Received: 23 September 2020 | Revised: 20 April 2022 | Accepted: 3 June 2022

DOI: 10.1111/jpim.12639

ORIGINAL ARTICLE

JOURNAL OF PRODUCT INNOVATION MANAGEMENT pdma

The combined impact of direct and indirect ties on innovation: The moderating role of similarity in alliance subtypes

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Funding information
National Key Research and Development Program of China, Grant/Award Number: 2021YFB3300701; National Natural Science Foundation of China, Grant/Award Numbers: 71972150, 71902155; National Philosophy and Social Sciences Foundation of China, Grant/Award Numbers: 20VYJ052, 20AGL004; Shaanxi Soft Science Project, Grant/Award Number: 2022KRM151

Associate Editor: Martin Spann

Abstract

Firms increasingly use networks of alliances to pursue innovation. The current innovation literature has offered insights into how direct ties (between a focal firm and its partners, forming direct alliances) and indirect ties (between a focal firm's partner and its partners' partners but not including the focal firm, forming indirect alliances) function as independent antecedents to corporate innovation. It is, however, unclear how direct ties and indirect ties work in combination to impact innovation in a focal firm. Moreover, because different subtypes of financial or marketing alliances may operate with distinct governance structures and offer heterogeneous or incoherent resources for exchange, similarity in financial or marketing alliance subtypes, defined as the degree of overlap in financial or marketing alliance subtypes between direct and indirect ties, may significantly influence the extent to which corporate innovation can benefit from these ties. This study aims to examine the combined impact of direct and indirect ties on a focal firm's innovation by considering the moderating role of similarity in financial or marketing alliance subtypes. The results obtained by analyzing a longitudinal dataset extracted from US firms operating in the biotechnological and pharmaceutical industries support our hypotheses. Direct ties and indirect ties in combination have a negative effect on innovation as measured by patents and this effect is less negative when similarity in financial alliance subtypes is greater but more negative when similarity in marketing alliance subtypes is greater. We extend the innovation and alliance network literatures by offering novel evidence that direct and indirect ties in combination may diminish a focal firm's innovation and that such a negative combined effect depends on similarity in financial or marketing alliance subtypes.

KEYWORDS
alliance network, direct ties, indirect ties, innovation, similarity in alliance subtypes

1 | INTRODUCTION

Allying with other organizations has proved critical in helping firms develop innovation (Phelps et al., 2012; Zhang et al., 2019). Alliances established by a focal firm, that is, direct alliances, and those established by its partners and partners' partners excluding the focal firm, that is, indirect alliances, form a network of strategic alliances (Baum et al., 2000; Phelps, 2010). Centering on the focal firm, direct alliances create direct ties and indirect alliances create indirect ties. As such, innovation in a focal firm could be simultaneously influenced by direct ties and indirect ties in its strategic alliance network. This phenomenon can be seen in many industries, including the biopharmaceutical sector which is the empirical context of our study, where new product development requires knowledge inputs from a wide spectrum of fields, requesting firms operating in the biopharmaceutical industry to form alliances with a range of organizations (Mazzola et al., 2018; Powell et al., 2005; Schilling, 2015). Taking Johnson & Johnson as an example, the company was, as of 2001, maintaining direct ties with, among other firms, Celltech, Alere, and Alza as well as indirect ties with, among other firms, Abbott, Celgene, and Merck, as shown in Figure 1. The current literature suggests that innovation in a focal firm such as Johnson & Johnson can be individually influenced by direct and indirect ties (solid and dashed lines in Figure 1, respectively; Ahuja, 2000; Jiang et al., 2020), but it remains unclear regarding a critical question: *How do direct and indirect ties in combination influence innovation in a focal firm*?

From the structuralist perspective, network exchange theory posits that the collective effect of direct and indirect ties depends on the structure or configuration of ties in an alliance network (Borgatti & Halgin, 2011; Burt, 2004). Adding an indirect partner to a direct tie will create a tripartite relationship that may strengthen the relative power of a direct alliance partner (Borgatti & Halgin, 2011). Because of this, the tripartite relationship could distract the direct alliance partner's attention and

Practitioner points

1. Although direct ties and indirect ties may individually enhance a focal firm's innovation, their combination hurts firm innovation.
2. To alleviate the negative combined effect of direct ties and indirect ties on a focal firm's innovation, the firm should establish financial alliances with similar subtypes as to its indirect financial alliances.
3. When establishing marketing alliances, a focal firm should avoid alliance subtypes that are similar to its indirect marketing alliances.

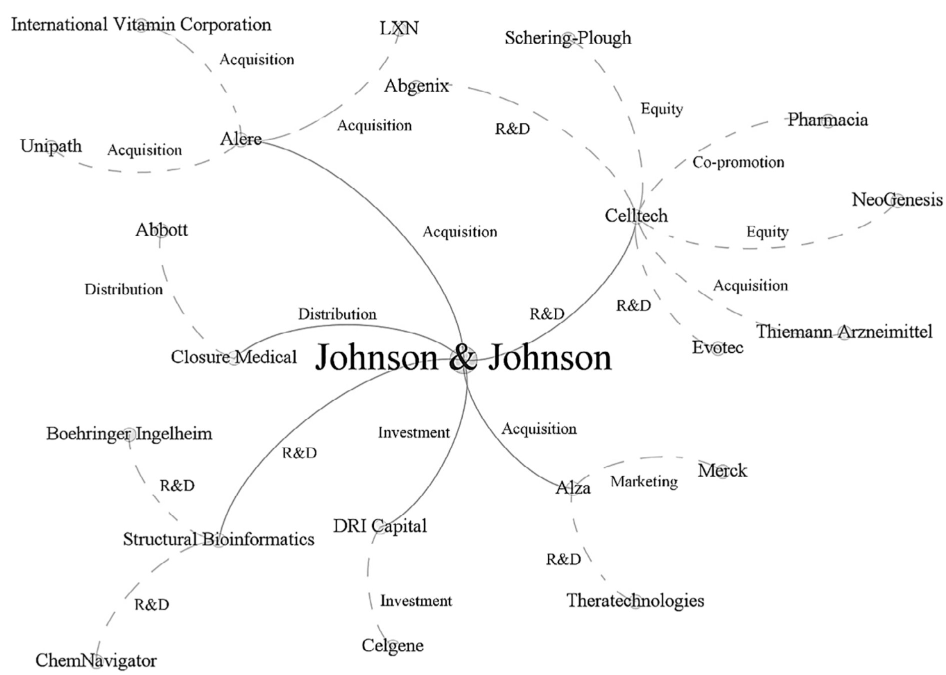

FIGURE 1 Johnson & Johnson's alliance network in 2001. Nodes are Johnson & Johnson and its direct (connected by solid lines) and indirect alliance partners (connected by dashed lines). Edge labels indicate subtypes of alliances.

consume resources that the direct partner would devote to the direct alliance (Aggarwal, 2020; Ahuja, 2000), indicating a combined constraining effect of direct and indirect ties on a focal firm's innovation. Although network exchange theory offers inspiring insights into the combined effect of direct and indirect ties on innovation, few empirical studies however have examined this effect by considering the importance of such tripartite relationships (Beckman & Haunschild, 2002; Lee, 2007; Rojas et al., 2018).

Moreover, a focal firm could establish research and development (R&D) alliances, financial alliances, and marketing alliances to access and acquire innovation inputs from a range of partners (Aggarwal, 2020; Cui & O'Connor, 2012). For example, as shown in Figure 1, Johnson & Johnson established a R&D alliance with Celltech through a direct tie, a marketing (distribution) alliance with Closure-Medical through a direct tie, and its direct partner DRI Capital and indirect partner Celgene established their own financial (investment) alliance. Prior studies have focused on R&D alliances and offered ample evidence indicating the important role that R&D alliances play (Cui & O'Connor, 2012; Mariotti & Delbridge, 2012). However, the extant literature, surprisingly, lacks in-depth studies on the roles that financial and marketing alliances play in influencing innovation in a focal firm. Financial alliances and marketing alliances are often embraced to address key challenges in the innovation process (Cui & Xiao, 2019; Gilding et al., 2020; Powell et al., 2005). However, the network content of financial and marketing alliances is different: financial resources are easier to deploy and transfer but marketing resources tend to be context-specific and harder to transfer and absorb (Bello et al., 2010; Lee & Chang, 2014), so it is important to examine the roles that financial and marketing alliances play in driving firm innovation.

In this respect, any analysis of financial and marketing alliances should begin by acknowledging several important subtypes of both types of alliances. For example, financial alliances include joint ventures, investment alliances, equity alliances, and options alliances, whereas marketing alliances include co-marketing alliances, co-promotion alliances, and distribution alliances (Agostini & Nosella, 2017; Sorescu & Spanjol, 2008). In Figure 1 it can be seen, for example, that Johnson & Johnson, through direct (solid lines) and indirect ties (dashed lines), established subtypes of financial alliances including acquisition, investment, and equity alliances as well as subtypes of marketing alliances including distribution and co-promotion alliances. Distinct subtypes of financial or marketing alliances are designed with different governance structures, scopes of collaboration, and partners' roles and responsibilities (Das & Teng, 2000; Rojas et al., 2018; Sampson, 2007). It has been recognized that different subtypes of financial or marketing alliances are associated with distinct resources to be exchanged and varying governance mechanisms (Choi, 2020). For example, a co-promotion alliance requires more frequent interactions between partners than a distribution alliance (Agostini & Nosella, 2017). It is thus necessary to examine s*imilarity in financial or marketing alliance subtypes between direct and indirect ties* (in brief, similarity in alliance subtypes), that is, the degree of overlap in financial or marketing alliance subtypes between direct and indirect alliances that constitute an alliance network. Although the concept of similarity in alliance subtypes has not been addressed in the extant literature, we deem it important to a focal firm's innovation because it reflects *which* resources and knowledge can be shared and *how* they can be shared with partners, representing the *content* aspect of alliance networks (Aggarwal, 2020; Cui, 2013; Phelps et al., 2012).

