (Vanacker, Collewaert, & Zahra, 2017), even though we controlled for these characteristics. Likewise, the results may differ in other industries (e.g., less knowledge-intensive industries). Therefore, we encourage future research to explore our findings in other contexts.

Second, although we took several steps to minimize potential biases due to endogeneity, we cannot rule out that managers' decision-making during alliance formation may have influenced our empirical results. We reflected on exogenous sources of variation in the selection of alliance partners; nevertheless, for the same reasons as described in detail by Aggarwal (2020), we could not find an exogenous variable. However, we would expect that managers seeking to improve their invention performance choose alliance partners that, despite product market overlap, offer comparatively lower competitive tension (due to unobservable characteristics). Therefore, next to employing an empirical approach that mitigates potential biases by drawing on a large pool of control variables and firm fixed effects, we believe that such influences would imply an *underestimation* of the central role of product market overlap in spurring competitive tension in an alliance and thus decreasing a firm's invention performance. Thus, our estimates should be regarded as conservative.

Third, although our measure of product market overlap developed by Hoberg and Phillips (2010) is more fine-grained than the measures of market overlap based on industry presence, the use of product descriptions in SEC 10-K filings also has limitations. For example, by building on computer-aided text analysis of firms' product descriptions, which tend not to change too much from one year to the next, changes in this measure over time could underestimate the actual number of new products introduced. Moreover, although firms' product description are legally required to be accurate and updated each fiscal year (Shi et al., 2017), firms may exercise discretion in their reported level of detail. Thus, future research may find more sophisticated ways to measure product market overlap (e.g., by relying on a qualitative analysis of firms' products by industry experts). Finally, while we argued that the three dimensions of overlap influence the salience of learning and competitive tension between a firm and its partner, we were unable to measure these mechanisms directly. Therefore, we encourage future research to delve deeper into these complexities.

6 | CONCLUSION

This study examines how and under what circumstances three types of overlap between a firm and its partner influence the firm's invention performance by shaping learning and competitive tension in an R&D alliance. We found that technological overlap increases the firm's invention performance, while product market overlap decreases it. We also found that product market overlap negatively moderates the relationships between technological and geographical overlaps and the firm's invention performance. In all, our findings offer valuable new insights for the coopetition and alliance literature.

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DATA AVAILABILITY STATEMENT

Data are not shared owing to copyright and related legal third party restrictions.

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