Received: 3 June 2019 | Revised: 19 April 2022 | Accepted: 5 August 2022 | Published on: 16 September 2022

DOI: 10.1002/smj.3456

STRATEGIC MANAGEMENT JOURNAL WILEY

RESEARCH ARTICLE

Divestment of relational assets following acquisitions: Evidence from the biopharmaceutical industry

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Abstract

Research Summary: We examine whether acquisitions affect the divestment of firms' alliance-based relational assets. Using data from the biopharmaceutical industry and a matched case–control research design, we find that alliances are more likely to be terminated following acquisitions compared to alliances not subject to acquisitions. This higher termination likelihood is driven by acquisitions where the acquirer's alliance management capacity is stressed, and by alliances inherited from targets. The inherited alliance effect is attenuated by the target's partner's common connections with the acquirer but amplified by the target's partner's unique connections outside the merging firms' alliance portfolios. These findings are consistent with our relational view-based theorizing on the post-acquisition challenges of retaining alliance-based assets, contributing to corporate strategy scholarship on alliances and acquisitions.

Managerial Summary: In many industries, firms' portfolios of interorganizational alliances enable them to realize novel complementarities and, thereby, enhance their performance. In such sectors, managers also frequently acquire other organizations to obtain access to critical resources. However, what managers may overlook is that acquisitions can destabilize existing alliance relationships. In this study, we show that

All authors contributed equally; the order was decided at random.

the acquiring firm's capacity to effectively manage alliance-based assets is stressed once it inherits the target firm's alliances. In general, target firm alliances become more challenging to sustain, and, in particular, those that hold a higher potential for novelty become more unstable. Consequently, when evaluating acquisitions, managers should look beyond obvious measures of a target alliance's value and assess the post-acquisition integration challenges that may threaten its stability.

KEYWORDS

acquisitions, alliances, divestment, networks, restructuring

1 | INTRODUCTION

Acquisitions enable firms to obtain access to critical resources and capabilities (Capron & Mitchell, 2009; Kaul & Wu, 2016). Such access allows an acquiring firm to grow by recombining its existing resource base in novel ways, as well as by gaining new resources (Anand & Singh, 1997; Karim & Mitchell, 2000). To realize these benefits, acquirers usually restructure the combined entity's assets (Bowman & Singh, 1993), often selectively retaining a subset while divesting others (Capron, Dussauge, & Mitchell, 1998; Capron, Mitchell, & Swaminathan, 2001; Karim & Mitchell, 2000). However, the choices of which assets to retain versus divest are not straightforward, as the decision-making environment following an acquisition is "characterized by complexity, ambiguity, and contradictions" (Graebner, Heimeriks, Huy, & Vaara, 2016, p. 2), with studies estimating that 50% of post-acquisition divestitures may, in fact, be unsuccessful (Kaplan & Weisbach, 1992). Scholars have, therefore, devoted substantial research attention to examining asset divestment choices, focusing on various criteria firms use and their relationship to firm performance.[1]

A common thread in prior strategy research on divestment (e.g., Karim, 2006) is its focus on assets that reside wholly within the boundaries of the merging firms, and consequently under their full control (henceforth, referred to as internal assets). Though insightful, this focus is limited, particularly since decades of research has established that alliance-based relational assets (Dyer & Singh, 1998)—that is, interorganizational resources created through firms' strategic alliances with others—are sources of competitive advantage (Dyer & Singh, 1998; Hoehn-Weiss & Karim, 2014; Lavie, 2007; Mitchell & Singh, 1992).[2] Just as in the case of internal assets, acquisitions have the potential to unlock synergies when the relational assets of the acquirer and the target are integrated and recombined. These synergies could arise, for instance,

[1]These criteria include characteristics of resources (Capron et al., 1998; Capron et al., 2001; Karim & Mitchell, 2000) such as their functional attributes (e.g., R&D vs. marketing resources) (Capron et al., 1998) and their ownership (target- vs. acquirer-owned assets).

[2]For example, relational assets are known to be central to firm performance in many industries such as software (Lavie, 2007), semiconductors (Stuart, 2000), and biotechnology (Zollo, Reuer, & Singh, 2002).

from novel partnerships inherited from the target which allow the acquirer to access new resources in the network and recombine them with its existing portfolio of alliance-based assets (Hernandez & Shaver, 2018). Indeed, the potential for an acquirer to strengthen its network position can even motivate its choice of which specific target firm to acquire (Hernandez & Shaver, 2018).

Yet, obtaining intended synergies by acquiring alliance-based assets poses a distinctive set of challenges for acquirers compared to realizing synergies with internal assets. These challenges arise because of the unique value-generating mechanisms of alliance-based assets and the impact of the acquisition on these mechanisms. As the relational view (Dyer & Singh, 1998) describes, because control in strategic alliances is shared between the two collaborating firms, creating value requires both partners to jointly invest in specific mechanisms that overcome the hazards of interfirm exchange. These include, co-specializing each firm's resources to the needs of the partnership, creating interfirm routines to facilitate knowledge exchange, and fostering trust to reduce opportunism (Dyer & Singh, 1998). However, these mechanisms can be adversely impacted by the acquisition. Because the resources and needs of the acquirer differ from those of the target (and potentially change following the acquisition), additional co-specialization of alliance-based assets may be required to realize synergies. Since such co-specialization is unanticipated by the alliance partners, it may trigger instability in the affected relationships. Existing knowledge exchange routines that have been uniquely tailored to specific alliances (Jacobides & Winter, 2005; Nelson & Winter, 1982) may be disrupted when the acquirer attempts to reconcile distinct alliance management processes and systems. Trust, which is embedded in interpersonal interactions, may be eroded because key personnel can often leave or be replaced following the acquisition (Walsh, 1988). Concerns of opportunism among alliance partners may also increase because critical knowledge may now flow to firms that were hitherto not part of the network (Hernandez, Sanders, & Tuschke, 2015).

Additionally, envisaging and accounting for these distinct challenges prior to the acquisition may be even more difficult with alliance-based assets. As Barney (1988) highlights, information asymmetry often causes acquirers to overestimate the value of their targets' assets but underestimate the challenges of achieving synergies with them. Consequently, when the intended synergies do not materialize, these errors can lead to post-acquisition divestment (Ravenscraft & Scherer, 1987; Singh, 1993). When the acquirer must share control with other firms, as is the case with alliance-based assets, information asymmetry can further increase the gap between intended and realized synergies because partner firms' future commitments and the associated costs of managing and integrating these relationships, are even more difficult to predict. These key distinctions between internal and alliance-based assets, together with the emphasis of prior divestment research on internal assets, point to an important research gap—what happens to the alliances of the merging firms following an acquisition?

We build on foundational ideas from the relational view (Dyer & Singh, 1998; Kale, Dyer, & Singh, 2002) and insights from alliance portfolio research (Aggarwal, 2020; Asgari, Singh, & Mitchell, 2017) to propose hypotheses that examine this question. We first describe the post-acquisition challenges specific to alliance-based assets that increase their divestment likelihood. Our theory underscores the capacity constraints on the acquirer's non-scale-free alliance capabilities to manage an expanded portfolio of alliances (Kale & Singh, 2007; Levinthal & Wu, 2010; Mitchell & Singh, 1996; Shaver, 2006), the challenges posed by the evolutionary process of creating alliance-based assets and developing capabilities to manage them (Jacobides & Winter, 2005), the costs of integrating and coordinating across two different sets of alliance-based assets (Puranam, Singh, & Chaudhuri, 2009; Puranam, Singh, & Zollo, 2003), and the heightened hazards of governing existing alliances after the acquisition (Kale, Singh, & Perlmutter, 2000). We further develop this logic to propose characteristics of alliances that heighten or reduce these challenges.

We test our hypotheses in the biopharmaceutical industry—a context where both alliances and acquisitions are critical to firm performance (Rothaermel, 2001)—by tracking whether the merging firms' alliances are terminated (divested) or retained. We find that alliances are more likely to be terminated following acquisitions compared to a matched sample of alliances not subject to acquisitions. Examining the mechanism further, we show that this effect of higher termination likelihood is driven by cases where the acquirer's alliance management capacity is excessively stressed and by alliances inherited from target firms. Among the target's alliances, we find that the effect is attenuated when the target's partner has ties to the acquirer's existing partners but amplified when the target's partner has unique connections to firms outside the acquirer's and the target's alliance portfolios. This evidence is consistent with our theorizing on the conditions under which post-acquisition challenges specific to alliance-based assets might be exacerbated or alleviated.