This study aims, then, to investigate the combined effects of direct ties and indirect ties on a focal firm's innovation by considering the moderating roles of similarity in financial or marketing alliance subtypes. We examine our hypotheses in the setting of the US biopharmaceutical industry, where technological innovation is common and characterized by long development cycles, high costs, high risks, high rewards, and frequent collaborations (Devarakonda & Reuer, 2018; Mazzola et al., 2018; Pisano, 2006). In addition, financial and marketing alliances are common in this industry and play important roles in promoting innovation (Gilding et al., 2020). Results obtained by analyzing a longitudinal dataset (comprising 411 firms involved in about 4000 alliances) show that direct and indirect ties in combination have a negative effect on a focal firm's innovation as measured by patents and that this negative effect is weaker when similarity in financial alliance subtypes is greater but stronger when similarity in marketing alliance subtypes is greater.

Our research makes two main contributions to the innovation and alliance network literatures. First, we are among the first to examine the combined effect of direct and indirect ties on corporate innovation, offering a more complete understanding of how alliance networks impact a focal firm's innovation. Although the network literature has widely acknowledged the important role of direct and indirect ties as independent drivers of innovation (Beckman & Haunschild, 2002; Lee, 2007; Mazzola et al., 2018; Rojas et al., 2018), few studies have specifically analyzed the combined impact of these two types of ties. Based on network exchange theory, we suggest, and find, that adding an indirect tie to a direct tie may change the original power and positional advantage of the direct partner, undermining the advantages of being connected in alliance networks. In so doing, we enrich the innovation literature by examining how tripartite relationships as represented by the simultaneous consideration of direct and indirect ties in alliance networks impact corporate innovation.

Second, we contribute to the emerging alliance network literature by offering a novel concept—similarity in alliance subtypes between direct and indirect ties—which enriches the network literature by providing more nuanced evidence of the interplay between the content (composition) and structure of alliance networks in influencing innovation. Prior studies provide insights into how financial, marketing, and R&D alliances may contribute differentially to innovation (Choi, 2020; Cui & O'Connor, 2012). The extant literature still lacks highly granular knowledge about how alliance subtypes, especially regarding similarity in financial or marketing alliance subtypes, play their roles in impacting a focal firm's innovation. In addition, most existing interfirm network studies focus on the impact of network-structure factors, such as network position and structural holes, on innovation (Gilsing et al., 2016; Mazzola et al., 2018; Schilling, 2015). The novel concept of similarity in alliance subtypes proposed in our study acknowledges the importance of network content and indicates that coherence in the purposes of subtypes of financial or marketing alliances can affect the extent to which innovating firms could benefit from network structures, suggesting that network content functions as important boundary conditions that alter the impact of network structures on a focal firm's innovation.

2 | THEORETICAL BACKGROUND

2.1 | Direct ties, indirect ties, and innovation

Extant research shows that some characteristics of a strategic alliance network, such as the number or quality of ties, the strength of ties, the length of ties, or network structure, can affect the resources, knowledge, and information that a focal firm can obtain from the network (Phelps et al., 2012; Zhang et al., 2019). In an alliance network, a focal firm could form two kinds of connections: direct ties and indirect ties. Both direct ties and indirect ties provide innovation benefits to a focal firm. Direct ties benefit innovation by providing knowledge-sharing, complementarity, and scale while indirect ties benefit innovation by offering additional inputs beyond direct ties (Ahuja, 2000). The current literature reveals an inverted U-shaped relationship between direct ties and core and noncore technology development while indirect ties have a positive effect on noncore technology development (Vanhaverbeke et al., 2012). In addition, when a focal firm is directly connected with many organizations, enabling it to hold a critical or central position in a network, its partners are more willing to share with and transfer their knowledge to that firm (Rodan & Galunic, 2004; Salman & Saives, 2005). In addition to the information that a focal firm can acquire from its direct partners, the firm can also attract new alliance partners that form alliances with its indirect partners, leading to triadic closure among these firms (Zhelyazkov, 2018).

The current literature pays inadequate attention, however, to the combined effect of direct ties and indirect ties. Network ties can be assessed by several measures such as eigenvector centrality, betweenness centrality, and closeness centrality (Mazzola et al., 2015; Mazzola et al., 2018; Salman & Saives, 2005). However, these measures leave out many details involved in interaction between direct ties and indirect ties in strategic alliance networks. Therefore, a more in-depth examination of interaction between direct ties and indirect ties is still needed.

2.2 | Similarity in alliance subtypes between direct alliances and indirect alliances

In social network studies ties, such as kin ties or acquaintance ties, are differentiated by type based on their characteristic edges, reflecting the content of a network (Koka & Prescott, 2002; Phelps et al., 2012). To reflect network content, strategic alliances can be classified according to the nature of the involved alliance partners, such as universities, customers, and suppliers, as such partners may offer distinct resources, knowledge, and support (Cui, 2013). More often, strategic alliances are categorized on the basis of their main functions, such as financial operations, marketing, and R&D, given that alliance functions determine what resources can be shared and how those resources are shared (Cui & Xiao, 2019). In the biopharmaceutical industry, companies face multiple tasks when attempting to access new knowledge, raising funds, or commercializing new inventions (Gilding et al., 2020), requiring them to establish a variety of alliances to address these challenges (Gilding et al., 2020; Powell et al., 2005). With respect to knowledge- and tech-intensive industries, prior studies have conducted insightful investigations of the positive role that R&D alliances or collaborative R&D activities play in impacting firm-level innovation (Aggarwal, 2020; Choi, 2020; Cui & O'Connor, 2012; Martínez-Noya & Narula, 2018;

Sampson, 2007). The enlightening insights from these prior studies offer a guide for investigating the role that subtypes of financial and marketing alliances play in affecting the combined effect of direct and indirect ties on firm innovation, an area that has been relatively understudied.

Financial alliances are formed to acquire and allocate financial factors and resources, such as cash flows, property rights, shareholder exchanges, cost-sharing, revenues, and profits (Ozmel et al., 2013; Pahnke et al., 2015). In general, financial alliances offer fiscal capital and financial information that firms can use to facilitate the timely and successful development of innovations (Baum et al., 2000; Pahnke et al., 2015; Sorescu & Spanjol, 2008). There are four main subtypes of financial alliances: joint ventures, investment alliances, equity alliances, and option alliances (De man, 2013; Gilsing et al., 2016; Sorescu & Spanjol, 2008). Financial alliances offer partners access to financial resources that are generic in nature and function as unabsorbed assets, suggesting that such resources can be easily absorbed and redeployed (Tan & Peng, 2003; Teirlinck, 2020; Zahra & George, 2002).

Marketing alliances are established to conduct joint marketing activities, including advertising, distribution, sales, and promotion (Agostini & Nosella, 2017; Fjeldstad & Sasson, 2010; Lee & Chang, 2014). Marketing alliances are innovation-friendly because they can provide partners with market insights into customer needs and preferences as well competitive intelligence about industry practices related to pricing, promotion, and distribution (Bucklin & Sengupta, 1993; Cui & Xiao, 2019; Tolstoy & Agndal, 2010). There are also four subtypes of marketing alliances: marketing alliances, co-marketing alliances, co-promotion alliances, and distribution alliances (Agostini & Nosella, 2017; Fjeldstad & Sasson, 2010; Lee & Chang, 2014). In the biopharmaceutical industry, each of these four subtypes of marketing alliances has its own emphasis. Marketing alliances focus on brand development and relationship-building. Co-marketing alliances focus on providing therapeutic solutions for consumers or analyzing the market. Co-promotion alliances involve promoting specific drugs, while distribution alliances involve sharing channels for active pharmaceutical ingredients or drugs, including distribution licenses for domestic and international markets (De Man, 2013; Gilding et al., 2020). As such, each subtype of marketing alliances operates under its own governance structure and offers distinctive partner-, task-, and project-specific resources which are difficult to transfer and absorb.

The above discussions indicate that financial or marketing alliance subtypes are meaningful for a focal firm's innovation in its alliance network. First, financial or marketing alliance subtypes determine which resources, knowledge, information, and other benefits a focal firm can access and acquire from its alliances. For example, joint ventures and equity alliances differ greatly, as the former require establishing a child company of partnering firms whereas the latter require only one partner to purchase another partner's equity without establishing an independent organization (Choi, 2020). Similarly, co-promotion and distribution alliances also differ. Co-promotion alliances require joint efforts by partners to advertise, propagate, and promote ideas, products, and services, whereas distribution alliances are formed to share marketing channels (Agostini & Nosella, 2017; De Man, 2013). As such, these various subtypes of financial and marketing alliances determine *which* resources, information, and knowledge can be shared and acquired in particular alliances.

Second, distinct alliance subtypes also require specific governance mechanisms to motivate partnering firms to pool complementary resources, skills, and knowledge, while in the meantime limiting the corresponding risk of misappropriation (Choi, 2020; Sampson, 2007). For example, partners in a co-marketing alliance need to interact with each other more frequently than partners in a distribution alliance, indicating that the frequency of interaction between partners differs greatly across subtypes of alliances (Bucklin & Sengupta, 1993). As such, different subtypes of financial or marketing alliances require differing cooperating procedures, business norms, managerial routines, and distributions of common gains (Rojas et al., 2018), determining *how* resources, knowledge, and skills are to be shared or acquired. In Table 1, we summarize the differences between distinct subtypes of financial or marketing alliances in resource exchange and governance mechanisms.

Given the differences between distinct subtypes of financial or marketing alliances shown in Table 1, similarity in alliance subtypes between a focal firm's direct and indirect alliances thus determines the degree of coherence or heterogeneity regarding *which* resources, knowledge, and skills are to be shared or acquired in the firm's alliance network and *how* they are to be shared or acquired. As such, the focal firm's direct and indirect ties constitute the *structure* of its alliance network, whereas similarity in alliance subtypes reflects the *content* of this network. With this in mind, this study examines the combined effect of direct ties and indirect ties on a focal firm's innovation along with the moderating roles of similarity in alliance subtypes. In so doing, we address the impact of a focal firm's network structure on its innovation as well as the boundary effect of network content on this impact. Figure 2 depicts our conceptual framework and research hypotheses, which we develop next.

TABLE 1 Summary of alliance subtypes

Alliance type	Alliance subtype	Exchange of resources	Governance mechanism: Main governance mechanism	Governance mechanism: Resource exchange mechanism	Governance mechanism: Interaction level	Governance mechanism: Noncompetition covenants?	Governance mechanism: Veto power
Financial alliances	Joint venture	Cash flows, property rights, shareholder exchanges, operating and financial experts	Contractual governance and relational governance	Pooling resources	Two-way interaction	Yes	To two parties
	Investment	Cash flows, shareholder exchanges, loans and debts	Contractual governance	One directional resource flowing	One-way interaction	No	To one party
	Equity	Cash flows, shareholder exchanges	Contractual governance	One directional resource flowing	One-way interaction	No	To one party
	Option	Cash flows, shareholder exchanges, rights to buy or sell certain asset	Contractual governance,	One directional resource flowing	One-way interaction	No	To one party
Marketing alliances	Marketing	Specific marketing knowledge, specific marketing experts, specific customer information, advertising channels, organization's public relation	Contractual governance	One directional resource flowing	One-way interaction	Yes	To two parties
	Co-marketing	Specific marketing knowledge, specific marketing experts, specific customer information, advertising channels	Contractual governance and relational governance	Pooling resources	Two-way interaction	Yes	To two parties
	Co-promotion	Specific marketing experts, advertising channels, sharing locations, product knowledge, brand recognition/reputation, public awareness	Contractual governance and relational governance	Pooling resources	Two-way interaction	Yes	To two parties
	Distribution	Distribution channels, licenses and infrastructure, product knowledge	Contractual governance	One directional resource flowing	One-way interaction	Yes	To one party

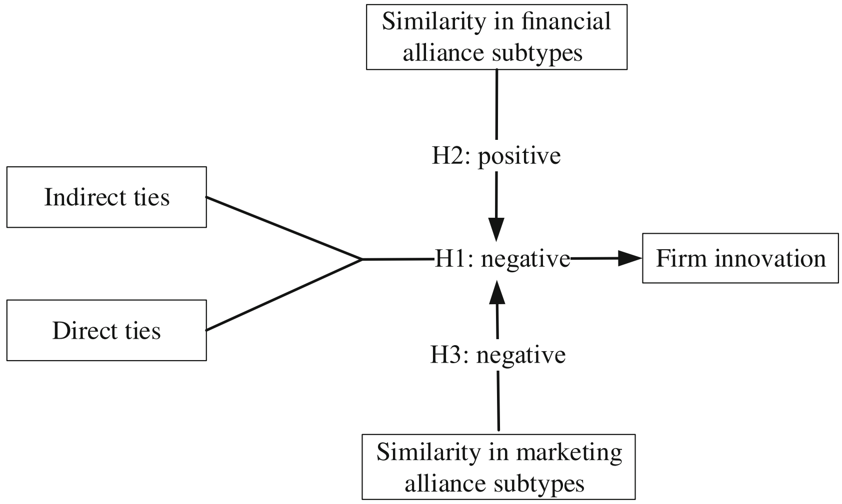

FIGURE 2 Conceptual framework and research hypotheses

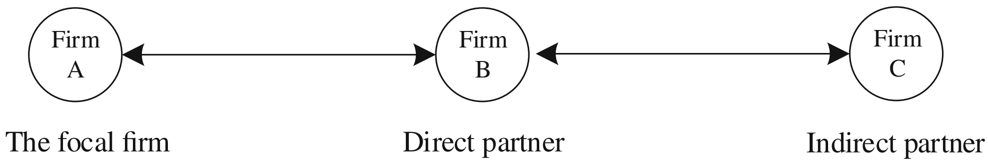

FIGURE 3 Direct alliance and indirect alliance exchange in a strategic alliance network.

3 | HYPOTHESIS DEVELOPMENT

3.1 | Effects on innovation of interaction between direct ties and indirect ties

Network exchange theory holds that the distribution of relational outputs in a network is an exchange relationship and the distribution of collaborative results depends on the power of each actor, which is partially determined by network structure (Cook & Richard, 1978). Specifically, holding all else equal, an actor that occupies a dominant position in a network enhances other actors' reliance on that dominant actor. Because its bargaining power is stronger, the dominant actor can access resources more easily than others but probably has no obligation to share its resources equally with its partners (Cook & Richard, 1978; Easley & Kleinberg, 2010).

We therefore argue that direct ties and indirect ties in combination should have a *negative* impact on a focal firm's innovation, specifically its patentable innovation. First, network exchange theory posits that the addition of indirect alliances to a focal firm's alliance network can change the network structure, which could affect the allocation of network resources to the focal firm (Borgatti & Halgin, 2011). For example, when a new alternative alliance which creates an indirect tie for Firm A, as shown in Figure 3, is formed, the initial balance between Firms A and B is dissolved and Firm A, which is supposed to be the focal firm, becomes less powerful (Xia, 2011). That is, Firm A becomes peripheral and finds itself disadvantaged as compared with the power it wielded in its previous position when the network consisted only of Firms A and B (Borgatti & Halgin, 2011; Easley & Kleinberg, 2010). Thus, adding an indirect tie (between Firms B and C) may undermine Firm A's network advantage, because in the new tripartite relationship Firm B determines whether or not to invest corresponding resources and knowledge into the A–B or B–C alliance (established by Firms A and B and Firms B and C, respectively). As such, Firms A and C become more heavily dependent on Firm B, giving Firm B more power (Gulati & Sytch, 2007). Firm B can now exclude Firm A or Firm C from its exchange relationships, whereas Firms A and C must compete for Firm B's limited resources, knowledge, and attention, consequently reducing Firm A's patentable innovation.

Second, the resource-based view of alliances suggests that resource transfer in indirect alliances may cause information redundancy and overload problems that may increase innovation costs and prevent a focal firm from benefiting from direct alliances (Das & Teng, 2000; Lavie, 2006; Mariotti & Delbridge, 2012). A focal firm does not have direct access to or control over the resources involved in its indirect ties and therefore has to rely on direct alliance partners to transfer these resources. As such, the resources the focal firm obtains from indirect ties are less mobile and more difficult to absorb. Therefore, the cost of mobilizing resources accessed through indirect ties to be transferred to direct ties is high (Ahuja, 2000). Because of causal ambiguity, resources accessed through indirect ties are also more difficult to integrate with those accessed through direct ties (Das & Teng, 2000; Sarkar et al., 2009). Information redundancy between direct and indirect ties may overload a focal firm's capacity to absorb diverse new knowledge, reduce its capacity to innovate, force it to overspend on existing innovation projects, and reduce its operational efficiency, thus diminishing its innovation inputs and outputs (Burt, 2004; Vanhaverbeke et al., 2012). In addition, from the perspective of patent regulations, patentable innovation applications are required to be original and cannot infringe on the scope of the rights granted through existing patents (Demaine & Fellmeth, 2002). When a focal firm maintains too many indirect alliances, patenting by its indirect alliance partners can limit the patentable scope of its direct alliance partners or even itself, which in turn will reduce its patentable innovations.

To summarize these considerations, we thus propose:

> **Hypothesis 1.** In combination, a focal firm's direct ties and indirect ties in its alliance network have a negative effect on innovation. Specifically, when the interaction term of the focal firm's direct and indirect ties rises in value, the focal firm's innovation decreases.

3.2 | Moderating effects of similarity in financial alliance subtypes

We argue that similarity in financial alliance subtypes can weaken the negative combined effect of direct and indirect ties on a focal firm's innovation. First, the governance structures associated with distinct financial alliance subtypes are similar, reducing the concern that a focal firm may lose its positional advantage in a tripartite relationship in its alliance network. Alliance governance mechanisms include contractual arrangements, co-investment requirements, and revenue-sharing rules (Choi, 2020; Das & Teng, 2000). The combination of similar governance mechanisms and shared routines reduces information asymmetry and ambiguity (Sampson, 2007). Financial alliance activities, such as exchanging assets or raising capital, follow standard operating procedures and generally agreed-on contract structures and terms (De Man, 2013). When similarity in financial alliance subtypes reaches high levels, direct alliances and indirect alliances tend to share common operating routines, knowledge bases, and even collaborative visions (Phelps et al., 2012; Soh, 2003), reducing competition but increasing collaboration between direct and indirect alliance partners. As such, similarity in financial alliance subtypes similarity also reduces the likelihood that a focal firm will lose its network position in tripartite relationships.

Second, because financial resources represent unabsorbed organizational slack, they are readily available, easy to absorb, and effortlessly redeployed for other purposes (Tan & Peng, 2003; Teirlinck, 2020), thus mitigating network redundancy and information overload. Financial slack provides firms with financial resources that can be utilized and deployed without specific restrictions and can be used flexibly (Kuusela et al., 2017). The more financial slack a focal firm has, the better the firm can pursue resource-consuming strategies such as advancing technological frontiers and maintain multiple projects in parallel (Kuusela et al., 2017), creating more patents. In the biopharmaceutical industry, when financial alliance subtypes between direct alliances and indirect alliances become similar, financial resources obtained from indirect ties are more likely to flow into direct ties. Moreover, the homogeneity and coherence of information flow in direct and indirect ties make the transferred knowledge more easily assimilated, transformed, and exploited for innovation purposes (Das & Teng, 2000; Zahra & George, 2002). As such, similarity in financial alliance subtypes provides the focal firm with ample and readily absorbable financial resources which can easily be deployed to overcome information redundancy and overload in its alliance network. We therefore propose:

> **Hypothesis 2.** When similarity in financial alliance subtypes between direct and indirect alliances increases, the negative combined effect of direct ties and indirect ties on a focal firm's innovation weakens (becomes less negative).