Our paper makes important contributions to strategy research at the intersection of alliances and acquisitions. We extend the literature on post-acquisition asset restructuring (Bowman & Singh, 1993; Capron et al., 1998; Capron et al., 2001; Karim & Mitchell, 2000; Singh, 1993) into the domain of alliance-based relational assets (Dhanaraj & Parkhe, 2006; Lavie, 2006). Our finding that acquirers are more likely to terminate the target's alliances compared to their own hints at the possibility that they lack the detailed knowledge required to accurately assess and realize synergies with inherited alliance-based assets. Indeed, factors such as common partners, which are known to lower information asymmetry in exchange relationships, appear to reduce this tendency, thus further bolstering this mechanism.

Our study also complements scholarship on alliance termination that assumes stability in ownership over the life of an alliance by examining terminations triggered by a change in the ownership of a partner (e.g., Asgari, Tandon, Singh, & Mitchell, 2018; Dyer, Singh, & Hesterly, 2018; Greve, Baum, Mitsuhashi, & Rowley, 2010). We also provide an alternative lens to the real options perspective on alliance termination, which views alliances as temporary hedges against uncertainty in the firm's technological environment. While studies in this tradition (e.g., Folta & Miller, 2002; Leiblein, 2003; Vassolo, Anand, & Folta, 2004;) link alliance termination to the resolution of such uncertainty, our paper shows that termination can also be triggered by ownership change and internal restructuring.

Finally, we contribute to recent research on interorganizational networks in the context of acquisitions, which shows that acquirers choose targets to improve their network positions (Hernandez & Shaver, 2018). Our findings show that this novel perspective can be enriched by incorporating the heterogeneity in the termination likelihood of alliances post acquisition.

2 | THEORY AND HYPOTHESES

Research has shown that an acquisition can trigger major business restructuring as the acquirer integrates its resources with those of the target (Capron et al., 2001). A common consequence of such restructuring is asset divestment, where the acquirer discards, through sale or termination, a subset of its post-acquisition portfolio of resources (Capron et al., 1998; Karim & Mitchell, 2000). Studies have shown that the likelihood of divestment increases after an acquisition because the acquirer reevaluates all assets and purges those that are misaligned or not worth retaining (Bowman & Singh, 1993; Capron, 1999; Karim, 2006; Karim & Capron, 2016; Ravenscraft & Scherer, 1987; Singh, 1993). To examine whether acquisitions also trigger divestments of alliance-based assets, we first identify the theoretical mechanisms that specifically impact these assets. Our mechanisms, anchored in the relational view (Dyer & Singh, 1998), constitute a framework that lets us examine additional contingencies. Following prior research, we adopt the acquiring firm's perspective because "post-acquisition decisions are housed primarily within the acquirer" (Zollo & Singh, 2004, p. 1234).

2.1 | Acquisitions as triggers to restructure relational assets

Studies taking a relational view perspective posit that alliances create value for firms (also referred to as "relational rents") when they allow them to access the complementary resources of their partners (Dyer et al., 2018; Dyer, Kale, & Singh, 2001; Lavie, 2007). To aid the discovery and attainment of such complementarities, the two firms engaged in the alliance invest in specific rent-generation mechanisms: they co-specialize their assets to the partnership, create superior coordination routines to facilitate knowledge exchange between their personnel, and develop high levels of trust to economize on the transaction costs of governing the collaboration (Dyer et al., 2018; Dyer & Chu, 2003; Dyer & Singh, 1998). While, in theory, an acquiring firm would seek to retain alliances that create such value, the acquisition poses several distinct challenges to the continued generation of relational rents via these mechanisms.

First, the acquirer's alliance portfolio expands once it inherits the target's set of alliances. This expansion puts direct stress on the acquirer's alliance capability—that is, its capacity to manage this portfolio of interfirm relationships (Kale & Singh, 2007; Schreiner, Kale, & Corsten, 2009). The acquirer's alliance capability is central to its effectiveness in coordinating and governing alliance activities, including capturing, integrating, and recombining knowledge across them (Kale et al., 2002). However, this capability, particularly in the short run, is subject to capacity constraints. Like most resources and capabilities that involve firm-specific management teams, managing a portfolio of alliances requires time and attention[3] that are limited (Asgari et al., 2017; Levinthal & Wu, 2010; Ocasio, 1997; Shaver, 2006). Additionally, deriving the benefits of complementarities, such as the transfer of specialized knowledge and expertise from partner firms requires the attention of skilled individuals (e.g., key scientists or engineers). Because such expertise is non-scale-free, multiple claims on their use can congest and ultimately devalue these resources (Aggarwal, 2020). The deployment of alliance resources to one alliance at any point in time can preclude their simultaneous use in other alliances (Levinthal & Wu, 2010). Thus, the acquiring firm's alliance capability is subject to opportunity costs such that some alliances are likely to be retained at the cost of disbanding others.

Second, the acquisition necessitates additional co-specialization of at least a subset of the merging firms' existing alliance-based assets. At the time of the acquisition, co-specialized assets in the alliances of each firm (acquirer and target) are uniquely tailored to the resources of that firm and its exchange needs (Jacobides & Winter, 2005). However, these resources and needs change following the acquisition. To derive merger synergies, the acquirer and the target will seek to not only integrate their asset bases (Zollo & Singh, 2004) but also create unique

[3]For example, the knowledge and capabilities to decide allocation of roles and responsibilities in an alliance and to develop communications and contingency plans between partners often reside with alliance managers (Argyres, Bercovitz, & Mayer, 2007).

combinations from these resources (Barney, 1988; Singh, 1993). Such integration and recombination require resource reconfiguration and, quite often, a structural redesign to manage the post-acquisition organization (Bodner & Capron, 2018; Karim & Mitchell, 2004). However, to be effective, these changes cannot be confined to firms' internal resources but will also need to percolate to alliance-based assets that are interdependent with these resources. Indeed, the demands of additional co-specialization will not only tax the acquirer's already constrained alliance capacity, but also its corresponding alliance partners, who will need to buy in to this unanticipated reconfiguration and make reciprocal commitments. Thus, we predict that these changes will provoke instability in affected partnerships.

Third, the acquisition disrupts existing interfirm knowledge-sharing routines that undergird the discovery and transfer of complementary resources from the partner firms (Ahuja & Katila, 2001; Jemison & Sitkin, 1986). These disruptions are particularly detrimental in technology-intensive contexts such as the biopharmaceuticals, where intense interactions between personnel are required to access complementary knowledge that may be tacitly embedded and socially complex (Dyer et al., 2018; Grant, 1996; Kale & Singh, 2009). Routine disruptions can be triggered in the post-merger integration phase when the merged entity attempts to homogenize interorganizational procedures and rules in order to attain compatibility and efficiency across distinct sets of alliance management routines, systems, and teams of the acquirer and the target (e.g., Puranam, Singh, & Zollo, 2006). Such changes can additionally precipitate the unexpected loss of executive, scientific or technical personnel who are germane to the stable functioning of these interfirm routines (Ernst & Vitt, 2000; Ng & Stuart, 2021; Ranft & Lord, 2000, 2002; Walsh, 1988). Ultimately, these disruptions will destabilize ongoing partnerships and increase their termination likelihood.

Finally, the acquisition can increase the costs of governing existing partnerships both by eroding existing trust between the firms and by posing new exchange hazards. Because trust is embedded within interpersonal interactions among firms' personnel (Kale et al., 2000), the aforementioned turnover of alliance-based employees following the acquisition can increase negotiation costs and create frictions in ongoing collaborations (Zaheer, McEvily, & Perrone, 1998). Additionally, because the acquisition brings together not only the acquirer and the target but also their two distinct sets of partners via a combined portfolio of alliances, it can accentuate the risk of exchange hazards. The acquirer, its preexisting partners, and the target's partners may develop concerns about knowledge leakage and spillovers to firms that were not part of their pre-acquisition set of collaborators (Asgari et al., 2018; Hernandez et al., 2015; Lavie, 2007). It follows then, that to retain existing alliances, the acquiring firm may need to further extend its already-constrained alliance management capacity to resolve new governance challenges.