3.3 | Moderating effects of similarity in marketing alliance subtypes

We suggest that, in light of two considerations, similarity in marketing alliance subtypes may strengthen the negative combined effect of direct ties and indirect ties on a focal firm's innovation. First, in the biopharmaceutical industry, governance mechanisms in marketing alliances focus more intently on knowledge protection and constraints on information flows, increasing the concern that a focal firm could lose its positional advantage. Firms pay great attention to protecting their proprietary marketing know–how when engaging in marketing collaborations (Gilsing et al., 2016; Lee & Chang, 2014). When faced with similar indirect alliances, direct alliance partners will strengthen the protection of their core knowledge against imitation (Ritala & Hurmelinna-Laukkanen, 2013). Such protection is usually carried out using any of several methods, such as formal contractual mechanisms, isolating mechanisms, and business secrets (Lavie, 2006; Zhao et al., 2021). Knowledge protection persuades alliance partners to strictly monitor collaborative behaviors involving goals, obligations, and knowledge exchange and transfer (Devarakonda & Reuer, 2018; Hoetker & Mellewigt, 2009). As such, partners become more protectionist and more competitive if similarity in marketing alliance subtypes increases, undermining and endangering a focal firm's positional advantage in tripartite relationships.

Second, because marketing resources are difficult and costly to assimilate and integrate into a focal firm's other resources (Bello et al., 2010; Bucklin & Sengupta, 1993; Lee & Chang, 2014), similarity in marketing alliance subtypes may exacerbate resource redundancy and information overload. In the biopharmaceutical industry, every marketing alliance has its own specific knowledge domain, focuses on a specific product, and serves a particular market segment (Gilding et al., 2020). For example, marketing campaigns and experiences with AIDS drugs from one marketing alliance may not be applicable to cancer therapies that are promoted by another marketing alliance. In addition, marketing knowledge, such as the experience gained by negotiating with agencies for the distribution of a drug across regions, is tacit, experience-based, and noncodifiable, making marketing knowledge difficult to share and transfer (Aggarwal, 2020). Although similarity in marketing alliance subtypes makes it easier to transfer marketing information and resources between direct and indirect ties, the transferred marketing information and knowledge are incoherent and difficult to absorb, transform, integrate, or exploit in innovation activities conducted by a focal firm (Zahra & George, 2002). Because similarity in marketing alliance subtypes eases knowledge flow but does not facilitate knowledge assimilation, it may exacerbate network redundancy and information overload for a focal firm, reducing its innovation outputs (Lavie, 2006; Vanhaverbeke et al., 2012). In addition, low similarity in marketing alliance subtypes increases the diversity and heterogeneity of inputs and complementary assets for developing patentable innovation in the focal firm (Cui & O'Connor, 2012; Teece, 1998). This could reduce the negative combined effect of direct and indirect ties on the focal firm's innovation.

Based on the above discussion, we hypothesize:

> **Hypothesis 3.** When similarity in marketing alliance subtypes between direct and indirect alliances increases, the negative combined effect of direct ties and indirect ties on a focal firm's innovation becomes stronger (more negative).

4 | METHODOLOGY

4.1 | Sample and data

We tested our research hypotheses by analyzing a longitudinal firm-level panel dataset for a period running from 1990 through 2001, focusing on alliance activities in the US biopharmaceutical industry. A sample of firms operating in this industry is suitable for studying the effects of strategic networks on innovation. First, the 1990s witnessed the establishment of collaboration between science and business in biotechnology. In the biopharmaceutical industry, the business environment changed rapidly during this period (Evens & Kaitin, 2015). Molecular medicine came to the fore and developed rapidly. First-in-class drugs involving gene-to-medicine emerged and changed the entire industry. The number of biotechnology companies exploded from 100 firms in 1980 to more than 4000 by the end of the 1990s (Giovannetti & Morrison, 2000). Before 1990, alliance activities in the industry were relatively scarce (Aggarwal, 2020). The year 1990 thus provides a good starting point for this study. In addition, the year 2001 was an important turning point, as total sales in the industry reached nearly 15,000 million USD (in 1989 it was under 2000 million USD) and total investments peaked in 2000 (Pisano, 2006, p. 5, 141).

Second, because new knowledge and technology breakthroughs drive development in the biopharmaceutical industry, competitive advantage resides in innovation (Schilling & Phelps, 2007; Wuyts & Dutta, 2014). Patenting is an important mechanism for protecting technologies and maintaining competitive advantage, so firms are keen on applying for patents in the industry (Gilding et al., 2020). Therefore, patents provide a reliable measure of innovation output for biopharmaceutical companies. We performed robustness tests based on the number of patent citations that occurred five years after patent application.

The dataset is constructed from three sources. Patent data are gathered from the NBER citation dataset (Hall et al., 2001). Information on alliance activities is drawn from the Recap database. Firm-level attributes and demographics are acquired from the Compustat database. The alliance networks we construct include all sampled firms and other kinds of organizations (such as private firms, universities, public research institutions, and hospitals) that formed alliances with the sampled firms during the period. Our data do not include information related to alliance termination dates, which are rarely reported (Schilling, 2015; Schilling & Phelps, 2007). To solve this problem, we follow prior research (Schilling & Phelps, 2007) in assuming a 3-year life span for all alliances. That is, we use a moving 3-year window to establish an unbalanced panel dataset. We merge the three data sources into one panel dataset based on Global Company Key (GVKEY) to ensure that all observations in the final panel appeared in all three data sources. We limit our sample to publicly listed companies to ensure data availability and completeness. Following the above steps, the sampling frame includes 411 firms (SIC Code 2833, 2834, 2835, and 2836) and about 4000 strategic alliances spanning one decade. This selection strategy does not lead to sample selection bias because it is very common for firms in the biopharmaceutical industry to apply for patents, forge alliances, and go public (Powell et al., 2005). To measure the network index, we construct adjacency matrices for every period.

4.2 | Variables

4.2.1 | Dependent variable

The dependent variable is innovation output, which is measured by patent applications, letting P_{it} represent the number of patents applied for by firm i in year t. Patent applications typically take a long time to be processed and patents applied for are granted in or after year t. For each sampled firm, the value of innovation outputs is zero when it did not apply for any patents in a given year; otherwise, we record the number of applications. Patent applications can capture the complete timing of the innovation process (Griliches, 1990) and patent data have been used widely to measure firm-level innovation output (Gilding et al., 2020; Schilling, 2015; Schilling & Phelps, 2007) as patents include unique new high-quality knowledge (Ahuja & Katila, 2001). Studies also show that at least 50% of patents are involved in commercialization attempts and more than 50% of patentees pay patent maintenance fees for at least 10 years, which indicates that patents have great economic value to their holders (Griliches, 1990). In our data, the maximum value of the variable is 1223 and the minimum value is zero. The skewness of the distribution of the variable is 6.18, which means the distribution has a long, fat tail. It should be noted that appropriability can be achieved through mechanisms other than patenting, such as trademarks, secrecy, and technological complexity (Barros, 2021). Although patents have been regarded as a suitable measure of innovation in the biopharmaceutical industry, it may not be readily suitable for other industries (Bessen & Meurer, 2008).

4.2.2 | Independent and moderating variables

Direct ties

Consistent with prior studies, direct ties were measured by degree centrality (Ahuja, 2000). This metric equals the number of a focal firm's direct alliance partners.

Indirect ties

For a focal firm, the number of its indirect ties equals the number of organizations it can access within two steps minus the number of its direct ties. These indirect firms are indirectly connected with the focal firm through its direct alliance partners.

Similarity in alliance subtypes

We refer to Aggarwal (2020), Cui (2013), and Cui and O'Connor (2012) to calculate similarity in alliance subtypes between direct ties and indirect ties through the following process:

Step 1

We generate a dummy variable that equals one if an alliance includes a certain alliance subtype and zero if the alliance does not include that alliance subtype. Financial alliances include four subtypes: joint ventures, investment alliances, equity alliances, and option alliances. Marketing alliances also include four subtypes: marketing alliances, co-marketing alliances, co-promotion alliances, and distribution alliances. Therefore, for each direct tie or indirect tie, eight dummy variables determine whether an alliance belongs to a certain alliance subtype or not.

Step 2

We use the following equation to measure similarity in alliance subtypes between a certain direct tie and its connected indirect tie. In the equation, Firm A is the focal firm, Firm B is the focal firm's direct partner, and Firm C is Firm B's partner but not the focal firm's partner, as denoted in Figure 3.

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$$\text{Similarity} = \frac{\text{The number of overlapped alliance subtypes of the AB tie and the BC tie}}{\text{The number of overall alliance subtypes of the AB tie and the BC tie}}$$

For example, if alliances involved in an indirect tie were of the same subtypes as those in its matched direct tie, the similarity in alliance subtypes between these two ties is one. The similarity in alliance subtypes ranges from zero to one.

Step 3
The number of direct alliances and the number of indirect alliances differs significantly between firms. To control for the network-size effect, we measure two kinds of similarity in alliance subtypes for a focal firm and control for network size by calculating the mean of the similarities in alliance subtypes in the focal firm's two-step network.

Step 4
To control for relationships between direct partners such as in triadic closure, we weight the values of similarity in alliance subtypes by the clustering coefficient. The clustering coefficient is used as a tool for examining the connection between directly linked actors (McMahan & McFarland, 2021). Specifically, it measures the proportion of actual ties that exist between alliance partners that are directly connected to a focal firm as compared with the ties that could develop between all alliance partners.

4.2.3 | Control variables

To minimize confounding effects and alternative explanations, we control for several important firm-level and network-level factors that may affect the process involved in and the outcomes of innovation activities. The independent variables and control variables in the analyses are lagged by 1 year to ensure that the dependent variable in the current period does not influence the results for the independent variables and control variables in the previous period. The variables used in this study are described in Table 2.

Number of R&D alliances
Frequent knowledge-sharing and creation in R&D alliances may have a strong effect on a focal firm's innovation (Zhang et al., 2019), so we include the number of R&D alliances as a control variable.

Prior ties
Prior alliance experience influences trust and knowledge-sharing between alliance partners (Choi, 2020; Phelps, 2010). We therefore control for the number of prior alliances with the same partner.

Proportion of indirect ties
Differences in the number of direct and indirect ties may have differing effects on innovation (Ahuja, 2000). In addition to controlling for the numbers of direct ties and indirect ties, we also control for the proportion of a focal firm's indirect ties among its one- and two-step ties.

Interactive alliance mechanism
The degree of interaction between alliance partners may affect a focal firm's innovation. We refer to Choi (2020) to construct this variable based on specific alliance tasks. We first assign scores for inter-partner interaction according to the tasks involved in an alliance, that is, pooled tasks (0), sequential tasks (1), and reciprocal tasks (2). We then sum all a focal firm's scores to measure the degree of interaction intensity.

Ownership arrangement
When both direct and indirect alliances involve equity arrangements such as joint ventures or equity purchases, the shared equity may facilitate joint patenting by firms in both alliances (Das & Teng, 2000). Accordingly, we control for the number of shared equity arrangements between a focal firm's direct and indirect alliances.

R&D expenditures
We control for a focal firm's R&D expenditures because they positively affect innovation outputs and are strongly correlated with patent counts (Rojas et al., 2018).

Assets in mergers and acquisitions
In addition to gaining external resources through strategic alliances or arm's-length transactions, firms can also obtain and acquire external resources and knowledge from mergers or acquisitions (M&As). It has been shown that M&As influence innovation significantly (Ahuja & Katila, 2001). We, therefore, include total assets acquired through M&As in the current year as a control variable.

Firm size
Corporate size may affect innovation outcomes (Ahuja, 2000; Phelps, 2010). The larger the firm, the more resources it can invest in innovation activities and the more likely it is to innovate. A large company may also deploy more departments with alliance-related responsibilities, which can impact the flow of knowledge between alliance partners. We use the natural logarithm of the number of employees and total sales to assess firm size.

Internal resources
The availability and quality of internal resources affect a firm's innovation outcomes. The combination of internal and external knowledge can benefit those outcomes

TABLE 2 Overview of variables used in the statistical model

Variables	Data source	Description
Dependent variables		
Patent applications	NBER	Number of patent applications captured in year $t+1$
Patent citations	NBER	Citation number of patent applications in year $t+1$ till 2006
Independent variables		
Direct ties	Recap	Number of strategic alliances of the focal firm
Indirect ties	Recap	Number of strategic alliances not directly linked to the focal firm but indirectly linked
Similarity in financial alliance subtypes	Recap	The similarity degree of financial alliance subtypes of direct ties and indirect ties of the focal firm (see text for full description)
Similarity in marketing alliance subtypes	Recap	The similarity degree of marketing alliance subtypes of direct ties and indirect ties of the focal firm (see text for full description)
Control variables		
Number of R&D alliances	Recap	Number of R&D alliance
Prior ties	Recap	Number of collaborations between the focal firm and alliance partners
Proportion of indirect ties	Recap	The proportion of indirect ties to all 1- and 2-step ties
Interactive mechanism	Recap	Interaction intensity between alliance partners
Ownership arrangement	Recap	the number of shared equity arrangement between direct alliances and indirect alliances
R&D expenditures	Compustat	Total expenditure of R&D ($M)
Mergers & acquisitions	Compustat	Total amount of mergers and acquisitions ($M)
Cash	Compustat	Total amount of cash ($M)
Employment	Compustat	Log of number of employees
Intangible assets	Compustat	Total amount of intangible assets ($M)
Property	Compustat	Value of property, plant, and equipment ($M)
Sales	Compustat	Log of the amount of sales
Market value	Compustat	Market value ($M)

(Wuyts & Dutta, 2014). Thus, we construct three variables to reflect a focal firm's internal resources: the value of its cash; its property, plant, and equipment; and its intangible assets. These resources reflect the availability to a focal firm of cash flow, tangible assets, and intangible assets.

Corporate performance

We use a focal firm's market value in the current year to measure its performance. Corporate performance may have a negative impact on innovation owing in part to the problematic search mechanism but it might also have a positive impact because of threat rigidity (Mone et al., 1998). Firms that have achieved superior performance in the past are better situated to innovate successfully. Therefore, a focal firm's past performance is likely to affect its innovation outcomes in the current period.

Time trends and year effects

To control for changes in macroeconomic conditions or industrial environments (Schilling & Phelps, 2007), we also include year dummy variables.

4.3 | Model specification

Insofar as the dependent variable, the number of patent applications, is a count variable, for which the means (27.97) and variances (100.1) exhibit wide differences, we use a negative binomial regression model rather than Poisson regression to test our hypotheses (Hilbe, 2011). Following previous studies (Dawson & Richter, 2006), we examine the combined effect of direct ties and indirect ties on a focal firm's innovation (Hypothesis 1) using a two-way interaction term and the moderation effects of similarity in financial/marketing alliance subtypes (Hypotheses 2 and 3) using a three-way interaction term. To reduce the threat of multicollinearity, we construct interaction terms after each variable is mean-centered.

To avoid the influence of outliers and extreme values in the regression analyses, we perform a 98% winsorization on the dependent variable. To avoid spurious regression problems, a stationarity time serial and unit root test is required (Maddala & Shaowen, 1999). Because the panel data are unbalanced, we use the Fisher test and verification method augmented by a Dickey–Fuller test (Maddala & Shaowen, 1999). The test results show that the data do not have a unit root, the sequence is stable (Chi-square $= 1005.78$, $p = 0.004$), and there is no corresponding trend problem. The mean of the variance inflation factor (VIF) of the variables is 3.98 and the maximum value is 7.58, indicating that multicollinearity is not a concern. To address the potential for heteroskedasticity, we adopt robust standard errors.

4.4 | Heterogeneity

Endogeneity might affect the relationship between strategic network and innovation outcomes as a result of omitted variables or reverse causality. Although previous studies have shown that network structure is an exogenous variable and can be included in regression models (Phelps, 2010), we still adopt several tactics to eliminate the potential for endogeneity to confound our results. First, to minimize confounding effects and alternative explanations, we control for several important firm-level and network-level factors that may affect the process and outcomes of innovation activities. Second, to ensure that causality flows from network ties to innovation outputs rather than in the reverse direction, the independent variables and control variables in all models are lagged by 1 year. Moreover, we address the cross-sectional heterogeneity problem. In panel data, even after controlling for important characteristics of a focal firm, there remain heterogeneous factors that are difficult to observe but may impact the focal firm's patent applications. Fixed-effects models or random-effects models are estimated to control for unobserved time-invariant or time-varying factors. A fixed-effects model assumes that the unobservable factors are fixed and unchanging over time, whereas a random-effects model assumes that the unobserved factors can be divided into individual effects and random effects. Thus, a random-effects model requires unobservable factors and explanatory variables to be uncorrelated, which is a more stringent constraint. We use a Hausman test to determine whether we should use a fixed-effects model or a random-effects model to address heterogeneity (Sun et al., 2021).

5 | RESULTS

5.1 | Statistical results

Descriptive statistics and the correlation matrix are reported in Table 3, showing that, on average, the firms in our sample applied for 28 patents, had 5 alliance partners, and maintained about 50 indirect partners per year.

Table 4 presents the results obtained with four negative binomial regression models we used to test Hypotheses 1, 2, and 3. Model 1 is a baseline model that includes only the control variables, providing a benchmark for examining how direct ties, indirect ties, and similarity in alliance subtypes interactively impact a focal firm's innovation. Model 2 provides results that show the combined effect of direct ties and indirect ties on innovation. The results derived from Models 3 and 4 indicate the moderation effect of similarity in financial and marketing alliance subtypes, respectively. The values of the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) in Models 2, 3, and 4 are lower than their values in Model 1, indicating that these models achieve better model fit than Model 1 (Cameron & Trivedi, 2013, pp. 199–200). We also report the p-values of the Hausman test results and the models chosen. When a p-value is not significant ($p > 0.05$), there is no difference between the estimation results obtained with the random-effects model and those obtained with the fixed-effects model. When this happens, we choose the results obtained with the random-effects model to test our hypotheses.

Our Hypothesis 1 is supported, as the findings derived from Model 2 and reported in Table 4 suggest that interaction between direct ties and indirect ties has a negative and significant impact on a focal firm's innovation ($b = -0.0000679$, $p < 0.005$). The findings also indicate that the individual effect of direct ties or indirect ties on innovation is positive ($b = 0.00411$, $p < 0.005$; $b = 0.00134$, $p < 0.001$, respectively). Note that the overall effect of direct ties and indirect ties is still positive even though the interaction term is negative. The results derived from Model 3 show support for Hypothesis 2 ($b = 0.0172$, $p < 0.001$). The results derived from Model 4 support Hypothesis 3, as the three-way interaction coefficient is negative and significant ($b = -0.0134$, $p < 0.001$).