Given these considerations, we expect acquisitions to trigger a restructuring of relational assets that ultimately leads to an increased likelihood of alliance termination. We therefore hypothesize:

Hypothesis H1. *Acquisitions increase the likelihood of termination of alliances.*

If the above mechanism were true, we should observe a stronger alliance termination effect for those acquisitions where the acquirer's capacity to manage alliances is excessively stressed following the acquisition. A larger proportional increase in the alliance portfolio size will exacerbate the challenges involved in employing the acquirer's non-scale-free alliance capacity to manage both the acquirer's and the target's alliances including (a) attempting additional co-specialization of alliance-based assets to serve new post-acquisition needs, (b) managing disruptions and incompatibilities in knowledge-sharing routines, and (c) resolving new governance challenges that emerge following the acquisition. In other words, if the acquirer inherits a disproportionately large portfolio of alliances relative to its own portfolio of alliances on which its capacity is based, the termination likelihood of alliances is likely to be greater following the acquisition. Therefore, we hypothesize:

> **Hypothesis H2.** *The increased likelihood of alliance termination following acquisitions is amplified for those acquisitions that pose a greater stress on the acquirer's capacity to manage alliances.*

Thus far, we have theorized that acquisitions increase the termination likelihood of alliances and that this effect is exacerbated in acquisitions where the acquirer's alliance management capacity is more stressed. However, there are likely within-portfolio differences among these alliances such that retaining some alliances may place greater demands on the acquirer's partnering capability than others do. Specifically, alliances will differ in the extent to which they require the acquirer to make additional investments in asset co-specialization, manage disruptions and incompatibilities in knowledge-sharing routines, and resolve new governance challenges, following the acquisition. We unpack this heterogeneity in the remainder of our theory section.

2.2 | Target firm's versus acquiring firm's alliances

We first distinguish between the post-acquisition vulnerability of alliances formed by the acquirer before the acquisition (i.e., preexisting alliances) versus those that the acquirer obtains from the target firm after the acquisition (i.e., inherited alliances).

First, inherited alliances are likely to require greater co-specialization and customization because their asset specificity is more likely to change compared to the acquirer's preexisting alliances. This heterogeneity arises because of the difference in the interconnectedness of these alliances with the combined resources of the merged entity and the difference in the extent to which these resources themselves are reconfigured. Whereas the acquirer's preexisting alliances are interdependent with the acquirer's own resources, the inherited alliances are interdependent with the target firm's resource base. However, as studies have consistently shown, to obtain post-acquisition synergies, the target's resources are more likely to be reconfigured compared to the acquirer's resources (Karim & Mitchell, 2000; Karim & Mitchell, 2004). Thus, at the margin, the specific assets that need customization will be those that belonged to the target firm and will therefore require additional investments to co-specialize affected inherited alliance-based assets.

Second, knowledge sharing in inherited alliances is more likely to be disrupted, both because the acquirer faces greater information asymmetry in assessing the source of value in these alliances (Barney, 1988) and because its own alliance management processes and systems are likely to be less compatible with those of the inherited alliance partners (Dyer & Singh, 1998). The information asymmetry that accompanies the valuation of any target asset is even higher for *inherited alliance-based* assets, where the knowledge to explore potential complementarities is not fully contained in the target firm but embedded within interfirm routines and interpersonal interactions between the personnel of the target and its partner firms (Zaheer, Hernandez, & Banerjee, 2010). Indeed, as firms tend to rely on the "tacit accumulation of experiences in the minds of 'expert personnel'" in the alliance context (Zollo & Winter, 2002,

p. 347), the know-how to operate the alliance will be less accessible to the acquirer, and the value of the asset itself will be less apparent. Moreover, because the acquisition triggers turnover of target employees at higher rates (e.g., Ernst & Vitt, 2000; Ng & Stuart, 2021; Ranft & Lord, 2000, 2002; Walsh, 1988, 1989), critical tacit knowledge can be permanently lost. Consequently, ensuring deep knowledge exchange in these alliances to create value through them will be more challenging and place greater demands on the acquirer.

Relatedly, realizing complementarities is "conditioned on compatibility in decision processes, information and control systems, and culture" (Dyer & Singh, 1998, p. 668). Here, the acquirer's alliance capability—which encompasses such processes and systems—and its culture will be more aligned with its preexisting partners than with the inherited alliance partners. This divergence stems from the evolutionary process of alliance capability formation (Jacobides & Winter, 2005; Nelson & Winter, 1982). The acquirer's alliance capability reflects its own prior approaches and mutual adjustments with its own partners in minimizing transaction costs in interfirm exchanges (Jacobides & Winter, 2005). Such capabilities evolve over time through highly subjective organizational learning (Heimeriks, 2010; Zollo, 2009) and are based on idiosyncratic (i.e., partner-specific) experiences (Zollo et al., 2002). Put differently, these capabilities will be less effective in managing inherited alliances that have had their own distinct evolutionary paths with different partner firms. Obtaining complementarities from these alliances will therefore require the acquirer to expend more managerial attention, engage in deeper communication, and make greater deliberate investments (Zollo & Singh, 2004; Zollo & Winter, 2002) compared to preexisting alliances.

Finally, as the acquirer integrates and homogenizes alliance management systems to obtain synergies, it is more likely to disrupt, even if inadvertently, informal governance mechanisms in inherited alliances. When the acquirer superimposes its own alliance systems and personnel to manage the target's alliances, it risks undermining previously established norms and accumulated relational capital; in other words, the acquirer inherits the target's alliances but not the trust the inherited alliance partners had in the target. Any informal governance arrangement that the target and its partners relied upon faces further disruption through target employee turnover. Because trust relies upon such interpersonal ties and familiar exchange processes (Dyer & Singh, 1998; Kale et al., 2000), absent these credible safeguards, the inherited partner may be reluctant to make the required investments in the relationship, thus undermining the rent-generating potential of the alliance. The retention of the inherited alliances may also heighten exchange hazards in the acquirer's preexisting alliances, as it exposes both the acquirer and its partners to new sets of firms (i.e., the inherited alliances' partners). Indeed, prior research has shown that existing dyadic safeguards to limit opportunistic behavior may be insufficient to overcome the risks of knowledge leakage to firms that are indirectly linked to alliance partners (Hernandez et al., 2015). Thus, the acquirer may need to expend its limited alliance capacity on managing these new governance challenges.[4]

[4]It is important to note that even if the acquirer were to leave the target's alliance management systems unchanged and allow inherited alliances to maintain autonomy, it incurs additional costs and limits future rent generation. With autonomy, coordination costs increase because the acquirer must manage two distinct and likely incompatible systems (Puranam et al., 2006). Without integration, it is also difficult for the acquirer to discover and realize novel complementarities in the alliance portfolio (Vasudeva & Anand, 2011) because it is restricted to being a "holding" firm (Bodner & Capron, 2018). Thus, the acquirer cannot obtain the unique advantages of integration by recombining knowledge from different alliances. Besides, the acquirer also cannot credibly guarantee against any future intervention in inherited alliances (Williamson, 1985); the target's partners may therefore still withhold resource commitments because of this uncertainty, thus diminishing even existing gains from the alliance.

Taken together, because of greater co-specialization needs, higher disruption of and incompatibilities in interfirm routines, and elevated risk of new governance issues, inherited alliances will pose a larger burden on the constrained partnering capability of the acquirer compared to its own preexisting alliances. Thus, we hypothesize:

Hypothesis H3. *The increased likelihood of alliance termination following acquisitions is amplified for alliances inherited from the target firm.*

2.3 | Which alliances of the target firm are acquirers more likely to retain?

We have argued that while acquisitions heighten the termination likelihood of alliances, this effect is stronger for alliances inherited from target firms. We call this mechanism the "inheritance effect." However, because the inherited alliances may have been a motivating factor behind the acquisition, acquirers might be expected to reconcile these challenges with the need to create synergies through these alliances. Therefore, we expect that the retention decision will vary across the set of inherited alliances, such that the acquirer will invest in retaining a subset of these alliances.

To further unpack this heterogeneity and identify the conditions when the inheritance effect varies across target alliances, we examine the connections that an inherited partner (i.e., partner of the target) may have to other firms, particularly as prior research has shown that these interconnections can affect the relational rent-generation challenges in alliances (Dyer & Nobeoka, 2000; Gulati, Nohria, & Zaheer, 2000; Kogut, 2000; Lavie, 2006). We contend that these interconnections hold informative cues when the acquirer lacks direct relationships with the inherited alliance partners. We elaborate on two types of connections: (a) those between an inherited alliance partner and the acquiring firm's preexisting alliance partners (henceforth referred to as common partners), and (b) those between an inherited alliance partner and firms that do not have prior ties to either the acquirer or the target firm (henceforth referred to as unique partners).

2.4 | Interconnections of the inherited alliance partner with common partners

Our logic for the inheritance effect underscored additional co-specialization needs after the acquisition, the disruption and incompatibility in underlying knowledge-sharing routines, which exacerbates information asymmetry problems between the acquirer and the target, and increased governance challenges specific to inherited alliances. We posited that these mechanisms put the acquirer's non-scale-free alliance capabilities under stress and trigger termination. How are these mechanisms altered when inherited alliance partners share common partners with the acquiring firm?

First, whereas inherited alliances have greater co-specialization and customization needs compared to the acquirer's preexisting alliances, the acquirer will face fewer hurdles in successfully effecting these changes when it shares common partners with the target's collaborators. The costs of negotiating such changes and managing potential conflicts depend upon both the alignment of the acquirer with the target's partner and trust between them in the absence of prior direct interactions (Dyer & Singh, 1998). The alignment with the target's partner—i.e., the extent to which the alliance management systems and knowledge sharing routines of the acquirer and those of the inherited partner are compatible (Dyer & Singh, 1998, p. 668, Proposition 3b)—is enhanced with the presence of common partners between them. Common partners imply that the acquirer and the inherited partner's interorganizational routines and alliance management systems have co-evolved to align with those of the *same* partner(s). Hence, they are likely to share common features and be more congruent with one another (Kale & Singh, 2007). Moreover, realizing additional post-acquisition asset customization within the target's alliances "is more easily attained when [the two] firms receive information about their partner's behavior through interaction with third parties than when they are atomized with no available information sources about each other" (Chung, Singh, & Lee, 2000).

Relatedly, common partners can also enhance the quality of knowledge-sharing and relation-specific investments in inherited alliances. By providing information about prospective business relationships, they reduce the information asymmetry involved in assessing the complementarities associated with inherited alliances (e.g., Chung et al., 2000). Indeed, "the larger the number of third partners two firms share, the more information these two firms are likely to have about each other" (Gulati, 1995: p. 627). Because the common partners possess knowledge about both the acquirer and the inherited partner, they can facilitate the identification and validation of potential synergies in the inherited relationship, thereby helping the acquirer and the inherited partner tailor their knowledge exchange processes toward realizing those synergies. Both compatibility and enhanced trust among a familiar group of partners may also boost *future* complementarity prospects for the acquirer (Ahuja, 2000; Dyer & Singh, 1998; Kale et al., 2000; Lane, Salk, & Lyles, 2001). Ultimately such interconnections will promote mutual dependence between the various partners in the portfolio, leading to greater stability in each of these relationships (Asgari et al., 2018).

Finally, the governance challenges from introducing an inherited alliance into the acquirer's portfolio of preexisting alliances (Kale et al., 2000) are mitigated when the inherited partner already has connections to these preexisting partners. To the extent, the preexisting partners in the acquirer's portfolio are familiar with the inherited partner, they are unlikely to be concerned about knowledge spillovers to unknown firms as a result of the acquisition (Hernandez et al., 2015). The same logic applies for an inherited partner as it evaluates the impact of the target merging with a new firm and potentially new pathways over which its knowledge might flow. From the acquirer's viewpoint, concerns of misappropriation are reduced if unintended outward knowledge spillovers through the target partner circulate among known partners. Thus, the greater the number of common partners, the more the acquirer can continue to rely on existing governance solutions without needing to resolve new challenges using its limited alliance management capacity.[5] Thus, we hypothesize:

> **Hypothesis H4.** *The increased termination likelihood for inherited alliances compared to preexisting alliances (as discussed in H3) is attenuated by the inherited alliance partner's connections to the acquirer's preexisting partners.*

[5] In institutional contexts with established collaboration norms, common partners not only can allow the acquirer to detect opportunistic behavior more easily and quickly, but they can also subject the violating firm to reputational damage (Polidoro, Ahuja, & Mitchell, 2011), thus restraining such behavior in the first place.

2.5 | Interconnections of the inherited alliance partner with unique partners

Unlike connections with common partners, the inherited partner's ties to firms that lie outside the merged entity's portfolio of partners *heighten* the acquirer's challenges in creating relational rents from the alliance. We posit that these unique partnerships will likely increase governance costs and reduce both the tenability of co-specialized investments and the feasibility of achieving complementarities in the future.

With regard to the governance costs, the inherited partner's unique connections expose the acquirer's knowledge to *new* firms that could indirectly obtain access to the acquirer's knowledge. The higher the number of such connections, the greater the potential pathways through which the acquirer's knowledge could leak (Hernandez et al., 2015). From a portfolio perspective, these ties not only increase the acquirer's knowledge spillover risks but also heighten its preexisting partners' exposure to misappropriation. Thus, to retain such a partnership, the acquirer will likely need to revisit its governance structure, consider new safeguards to limit these expropriation risks, and potentially impose additional monitoring mechanisms to control the flow of knowledge to its unique connections (Gulati & Singh, 1998). Ultimately, these concerns will lead to increased coordination and governance costs, further exacerbating the stress on the acquirer's alliance management capacity and increasing the likelihood of the alliance's termination.

However, it is conceivable that the acquirer might be willing to incur these increased exchange hazards and the associated governance costs if the partnership's resultant benefits were substantial. For example, access to distinctive clusters in the industry (through the inherited partner's unique ties) could spur innovative recombinations with the acquirer's knowledge or resources. In this case, however, the acquirer faces a different challenge—realizing such novel complementarities, particularly with unfamiliar resources, is predicated on trust between the *acquirer* and the *inherited* partner and well-established specialized routines (Zollo & Winter, 2002), both of which do not exist at the time of the acquisition.[6]

Co-creating these specialized routines after the acquisition, however, requires the inherited partner to weigh the corresponding opportunity costs—it must consider reallocating its own non-scale-free alliance resources away from existing collaborations toward a partnership whose value is uncertain because of the acquisition (e.g., Levinthal & Wu, 2010; Wu, 2013). Recent research has demonstrated that when there are competing demands on congestible and critical alliance resources (such as scientists or engineers who hold tacit knowledge); partners are forced to selectively withhold these resources from a subset of their alliances (Aggarwal, 2020). In our context, the inherited partner faces competing claims on its alliance resources from the acquirer and from its unique partners. Without overlap between its unique partners and those of the acquirer, the inherited partner is likely to find it difficult to realize economies of scope in allocating resources across its alliances. Nor can it resort to compatibility of routines between

[6]The routines that existed between the inherited partner and the *target* before acquisition are co-specialized to the target's purposes and do not necessarily support the acquirer's pursuit of novel recombinations. Further, those routines are likely undermined as the ownership transfers from the target to the acquirer. The target could lose managerial personnel, diminishing the informal governance.

itself and the acquirer to resolve its resource congestion; such compatibility is fostered through shared partners but unlikely to be facilitated by unique ties.[7] Indeed, the more unique partners the target partner has, the more likely that substantial co-specialization of the inherited alliances will be required (Jacobides & Winter, 2005), and the less likely that its existing alliance capabilities will be effective in managing this relationship (Zollo & Winter, 2002). Thus, the greater the challenges stemming from such congestion and the less likely that the acquirer will be able to successfully gain complementarities from the relationship.