Based on the regression results, in Figure 4 we plot the interaction effects of direct ties, indirect ties, and similarity in alliance subtypes on innovation. Following the prior literature (Dawson & Richter, 2006), we take the mean minus one standard deviation as the criterion for low indirect ties/similarity and the mean plus one standard deviation as the criterion for high indirect ties/similarity. For the three-way interaction effects, we follow Dawson and Richter (2006) and plot a regression fit line based on indirect ties and similarity in alliance subtypes for the role of direct ties on innovation in four separate scenarios: high indirect ties–high similarity, low indirect ties–low similarity, high indirect ties–low similarity, and

TABLE 3 Correlation matrix and description statistics

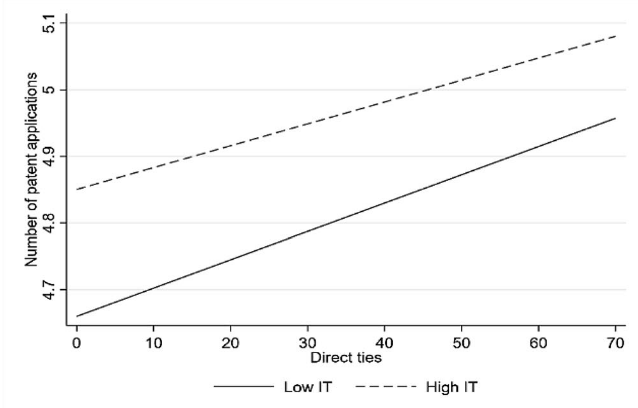
Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1. Patent applications	1																	
2. Direct ties	0.653*	1																
3. Indirect ties	0.514*	0.531*	1															
4. SFAS	0.015	0.006	−0.034	1														
5. SMAS	−0.016	−0.018	−0.109*	0.066*	1													
6. Number of R&D alliances	0.590	0.610*	0.522	0.053	−0.094	1												
7. Prior ties	0.491	0.773*	0.648	−0.003	−0.037	0.159*	1											
8. Proportion of indirect ties	0.019	0.094*	0.344*	−0.091*	−0.369	0.124*	0.109*	1										
9. Interactive mechanism	0.630*	0.352*	0.544*	0.040	−0.038	0.527*	0.602	0.116*	1									
10. Ownership arrangement	0.502*	0.497*	0.547	0.375	−0.029	0.498*	0.547	0.050	0.613*	1								
11. R&D expenditures	0.180*	0.205	0.172*	−0.004	−0.001	0.159*	0.180*	0.008	0.181	0.126*	1							
12. Mergers & acquisitions	0.271*	0.386	0.275	−0.012	−0.014	0.319*	0.426*	0.001	0.375*	0.184	0.172*	1						
13. Cash	0.564*	0.487	0.402*	−0.006	−0.009	0.459	0.385	0.021	0.474*	0.364*	0.189	0.295	1					
14. Employment	0.660	0.619*	0.483	−0.052	0.019	0.530*	0.477	0.031	0.579	0.436*	0.141*	0.328	0.518	1				
15. Intangible assets	0.611	0.508*	0.424*	−0.017	−0.002	0.417*	0.481*	0.020	0.484	0.307	0.207*	0.411	0.511*	0.471	1			
16. Property	0.777*	0.707	0.537	−0.003	−0.004	0.623*	0.598	0.003	0.678*	0.465	0.190	0.501*	0.746*	0.702	0.672	1		
17. Sales	0.597*	0.586*	0.476*	−0.066*	0.029	0.500	0.461*	0.051	0.548*	0.407	0.131	0.294	0.470	0.724*	0.430*	0.632	1	
18. Market value	0.520*	0.408	0.378*	−0.027	−0.008	0.382	0.320*	0.031	0.372	0.215*	0.278*	0.090*	0.412	0.333*	0.464	0.511*	0.313	1
Mean	27.97	5.249	50.54	0.740	0.041	2.641	1.410	0.854	6.809	0.937	2.768	91.26	268.9	6.112	419.2	1390	2224	3889
SD	100.1	7.792	71.12	0.117	0.095	4.617	3.538	0.118	0.949	1.654	55.70	758.1	1300	2.160	2557	5610	9136	32,400
Min	0	0	0	0	0	0	0	0.5	0	0	0	−324.078	0	0.001	0	0	0	0
Max	1223	84	630	1	1	46	48	0.988	102	20	2772	16,319	31,945	12.62	41,047	52,897	120,800	665,400
N	3829	3829	3829	3195	3195	3829	2931	3195	3195	3195	3832	2931	2691	2931	2931	2931	2931	2931

Note: *$p < 0.01$.
Abbreviations: SFAS, similarity in financial alliance subtypes; SMAS, similarity in marketing alliance subtypes.

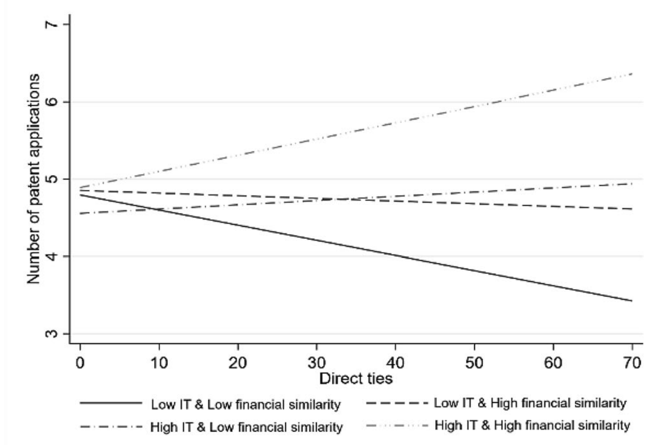
TABLE 4 Results from testing interaction effects of direct ties, indirect ties, and similarity in alliance subtypes on patent applications (negative binomial regression)

Variables	Model 1	Model 2	Model 3	Model 4
Direct ties (DT)		0.00411** (0.00136)	0.00985*** (0.00148)	0.00361* (0.00145)
Indirect ties (IT)		0.00134*** (0.000130)	0.000900*** (0.000141)	0.00132*** (0.000141)
H1: DT*IT		**−0.00000679** (0.00000217)**	**−0.0000168*** (0.00000257)**	**0.000000197 (0.00000258)**
Similarity in financial alliance subtypes (SFAS)			16.39*** (4.774)	14.86*** (1.992)
Similarity in marketing alliance subtypes (SMAS)			−13.92*** (4.223)	−28.17** (10.25)
DT*SFAS			−1.420 (0.822)	
IT*SFAS			−0.0506 (0.0445)	
H2: DT*IT*SFAS			**0.0172*** (0.00270)**	
DT*SMAS				0.375 (1.160)
IT*SMAS				0.249** (0.0883)
H3: DT*IT*SMAS				**−0.0134*** (0.00330)**
Number of R&D alliances	−0.00929*** (0.00111)	−0.00986*** (0.00113)	−0.0121*** (0.00116)	−0.0136*** (0.00118)
Prior ties	0.0113*** (0.00102)	0.0107*** (0.00107)	0.00961*** (0.00108)	0.00988*** (0.00108)
Proportion of direct ties	0.140 (0.0944)	−0.424*** (0.105)	−0.341** (0.107)	−0.475*** (0.106)
Interactive mechanism	0.00936*** (0.000654)	0.00841*** (0.00100)	0.0106*** (0.00103)	0.0127*** (0.00107)
Ownership arrangement	−0.00197 (0.00210)	−0.00137 (0.00217)	−0.0128*** (0.00245)	−0.00208 (0.00221)
R&D expenditures	−0.00000804 (0.0000167)	−0.00000627 (0.0000170)	−0.0000129 (0.0000170)	−0.0000194 (0.0000171)
Mergers and acquisitions	−0.0000109*** (0.00000251)	−0.00000886*** (0.00000260)	−0.0000119*** (0.00000262)	−0.00000932*** (0.00000262)
Cash	0.0000205*** (0.00000260)	0.0000212*** (0.00000261)	0.0000305*** (0.00000280)	0.0000212*** (0.00000262)
Employment	0.787*** (0.0169)	0.791*** (0.0169)	0.781*** (0.0171)	0.785*** (0.0170)
Intangible assets	−0.0000154*** (0.00000116)	−0.0000155*** (0.00000118)	−0.0000164*** (0.00000119)	−0.0000130*** (0.00000125)
Property	−0.000000408 (0.00000142)	0.000000132 (0.00000147)	0.00000175 (0.00000149)	−0.00000215 (0.00000148)
Sales	−0.00631 (0.0116)	−0.0217 (0.0117)	−0.0186 (0.0118)	−0.0195 (0.0117)
Market value	4.81e−08 (5.82e−08)	−3.63e−08 (5.90e−08)	−0.000000142* (6.05e−08)	1.12e−08 (5.91e−08)
Year dummy variables	Included	Included	Included	Included
N	1976	1976	1976	1976
AIC	18,172.7	17,909.4	17,765.3	17,821.5
BIC	18,290.1	18,043.5	17,927.4	17,983.5
Hausman test	FE, $p < 0.001$	FE, $p < 0.001$	FE, $p < 0.001$	FE, $p < 0.001$

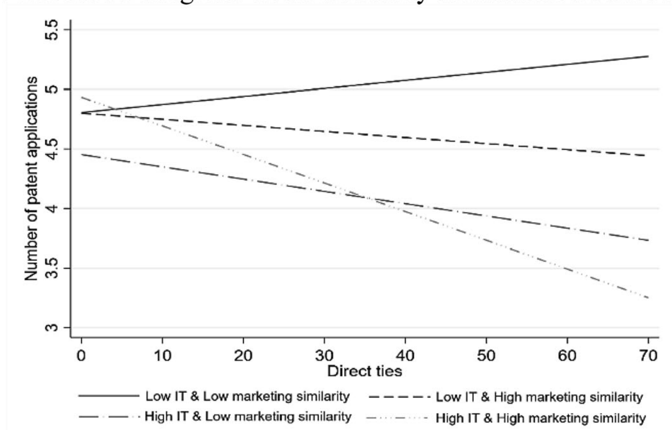
Note: Standard errors in parentheses. *$p < 0.01$; **$p < 0.005$; ***$p < 0.001$.
Abbreviations: FE, fixed-effects model; RE, random-effects model.