Moreover, the same concerns about knowledge spillovers to new firms that trouble the acquirer or its existing partners can also concern unique partners. The unique partners may thereby restrict the flow of their knowledge to the inherited partner or impose additional governance costs. Therefore, access to the unique partners' resources is likely to be costly, constricted, and uncertain. Thus, all things considered, we conclude that the acquirer is unlikely to jeopardize knowledge flows from its existing partners with the promise of an uncertain, if at all possible, access to novel resources. Thus:

> **Hypothesis H5.** *The increased termination likelihood for inherited alliances compared to preexisting alliances (as discussed in H3) is amplified by the inherited alliance partner's connections to unique partners.*

3 | METHODOLOGY

3.1 | Empirical setting and sample

We test our hypotheses in the global biopharmaceutical industry, where firms have long used acquisitions and alliances to access knowledge and technological capabilities (Bierly & Chakrabarti, 1996; Hess & Rothaermel, 2011; Pisano, 2006). Our sampling timeframe is between the years 1989 and 2000, a period when technological developments in biotechnology, and the associated uncertainty and competition, had spurred both alliance and acquisition activities in the industry. To create our sample, we first used the Osiris dataset to identify biopharmaceutical firms by their relevant North American Industrial Classification System (NAICS) codes.[8] We then used RECAP, a comprehensive dataset covering biopharmaceutical deals (Schilling, 2009), to obtain the alliances and acquisitions undertaken by these firms during our sampling period. A notable feature of this dataset is that it allows us to capture meaningful characteristics of alliances that drive value creation in the biopharmaceutical industry, including whether an alliance involves rare diseases and whether it utilizes novel combinatorial chemistry resources.[9] Overall, we identified 67 acquiring firms, which had a total of 1,836 preexisting alliances, and the acquisition targets

[7]These routines and systems evolve through a path-dependent process that is specific to a firm's experience with its partners (Dyer & Singh, 1998). They reflect the unique cultural distinctions in how firms transact across firm boundaries; allies arrive at a negotiated management system that reflects the common features of each. Unconnected firms do not build on such commonalities and are therefore likely to diverge. Hence, with an increase in the number of its connections with unique firms, the inherited partner's alliance management system is likely to have evolved in a direction divergent from that of the acquirer's. This effect is likely to increase the managerial incompatibility between the acquirer and the inherited partner, hurting the discovery of complementarities (Dyer & Singh, 1998).

[8]The NAICS codes are 325412, 325413, and 325414.

[9]As we discuss later, the dataset, along with other measures, also made it possible to compare alliances that are exposed to acquisitions (treatment sample) with others that are not, while control for many factors that affect the alliance value.

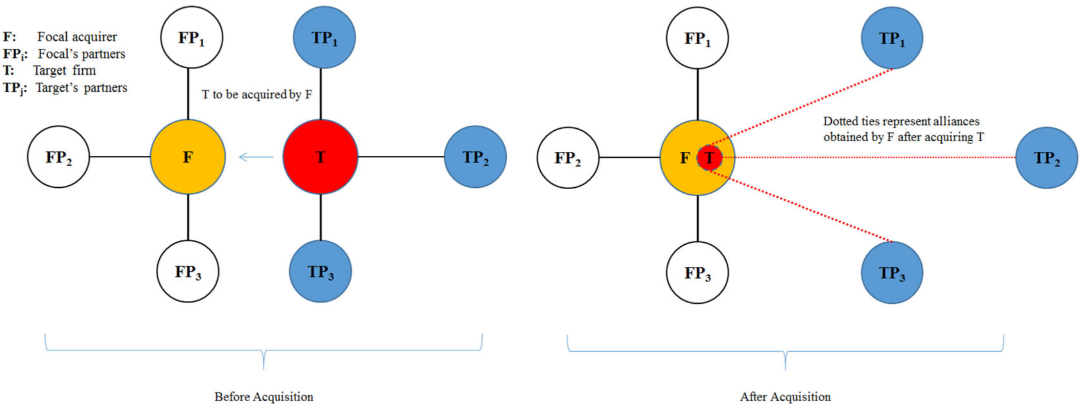

FIGURE 1 Acquiring firm, target firm, and their partners

corresponding to these acquiring firms, which had a total of 506 inherited alliances. We also identified 246 firms in this industry that did not engage in any acquisition activity (either as an acquirer or a target) which had a total of 2,379 alliances.[10] These alliances constituted our control group for testing Hypotheses H1–H3. Firms without alliances did not enter our sample of acquirers and targets or our control group. Figure 1 provides a stylized illustration of an acquiring firm, a target firm, and their respective alliances.

In Figure 1, "F" indicates the acquirer, and "T" the target firm acquired by F, while "FP$_i$" and "TP$_i$" correspond to each of their alliance partners. As the figure shows, F inherits the alliances that belong to T following the acquisition. We refer to an acquirer's preexisting alliances as "F-FPs" and a target firm's alliances that are inherited by the acquirer as "T-TPs." Our analyses estimate the post-acquisition termination likelihood of each alliance in the combined portfolio.

3.2 | Research design

In H1, we hypothesized that acquisitions increase the termination likelihood of alliances. H2 tests the capacity mechanism underlying H1 and posits a higher post-acquisition termination likelihood when acquirers face greater demands on their alliance management capacity. H3 further expounds these mechanisms to posit a greater termination likelihood for inherited alliances (i.e., T-TPs) compared to preexisting alliances (i.e., F-FPs). Because we focus on the effect of an *acquisition* on alliance termination, the ideal research design to test our hypotheses would compare the alliances' termination likelihood when they are exposed to an acquisition event to the termination likelihood of the *same* alliances had they not been exposed to such an event. Although such a counterfactual scenario is not practically feasible, our research design builds a close approximation to it using a propensity score matching (PSM) strategy. We compare the termination likelihoods across two groups of alliances: a treatment group consisting of alliances exposed to acquisitions and a control

[10]Because acquirers tend to be larger firms, it is not surprising that the extent of their alliance activity is also greater than alliance activity of nontarget firms that do not undertake acquisitions (i.e., the pool from which our control alliances are drawn). However, in our research design that employs matching, we ensure that the control alliances are equivalent to the treated alliances along a comprehensive set of observable value drivers. In separate robustness checks, we also verify that our results remain valid even when we limit our analyses only to those acquiring firms that had alliance portfolio sizes comparable to the firms from which we constituted the control group alliances.

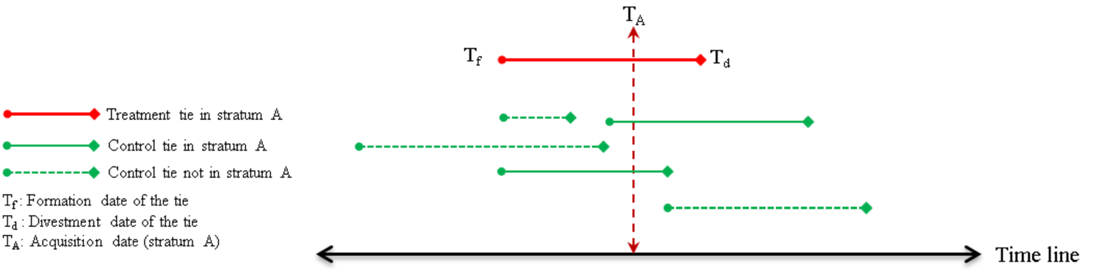

FIGURE 2 How control alliances are qualified to be in a specific stratum

group consisting of alliances that have a similar propensity to be treated (i.e., exposed to an acquisition) based on a range of alliance attributes (Angrist & Pischke, 2009).

To create the control group of alliances, we implemented a matching approach using a series of steps. First, we noted the specific dates of the acquisition events—our treated sample includes acquisition dates ranging from August 1989 through December 2000. We then used these dates as "strata" to identify control alliances. In other words, for a control alliance to match a treated alliance, the control alliance should first have been functional ("alive") on the date at which the treatment alliance was exposed to an acquisition. Figure 2 illustrates this matching strategy.