Panel A. The interaction between direct and indirect ties



Panel B. The moderating role of the similarity in financial alliance subtypes



Panel C. The moderating role of the similarity in marketing alliance subtypes

FIGURE 4 Interaction effects of direct ties (DT), indirect ties (IT) and similarity in alliance subtypes on patent applications (low value means −1 SD and high value means +1 SD). Panel A: The interaction between direct and indirect ties. Panel B: The moderating role of the similarity in financial alliance subtypes. Panel C: The moderating role of the similarity in marketing alliance subtypes.

low indirect ties–high similarity. Figure 4 shows the two-way interaction plot (Panel A) and three-way interaction plots (Panels B and C). The results obtained from slope difference tests as shown in Figure 4 are consistent with the regression results. In Panel A of Figure 4, the slope of the high indirect-ties scenario is slightly lower than that of the low indirect-ties condition, supporting Hypothesis 1. In Panel B of Figure 4, the slope of the condition of low indirect ties and low similarity in financial alliance subtypes is the lowest and negative, whereas the slope of the condition of high indirect ties and high similarity in financial alliance subtypes is the highest and positive. The slopes of the other two scenarios (high–low, low–high) fall between the slopes of the high–high and

TABLE 5 Results from testing interaction effects of direct ties, indirect ties, and similarity in alliance subtypes on patent citations (negative binomial regression)

Variables	Model 1	Model 2	Model 3	Model 4
Direct ties (DT)		0.0229* (0.0105)	0.0334** (0.0118)	0.0169* (0.0115)
Indirect ties (IT)		0.00219** (0.000787)	0.00215* (0.000870)	0.00237** (0.000838)
H1: DT*IT		**−0.0000616*** (0.0000149)**	**−0.000102*** (0.0000219)**	**−0.0000438* (0.0000178)**
Similarity in financial alliance subtypes (SFAS)			24.44 (22.71)	−0.642 (8.026)
Similarity in marketing alliance subtypes (SMAS)			−4.682 (3.967)	−42.66* (16.82)
DT*SFAS			−6.006 (5.067)	
IT*SFAS			−0.233 (0.228)	
H2: DT*IT*SFAS			**0.0519** (0.0190)**	
DT*SMAS				5.718 (5.062)
IT*SMAS				0.482 (0.312)
H3: DT*IT*SMAS				**−0.0381* (0.0208)**
Year dummy and control variables	Included	Included	Included	Included
N	1826	2029	1826	1826
AIC	14,722.7	14,595.9	14,501.9	14,502.9
BIC	14,849.5	14,753.1	14,572.7	14,573.7
Hausman test	FE, $p < 0.001$	FE, $p < 0.001$	FE, $p < 0.001$	FE, $p < 0.001$

Note: Standard errors in parentheses. The regression coefficients, standard errors, and significance levels of the main hypotheses are indicated in bold.
*$p < 0.01$; **$p < 0.005$; ***$p < 0.001$.
Abbreviations: FE, fixed-effects model; RE, random-effects model.

low–low situations. These results are consistent with the regression results and support Hypothesis 2. In Panel C of Figure 4, the slope of the condition of low indirect ties and low similarity in marketing alliance subtypes is positive, while the slope of the condition of high indirect ties and high similarity in marketing alliance subtypes is negative, consistent with the regression results and supporting Hypothesis 3.

5.2 | Robustness checks

To test the robustness of the results, we first use patent citations as an alternative measure of innovation output and rerun the regression analysis. Patent citations reflect the extent to which a focal firm's patents have been cited by other patents, indicating the importance of these patents (Hall et al., 2001). By using patent citations, we can control for the effect of frivolous patents, because frivolous patents will not be cited often by other patent applications. The results, which are obtained using the same controls as in the previous analyses (to save space, they are not shown), are reported in Table 5. All control variables in the model are lagged 1 year. As is the case with the estimation results reported in Table 4, here the coefficient of interaction between direct ties and indirect ties is negative and significant ($b = -0.0000616$, $p < 0.001$). Similarly, the coefficient of interaction between direct ties, indirect ties, and similarity in financial alliance subtypes is positive and significant ($b = 0.0519$, $p < 0.005$) and the coefficient of interaction between direct ties, indirect ties, and similarity in marketing alliance subtypes is negative and significant ($b = -0.0381$, $p < 0.01$).

We conduct an additional robustness test that incorporates the centrality of the whole network. We use two indicators as alternatives to degree centrality, reflecting firms' positions in the entire strategic network: betweenness centrality and eigenvector centrality (Mazzola et al., 2015, 2018). Betweenness centrality indicates how much control a given node has over the flow of information in a network. Eigenvector centrality is calculated based on degree centrality, considering the number of partners of direct alliance partners. When two firms have the same number of direct alliances, the firm with more indirect alliances has higher eigenvector centrality. The results are shown in Tables 6 and 7, respectively. These

TABLE 6 Results from testing interaction effects of betweenness centrality, indirect ties, and similarity in alliance subtypes on patent applications (negative binomial regression)

Variables	Model 1	Model 2	Model 3
Betweenness centrality (BC)	1.605* (0.672)	4.952*** (0.750)	0.994 (3.579)
Indirect ties (IT)	0.00189*** (0.000108)	0.00173*** (0.000115)	0.00299*** (0.000444)
H1: BC*IT	**−0.0164*** (0.00228)**	**−0.0281*** (0.00280)**	**−0.0110 (0.0115)**
Similarity in financial alliance subtypes (SFAS)		17.37*** (3.370)	4.237 (3.885)
Similarity in marketing alliance subtypes (SMAS)		−13.87*** (4.195)	−8.775 (10.27)
BC*SFAS		−433.5*** (53.6)	
IT*SFAS		0.0488 (0.0348)	
H2: BC*IT*SFAS		**18.59*** (2.579)**	
BC*SMAS			417.0 (320.0)
IT*SMAS			0.137 (0.151)
H3: BC*IT*SMAS			**−19.42 (13.73)**
Year dummy and control variables	Included	Included	Included
N	1976	1976	2029
AIC	17,851.7	17,723.0	13,965.0
BIC	17,985.8	17,885.1	14,144.7
Hausman test	FE, $p < 0.001$	FE, $p < 0.05$	RE, $p = 0.763$

Note: Standard errors in parentheses. The regression coefficients, standard errors, and significance levels of the main hypotheses are indicated in bold.
*$p < 0.01$; **$p < 0.005$; ***$p < 0.001$.
Abbreviations: FE, fixed-effects model; RE, random-effects model.

TABLE 7 Results from testing interaction effects of eigenvector centrality, indirect ties, and similarity in alliance subtypes on patent applications (negative binomial regression)

Variables	Model 1	Model 2	Model 3
Eigenvector Centrality (EC)	−0.124 (0.0704)	0.0589 (0.0767)	−0.460*** (0.0811)
Indirect ties (IT)	0.00181*** (0.000153)	0.00160*** (0.000160)	0.00217*** (0.000167)
H1: EC*IT	**−0.00103*** (0.000182)**	**−0.00210*** (0.000215)**	**−0.000519* (0.000206)**
Similarity in financial alliance subtypes (SFAS)		28.13*** (4.707)	15.28*** (1.999)
Similarity in marketing alliance subtypes (SMAS)		−17.05*** (4.342)	−41.98*** (12.26)
EC*SFAS		−168.9*** (32.31)	
IT*SFAS		−0.109 (0.0571)	
H2: EC*IT*SFAS		**1.436*** (0.168)**	
EC*SMAS			595.1*** (75.82)
IT*SMAS			−0.305** (0.114)
H3: EC*IT*SMAS			**−1.350*** (0.254)**
Year dummy and control variables	Included	Included	Included
N	1976	1976	1976
AIC	17,822.8	17,634.1	17,683.4
BIC	17,962.5	17,801.8	17,851.0
Hausman test	FE, $p < 0.001$	FE, $p < 0.001$	FE, $p < 0.001$

Note: Standard errors in parentheses. The regression coefficients, standard errors, and significance levels of the main hypotheses are indicated in bold.
*$p < 0.01$; **$p < 0.005$; ***$p < 0.001$.
Abbreviations: FE, fixed-effects model; RE, random-effects model.

results indicate that the direction and significance of the interaction terms are largely consistent with those indicated by the previous results, although the interaction term for betweenness centrality, indirect ties, and similarity in marketing alliance subtypes is not significant. This result may reflect the fact that the concept of similarity in alliance subtypes precisely captures the difference in alliance subtypes between direct ties and indirect ties, but the concept of betweenness centrality captures not only indirect alliance partners within two steps but also indirect partners beyond two steps. In addition, betweenness centrality reflects a centrality position in a whole network based on shortest paths rather than the richness of their direct and indirect connections, thus leading to a nonsignificant coefficient.

TABLE 8 Results from testing interaction effects of direct ties, indirect ties, and indirect ties squared on patent applications (negative binomial regression)

Variables	Model 1	Model 2
Direct ties (DT)	0.00602*** (0.00146)	0.00928*** (0.00256)
Indirect ties (IT)	0.00175*** (0.000191)	0.00312*** (0.000329)
IT*IT	−0.000000946*** (0.000000278)	−0.00000222** (0.000000765)
DT*IT		−0.0000964*** (0.00000874)
DT*IT*IT		0.000000120*** (9.73e−09)
Year dummy and control variables	Included	Included
N	1976	1976
AIC	17,847.0	17,692.2
BIC	17,986.7	17,843.1
Hausman test	FE, $p < 0.001$	FE, $p < 0.001$

Note: Standard errors in parentheses; *$p < 0.01$; **$p < 0.005$; ***$p < 0.001$.
Abbreviations: FE, fixed-effects model; RE, random-effects model.

5.3 | Additional analysis

The number of indirect ties may have a curvilinear effect on corporate performance. Redundant ties have an inverted U-shape effect on corporate innovation outcomes (Vanhaverbeke et al., 2012). When collaborating with others, firms may face the problem of the paradox of openness: disclosing knowledge can help firms achieve more inside–out innovations, but there is also the risk of knowledge leakage (Laursen & Salter, 2014). Once the threshold is crossed, returns from indirect ties become negative. Specifically, redundancy caused by indirect ties may occur only when a knowledge search is broad. We conduct an additional analysis to test this effect. The nonlinear regression results are shown in Table 8 and in Figure 5, with the control variables lagged 1 year. For Table 8, in Model 1 we include the square term of indirect ties. The coefficient of indirect ties is positive

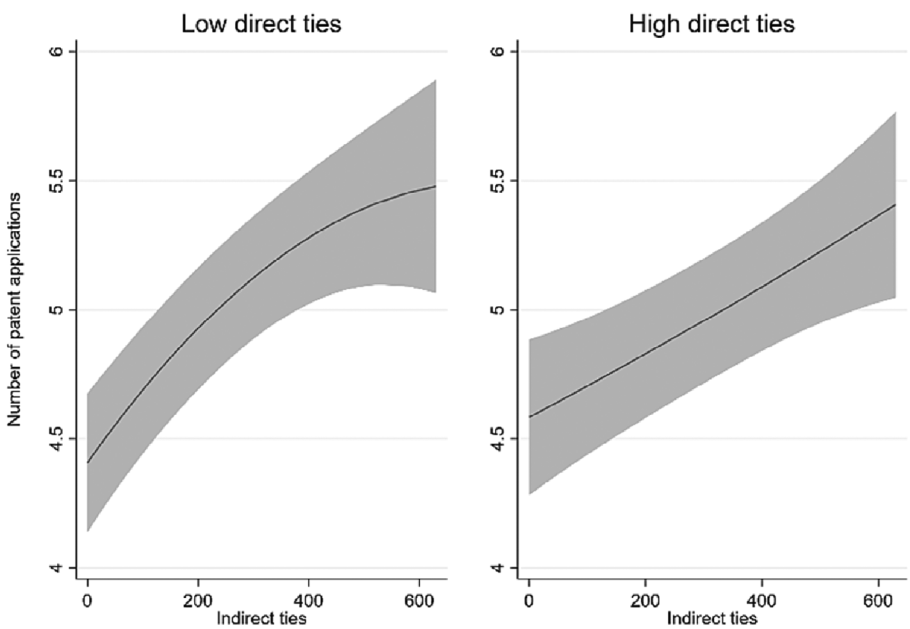


FIGURE 5 Moderating effect of direct ties on curvilinear effect of indirect ties on patent applications (low value of direct ties means −1 SD and high direct ties value means +1 SD)

($b = 0.00175$, $p < 0.001$), while the coefficient of the square term of indirect ties is negative ($b = -0.000000946$, $p < 0.001$), indicating that the effect of indirect ties on innovation assumes an inverted U-shape with a slightly negative effect. In Model 2, we include interaction between direct ties and the square term of indirect ties, and the coefficient is positive and significant ($b = 0.000000120$, $p < 0.001$), indicating that the effect of direct ties may flatten the noncurvilinear impact of indirect ties squared on firm innovation. The plot shown in Figure 5 is consistent with the regression results in that the nonlinear relationship approaches the linear relationship when direct ties are at high levels.

6 | DISCUSSION

6.1 | Theoretical contributions

Our study's theoretical contributions begin with its being the first to examine the combined effect of direct and indirect ties on a focal firm's innovation output as measured by number of patent applications. Although prior studies offer insights into the positive impact of direct/indirect ties on innovation (Ahuja, 2000; Baum et al., 2000; Cui & O'Connor, 2012; Mazzola et al., 2018), it is surprisingly rare for a study in the extant literature to investigate the collective influence of direct ties and indirect ties. Our findings from the biopharmaceutical industry indicate that direct ties and indirect ties when considered collectively have a negative impact on a focal firm's innovation. This finding is consistent with the structuralist view of networks, which suggests that the addition of an indirect tie to a bilateral relationship will create a tripartite relationship that endangers the original bilateral relationship and gives the direct partner more power (Borgatti & Halgin, 2011; Cook & Richard, 1978). Our findings do not, however, agree with the connectionist view of networks, which assumes that indirect ties expand the reach and richness of direct ties, offering firms a broader pool of resources for developing their own innovation (Koka & Prescott, 2002; Lavie, 2006).

The results obtained from our additional analysis show an inverted-U shaped relationship between direct ties and innovation, which suggests that having more indirect ties may overburden a focal firm with information overload and network redundancy (Koka & Prescott, 2002; Lavie, 2006; Mariotti & Delbridge, 2012). In addition, when we simultaneously consider the effects of direct ties and the square term of indirect ties, the three-way interaction term shows a positive impact on firm-level innovation, suggesting that the effect of indirect ties depends heavily on the structure of the direct ties. Taking these findings together, our research reveals that the structures of a focal firm's alliance network (including both direct and indirect alliances) and the direct alliance network are important factors that determine the extent to which the focal firm could benefit from its alliance network.

Moreover, our study enriches the alliance network literature by developing a novel concept of similarity in financial or marketing alliance subtypes to represent the content of a focal firm's alliance network. Strategic alliances differ by type and particular types of alliances such as marketing and finance alliances also have distinct subtypes (Cui & O'Connor, 2012; Martínez-Noya & Narula, 2018; Sampson, 2007). Prior studies offer insights into the importance of differentiating types of alliances (Aggarwal, 2020; Choi, 2020; Cui, 2013; Cui & Xiao, 2019). To move this line of inquiry forward, our concept of similarity in financial or marketing alliance subtypes adopts a more granular perspective to examine differences and similarities in alliance subtypes between direct and indirect ties. It is suggested that similarity in financial or marketing alliance subtypes determines what and how resources, information, and knowledge can be shared and transferred within an alliance network, which subsequently determines the network content and the extent to which a focal firm could learn from its direct and indirect partners. In so doing, we enrich the literature by showing the importance of network content or composition in offering innovation potential (Baum et al., 2000; Phelps, 2010).

Finally, our research also extends the extant innovation literature by simultaneously considering the impacts of the structure and content of a focal firm's alliance network on its innovation outcomes. The structure and content of an alliance network go hand in hand (Phelps et al., 2012) and, in this case, they should impact a focal firm's innovation jointly rather than separately. In fact, our findings show that similarity in financial alliance subtypes, as compared with similarity in marketing alliance subtypes, has a distinct moderating effect on the combined impact of direct and indirect ties on a focal firm's innovation. This finding shows that resources, skills, and knowledge shared in various subtypes of marketing or financial alliances are heterogeneous and, accordingly, a focal firm's innovation output is simultaneously determined by the structure and content of its alliance network.

6.2 | Managerial implications

The results of this research also provide several implications for managers. First, we suggest that managers should obtain alliance profiles of potential alliance partners through databases such as the Securities Data

Company or Recap to scan and monitor the alliance status of their indirect alliance partners. Our study shows that indirect alliances play a dual role: they can transfer additional information without incurring alliance costs and can influence resource gains from direct alliances. Switching costs and the limited availability of alternative partners make it difficult for managers to have any effects on indirect ties. However, understanding indirect alliance partners can help managers gain a more comprehensive view of the network environment (direct ties, indirect ties, and alliance subtypes) in which a firm is embedded, taking Figure 1 as an example. In addition, managers should also consider the impact of indirect ties when entering into new alliances. Generally, when selecting alliance partners, managers tend to base their decisions on partner characteristics, such as resource complementarity, resource compatibility, and knowledge heterogeneity. In fact, managers can select appropriate partners and choose specific alliance content based on an existing alliance structure and alliance content.

Second, when managing alliances or entering new ones, managers should focus on specific subtypes of alliances and adopt differentiated management strategies for different subtypes of alliances. When designing alliance portfolios, managers should consider alliance subtypes because involvement with multiple alliance subtypes may increase the heterogeneity of alliance resources and may involve distinct governance mechanisms for knowledge-sharing and resource acquisition. In addition, information on alliance subtypes can be used to conduct appropriate risk assessment and optimize innovation activities.

Finally, the empirical results reported here also confirm that strategic networks may have a dark side when it comes to firm innovation. Networks may be over-embedded, holding a firm hostage and limiting its directions when exploring innovation opportunities. Furthermore, indirect alliances in marketing networks can create excessive competition and limit innovation benefits that firms can acquire from direct alliance relationships. In a network environment, "the more the better" logic is not applicable. Managers need to be astute in maintaining the breadth of their firms' ties while avoiding the network trap. For example, when managers perceive that both their direct and indirect ties involve certain market-specific alliances, they need to be aware that this may undermine a firm's ability to capture the benefits of innovation from direct alliances.

6.3 | Limitations and future research directions

This study is subject to several limitations and it also offers several directions for future explorations. First, this study selected firms in the biopharmaceutical industry to control for industrial effects and to enhance the validity of inter-firm comparisons. Caution should therefore be exercised in generalizing our findings to other industrial contexts. For example, in some industries firms protect innovations through lead-time or secrecy rather than through patents. Research conducted in these industries could consider alternative options for measuring innovation. Second, due to data limitation, we consider only one important characteristic of alliance networks: similarity in financial or marketing alliance subtypes. It would be meaningful to further analyze interaction between alliance attributes and partner attributes, for example, to reveal how diversity in alliance subtypes and diversity in partner types (e.g. companies, universities, or hospitals) affect firms' innovation activities interactively. Future studies could also explore similarity between alliance contract terms for direct alliances and indirect alliances to show how specific governance mechanisms and contract term configurations could influence knowledge flows. Third, limits on the availability of data make it difficult to measure many variables in alliance governance, such as partner trust, governance models, and contract completeness. These missing variables may cause endogeneity problems. Future research could explore the roles these concepts play by combining methods such as questionnaires, contract text mining, and case studies. Future studies could also seek to control for endogeneity using instrumental variables and natural experiments. Finally, because of data limitations, our sample interval spans 1990 through 2001. In the rapidly growing biopharmaceutical industry, alliance activities may differ in other periods. Future research is thus needed to examine such differences that may have differential impacts on the relationship between network ties and innovation.

CONFLICT OF INTEREST

The authors have no conflicts of interest to disclose.

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How to cite this article: Yang, Zhangbo, Chengli Shu, Shanxing Gao, and Hui Wang. 2022. "The Combined Impact of Direct and Indirect Ties on Innovation: The Moderating Role of Similarity In Alliance Subtypes." *Journal of Product Innovation Management* 39(6): 847–870. https://doi.org/10.1111/jpim.12639