Here, the solid, red line represents a treated alliance. The solid, green lines represent control alliances that are in the same stratum as the treated alliance because they were functional at the time T_A when the treated alliance was exposed to an acquisition. After distributing the potential control alliances across acquisition-date strata, we calculated their propensity scores (de Figueiredo Jr., Feldman, & Rawley, 2019; Rosenbaum & Rubin, 1983) of being exposed to an acquisition (i.e., being treated) based on several observable alliance attributes.[11] Finally, we matched the treatments with up to 10 control observations using the nearest-neighbor matching technique (Austin, 2014; Guo & Fraser, 2014). We assessed the quality of our match in a variety of ways. First, we noted that the means of the covariates were not statistically different across the two groups, indicating a balanced match (Chang & Shim, 2015). We then examined the two statistics suggested by Rubin (2001): Rubin's B (which should be below 25) and Rubin's R (which should lie between 0.5 and 2). Our matching yielded Rubin's B of 17.5 and Rubin's R of 0.9, well within their respective acceptable ranges. Finally, we conducted a Kolmogorov–Smirnov test which further corroborated that our matches are balanced (Diamond & Sekhon, 2013).[12]

Because Hypotheses H4 and H5 are specific to the post-acquisition termination of target firm alliances vis-à-vis preexisting alliances and their interconnections, our sample to test these

[11]These include meaningful technology, market, and governance factors including the alliance's product-market breadth, its exclusivity, its interdependence complexity, its activity breadth, its age at the time of the acquisition, its association with rare-diseases, whether it involved novel combinatorial chemistry resources (Asgari et al., 2017; Lavie, 2006; Thomke & Kuemmerle, 2002; Thomke, Von Hippel, & Franke, 1998), and whether it is an equity alliance. The descriptions and rationale for these attributes are covered in the "control variables" section.

[12]We also assessed the use of coarsened exact matching (CEM), an alternative matching technique to PSM (Iacus, King, & Porro, 2012). However, a major concern is that CEM leads to imbalanced observations across groups and biased results, particularly when there is a sizeable loss of observations because of matching (e.g., Guo, Fraser, & Chen, 2020; Ripollone, Huybrechts, Rothman, Ferguson, & Franklin, 2020). Indeed, when evaluating CEM, we found that it led to a considerable reduction in sample size (e.g., our sample to test H1 dropped by 77%). Furthermore, we also confirmed that CEM did not create a balanced treatment-control match for our sample, both by comparing means of covariates and by running a Kolmogorov–Smirnov test.

hypotheses includes the acquirers' preexisting alliances (F-FPs) and the alliances from the target (T-TPs). The F-FPs are the baseline observations against which the T-TPs are compared.

3.3 | Dependent variable

Our dependent variable is a binary measure that captures whether an alliance was terminated within a 24-month window following an acquisition event.[13] To create this variable, we first needed to identify the termination date of all alliances, both those within our sample and those in our matched control group. While RECAP covers the formation of biopharmaceutical alliances in detail (Schilling, 2009), it only reports the termination of a limited subset of these alliances. Therefore, we used Factiva to extract the press releases that cover each alliance to record their termination dates.[14] For alliances whose termination events were not explicitly covered by a press release, we followed prior research (Ahuja, 2000; Asgari et al., 2017; Kumar & Zaheer, 2018) and recorded the year and the month of the last press release of the alliance as its termination date. We then coded the dependent variable by assessing whether the termination date of the alliance was within the 24-month window following the acquisition (*terminated* = 1) or outside it (*terminated* = 0).[15]

3.4 | Explanatory variables

To test H1—whether a baseline effect of acquisitions on alliance termination exists—our binary explanatory variable *tie exposed to acquisition* is set to 1 for those alliances that were exposed to an acquisition event (i.e., our main sample of alliances) and 0 for those alliances in the matched control group that were not exposed to an acquisition event. To test H2—whether this baseline effect is aggravated when the acquirer's capacity is stressed—we first measured the stress on the acquirer's alliance management capacity by creating the ratio of the number of inherited alliances (i.e., the additional number of target alliances the acquirer must now manage post acquisition) to the number of acquirer's preexisting alliances (i.e., the number of alliances to which the acquirer's existing alliance management capacity is allocated). We then used the same treatment and control groups of alliances that we used to test H1, but split the treatment group into two subgroups: a high-stress group (acquisitions where the stress on acquirer's alliance management capacity > sample's median stress on alliance management capacity) versus a low-stress group (stress on acquirer's alliance management capacity ≤ sample's median stress on alliance management capacity).[16] Similarly, to test H3 (i.e., whether this baseline effect is higher for

[13]Results remain robust with shorter (18 and 12 months) thresholds. We discuss these results later in the paper.

[14]To precisely identify press releases covering an alliance, in our search queries, we used the alliance's partners' names, therapeutic and technology areas the alliance is associated with, as well as multiple keywords from the subject of the alliance. Our queries looked for each alliance's press releases including termination announcement from the alliance's formation date until the time of building this dataset in 2012. Since our sample includes alliances formed up to the end of 2000, we were therefore able to trace the record of press releases of alliances for *at least* 12 years following their creation.

[15]We employed a similar method to measure the dependent variable for control alliances in the strata they are assigned to; the 24-month window was measured from the acquisition date of the matched treated alliances.

[16]The matched control alliances are automatically allocated to the same subgroups corresponding to their treated alliances.

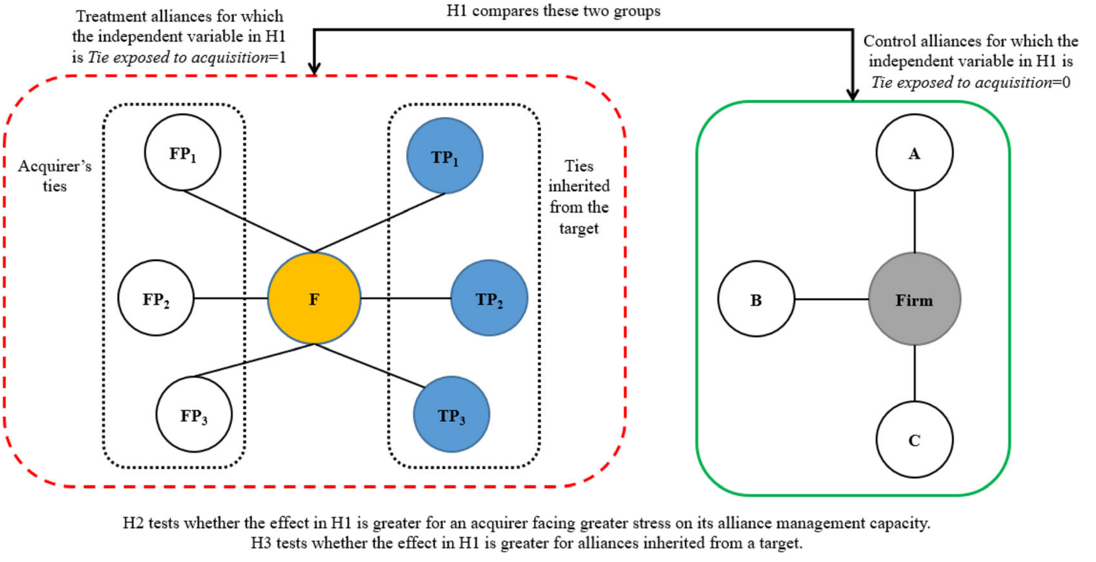

FIGURE 3 Comparison groups in Hypotheses H1–H3

inherited alliances), we split the treatment group into two subgroups: F-FP for the acquirer's alliances and T-TP for the alliances that are inherited from the target. Figure 3 helps clarify the comparisons in Hypotheses H1–H3.

Since Hypotheses H4 and H5 are specific to the post-acquisition retention of target firm alliances, we use a binary variable, *target's alliance*, to identify the alliances inherited from the target. The coefficient for this variable estimates the average probability of termination of alliances inherited from targets compared to the termination probability of the acquirer's pre-existing alliances. We are interested in how this probability is moderated—either attenuated or amplified—by our theoretical mechanisms. To capture these effects, we created two moderator variables, each measuring different aspects of the interconnections of these alliances.[17]

For H4, the variable *#common partners* measures the number of partners that either TP or FP shares with the acquirer's or the target's alliance portfolio, respectively, depending upon whether the alliance in question is an inherited alliance or an acquirer's preexisting alliance. In other words, if the alliance in question is a target alliance, then this variable indicates the number of common partners between this alliance partner's portfolio and the acquiring firm's pre-existing alliance portfolio. If the focal alliance is an acquirer's preexisting alliance, then this variable indicates the number of common partners between this alliance partner and the target firm's alliance portfolio. For H5, *#unique partners* measures the number of partners that the alliance partner (either TP or FP) has collaborations with that are nonoverlapping with *both* the target's and the acquirer's portfolio of alliances. In other words, this variable is the count of firms outside the combined (i.e., union of) relationships of the acquirer and the target.

[17]For the calculation of these moderator variables, we consider the pool of alliances entered into by the alliance partners themselves (in addition to alliances by focal and target firms). To identify this pool of alliances, we tracked these ties from formation to termination; for alliances whose termination data we did not have, we used the average duration of ties in our sample, 4 years. The alliances that were active at the time of acquisition entered the pool.

3.5 | Control variables

We controlled for several factors that are likely to affect the termination likelihood of alliances through alternative mechanisms. First, *alliance's product-market breadth*, measured as the number of therapeutic areas that an alliance is associated with, is used to capture the number of distinct markets addressable by the focal collaboration and thus control for its inherent value creation potential. *Rare-disease alliance* further captures the heterogeneity in value creation potential across alliances. A disease is considered rare by the Food and Drug Administration if it afflicts fewer than 200,000 individuals in the United States (e.g., Gaucher disease). Alliances associated with rare diseases could be more valuable because regulations provide special incentives to firms that work on such diseases (Danzon, 2018). In the same vein, *exclusive alliance* captures whether the alliance agreement involves exclusivity restrictions that may, in turn, influence its value. We also controlled for value-creation potential from an upstream, technological perspective. *Combinatorial chemistry alliance* identifies alliances involving combinatorial chemistry or high-throughput screening. These technologies were novel in the 1990s and considered valuable for their potential to accelerate drug discovery and lower associated costs of development (Asgari et al., 2017; Lavie, 2006; Thomke et al., 1998; Thomke & Kuemmerle, 2002).

Next, because interactions between alliance partners vary both in their nature and in how they are governed, and because these factors can affect post-acquisition retention decisions, we included three variables to account for this possible heterogeneity. *Complex interdependence* demarcates those collaborations that are characterized by dense knowledge exchange, with frequent and close interaction between the partners (Gulati & Singh, 1998). We used RECAP's contract description to categorize co-development, co-promotion, collaboration, cross-licensing, development, and research contracts as complex interdependence alliances.[18] *Equity alliance* indicates whether the alliance is governed through an equity arrangement (Oxley & Sampson, 2004), an arrangement that allows greater commitment and closer hands-on collaborations between the partners (Gulati & Singh, 1998). *Alliance's activity breadth* captures the scope of activities undertaken through the alliance, and thereby its value, by counting the number of different contract types associated with the alliance.

Alliance's age at acquisition captures the number of months elapsed from the formation of an alliance to the time of its exposure to the acquisition event and accounts for the natural obsolescence and lifecycle of partnerships (Dyer et al., 2018). Finally, *alliance formed after 1995* controls for the post-1995 capital market upheaval that may have systematically affected firms' resource allocation decisions (Core, Guay, & Van Buskirk, 2003).

In addition, in the logistic models to test H4 and H5, we controlled for several features of the M&A context, including features of the acquisition, the acquirer, the target, and the target's partner. We included *acquisition's value*, the dollar size of the acquisition deal, to capture expected synergies associated with the acquisition, which might affect the urgency or salience of relational asset retention decisions. Next, the variable *cross-border acquisition* indicates if the target and the acquirer are in different countries and captures, in part, the likelihood that the acquirer will accord greater autonomy to the target firm's managers post-acquisition (Bertrand & Capron, 2015). We also included variables to account for preexisting synergies in

[18]Following Gulati and Singh (1998), if an alliance involved two contracts, one indicating a more complex interdependence and another indicating a lower level of complexity, we coded the alliance as a more complex-interdependence type.

the acquirer's and the target's portfolios as well as the potential costs of restructuring these portfolios. *Post-acquisition portfolio size* is the sum of the acquirer's preexisting alliances and its inherited alliances. *Target's portfolio density* and *acquirer's portfolio density* measure the extent of interconnections among the target's and the acquirer's partners, respectively, by calculating the ratio of the number of actual alliances between these partners to the maximum number of their possible alliances.

Beyond the aforementioned alliance properties that capture the relationship's market or technological value, we also control for *partner's unique technological resources*, which measures the number of technology subclasses[19] in the patent portfolio of the focal alliance's partner that are distinct (novel) from the subclasses covered in the combined patent portfolio of the acquirer (F), the target (T), and all other partners of either F or T. This variable essentially captures the extent of the uniqueness of an alliance's technology area *relative* to the rest of the merged entity's portfolio.

Finally, *acquisition after 1995*[20] is a period-specific variable controlling for the mid-1990s market upheaval accounting for a potentially different base rate of post-acquisition alliance termination (Core et al., 2003). Table 1 shows the descriptive statistics of our sample.

3.6 | Estimation method

To calculate the difference between the likelihood of alliance termination for the treatment and control observations in Hypotheses H1–Hypothesis H3, we adopted a matched case–control approach using conditional-logistic models (Hosmer Jr., Lemeshow, & Sturdivant, 2013). Hypotheses H4 and H5 cover the alliance partners' relationships impact on the difference in termination likelihoods of inherited alliances versus preexisting alliances. We test these hypotheses using logistic regression models. One concern in these models pertains to the unobserved heterogeneity specific to different acquisitions—acquisitions could be undertaken with different strategic goals or by acquirers with specific alliance management capabilities, which, although unobserved, may still impact post-acquisition alliance retention decisions. To account for such unobserved heterogeneity, we included unconditional acquisition fixed-effects in the models (i.e., acquisition dummies). Unconditional fixed-effects allow us to include both time-variant and time-invariant acquisition-level controls and, thus, to examine both within and across acquisition variance. In robustness checks, we verify these results using "conditional fixed-effect" models. Furthermore, by clustering errors within acquisitions, our models also account for intra-group, correlated error terms to yield robust standard errors.

Prior literature cautions us against relying solely on logistic models' interaction term coefficients for interpretation (Ai & Norton, 2003; Hoetker, 2007). Therefore, we use extensive marginal analyses to better understand "how much a change in a variable changes the probability of the focal outcome" (Hoetker, 2007, p. 334) and validate our findings (Hoetker, 2007; Williams, 2012). We followed recent suggestions and practices in the strategy literature (e.g., Hoetker, 2007; Khanna, Guler, & Nerkar, 2018; Wiersema & Bowen, 2009) to validate the consistency of our findings across a range of scenarios in two ways. First, we followed Hoetker's (2007, pp. 336–337) recommendation to plot the marginal impact of different values

[19]As identified by the U.S. Patent and Trademark Office (USPTO).

[20]Rare-disease alliance, exclusive alliance, combinatorial technology alliance, complex interdependence, equity alliance, alliance formed after 1995, cross-border acquisition, and acquisition after 1995 are binary variables.

TABLE 1 Descriptive statistics

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1) Alliance termination	1											
(2) Target's alliance	0.17	1										
(3) Stress on acquirer's alliance capacity	0.08	0.30	1									
(4) #Common partners	0.07	0.06	0.02	1								
(5) #Unique partners	0.01	0.08	0.09	0.07	1							
(6) Acquisition's value	0.06	0.16	0.12	0.14	−0.07	1						
(7) Cross-border acquisition	−0.01	0.00	−0.03	−0.02	0.02	−0.09	1					
(8) Post-acquisition alliance portfolio size	0.06	−0.06	−0.19	0.10	−0.18	0.58	−0.18	1				
(9) Target's portfolio density	−0.02	0.06	0.03	0.05	0.00	0.05	0.14	−0.06	1			
(10) Acquirer's portfolio density	0.05	0.06	0.01	0.05	0.19	−0.09	−0.08	−0.29	0.26	1		
(11) Partner's unique technological resources	−0.04	0.04	0.08	0.04	0.46	−0.09	0.00	−0.21	0.04	0.11	1	
(12) Acquisition after 1995	0.11	−0.03	−0.05	0.03	0.15	0.12	0.11	0.32	−0.12	0.09	0.00	1
(13) Alliance's product-market breadth	−0.08	0.02	−0.02	0.03	0.00	−0.06	−0.02	−0.06	−0.02	−0.03	0.02	−0.11
(14) Rare-disease alliance	−0.08	−0.04	−0.04	0.01	0.06	−0.07	−0.02	−0.11	−0.03	−0.01	−0.01	−0.06
(15) Exclusive alliance	−0.10	0.04	−0.01	0.01	0.01	−0.06	0.03	−0.08	0.02	−0.01	0.00	−0.06
(16) Combinatorial chemistry alliance	0.03	0.00	−0.02	0.01	0.03	0.09	−0.02	0.03	−0.03	−0.01	−0.05	0.05
(17) Complex interdependence	0.04	−0.01	−0.02	0.03	0.01	0.05	0.03	0.00	−0.01	0.03	−0.03	−0.01
(18) Equity alliance	−0.07	−0.07	−0.04	−0.02	−0.06	−0.01	0.08	0.00	−0.02	−0.05	−0.06	−0.02
(19) Alliance's activity breadth	−0.09	−0.06	−0.02	0.00	−0.02	−0.01	0.09	−0.04	0.01	−0.02	−0.05	−0.06
(20) Alliance's age at acquisition	−0.02	0.05	0.01	0.04	0.08	0.00	−0.08	0.05	−0.06	0.00	0.06	0.05
(21) Alliance formed after 1995	0.08	−0.09	−0.10	−0.01	0.05	0.10	0.04	0.23	−0.07	0.08	−0.02	0.56
Mean	0.41	0.22	0.55	0.35	11.22	8.74	0.32	47.95	0.01	0.01	94.04	0.81
SD	0.49	0.41	0.94	1.62	14.4	20.42	0.46	24.07	0.02	0.01	250.83	0.39

Variables (continued)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)
(13) Alliance's product-market breadth	1								
(14) Rare-disease alliance	0.18	1							

TABLE 1 (Continued)

Variables (continued)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)
(15) Exclusive alliance	0.27	0.15	1						
(16) Combinatorial chemistry alliance	−0.06	−0.06	−0.01	1					
(17) Complex interdependence	0.10	0.03	0.11	0.20	1				
(18) equity alliance	0.18	0.10	0.37	0.12	0.18	1			
(19) Alliance's activity breadth	0.25	0.12	0.52	0.11	0.47	0.65	1		
(20) Alliance's age at acquisition	0.05	0.10	0.04	−0.05	−0.05	−0.01	0.01	1	
(21) Alliance formed after 1995	−0.14	−0.09	−0.09	0.07	0.02	−0.03	−0.09	−0.50	1
Mean	0.96	0.11	0.33	0.11	0.66	0.24	2.76	28.89	0.57
SD	0.84	0.31	0.47	0.32	0.47	0.43	1.60	27.55	0.49

of the moderators on the dependent variable across a range of typical cases. This method helps validate the robustness of our moderation effects over a wide range of scenarios. Second, we used Wiersema and Bowen's (2009) recommendation to validate the results by calculating the average marginal effect *across* observations. Their suggestion can be implemented by the commonly used (e.g., Arora & Nandkumar, 2012; Brahm & Tarziján, 2016) Stata's *inteff* command (Norton, Wang, & Ai, 2004). We discuss both approaches in more detail below.

4 | RESULTS

Table 2 shows the results of the conditional logistic models used to test Hypotheses H1–H3. Because the dependent variable in these regressions is alliance termination, a positive coefficient indicates a higher likelihood of termination. The coefficient of "*tie exposed to acquisition*" in Model 1 is positive ($b = 0.1033$; $p = .022$) and consistent with our Hypothesis H1 that when alliances are exposed to acquisitions, they are at a higher risk of termination. The odds of termination of alliances exposed to acquisitions are 11% greater than the odds of unexposed alliances.

In H2, we predicted that the increased likelihood of alliance termination following acquisitions in H1 would be amplified for those acquisitions that pose greater stress on the acquirer's alliance management capacity. Models 2 and 3 show the results for this hypothesis test. When we split our sample of treated alliances at the median value of the stress on alliance management capacity, we find that the coefficient of "*ties exposed to acquisition*" from the high-stress acquisition subsample of treated alliances (Model 2: $b = 0.2182$; $p = .001$) is greater than that of the treated alliances from the low-stress subsample (Model 3: $b = -0.0106$; $p = .869$). Furthermore, in the low-stress sample, the high p-value suggests that it is highly probable that acquisitions have no impact on terminations when the acquirer faces less stress on its alliance capabilities. These results support our prediction in H2. We also conducted an auxiliary chi-squared test to compare the coefficients across these two groups. The test rejected the null hypothesis that there is no difference between the subsamples' coefficients ($X^2 = 6.56$; $p = .010$), consistent with our prediction in H2. Comparing the termination odds of the high-stress subsample with that of the entire sample (i.e., the average termination odds), we find that termination odds are 1.12 times greater for alliances in the high-stress group.

In H3, we predicted that the increased likelihood of alliance termination following acquisitions would be amplified for alliances inherited from the target firm. We have referred to this effect as the *inheritance effect*. Models 4 and 5 show the results of our test for H3. When we split our sample of treated alliances by whether the tie is preexisting or inherited, we find that the coefficient of "*tie exposed to acquisition*" for the inherited alliances' subsample (Model 4: $b = 0.6848$; $p = .000$) is greater than the coefficient for the acquirers' preexisting alliances subsample (Model 5: $b = -0.0621$; $p = .230$). The high p-value in preexisting subsample suggests that it is highly probable that acquisitions do not affect the termination of preexisting alliances. These results are not only consistent with our prediction in H3 but also echo findings in divestment studies of internal assets (Capron, 1999). Further, an auxiliary chi-squared test ($X^2 = 46.05$; $p = .000$) also confirmed that this coefficient is not equal across the two models. Comparing the termination odds of the inherited alliances (i.e., T-TP ties) subsample with that of the entire sample (i.e., the average termination odds), we find that termination odds are 1.78 times greater for the inherited alliances.

TABLE 2 Conditional logit models for the tests of Hypotheses H1–H3 on alliance termination

	Model 1	Model 2	Model 3	Model 4	Model 5
	H1	H2		H3	
Variables	(All alliances)	Stress on acquirer's alliance capacity > median	Stress on acquirer's alliance capacity ≤ median	T-TP	F-FP
Tie exposed to acquisition	0.1033 (.022)	0.2182 (.001)	−0.0106 (.869)	0.6848 (.000)	−0.0621 (.230)
Alliance's product-market breadth	−0.1236 (.000)	−0.1378 (.000)	−0.1074 (.000)	−0.1815 (.000)	−0.1099 (.000)
Rare-disease alliance	−0.1817 (.001)	−0.1894 (.022)	−0.1739 (.028)	−0.1028 (.429)	−0.2014 (.002)
Exclusive alliance	−0.2822 (.000)	−0.2610 (.000)	−0.3028 (.000)	−0.1027 (.261)	−0.3353 (.000)
Combinatorial chemistry alliance	0.0894 (.136)	0.0809 (.310)	0.1121 (.223)	0.1936 (.134)	0.0592 (.384)
Complex interdependence	0.2508 (.000)	0.2465 (.000)	0.2539 (.000)	0.2046 (.020)	0.2599 (.000)
Equity alliance	−0.1193 (.009)	−0.0911 (.167)	−0.1458 (.021)	−0.0190 (.854)	−0.1449 (.004)
Alliance's activity breadth	−0.0032 (.838)	−0.0159 (.484)	0.0080 (.713)	−0.0187 (.603)	0.0024 (.890)
Alliance's age at acquisition	−0.0040 (.000)	−0.0057 (.000)	−0.0025 (.039)	−0.0081 (.000)	−0.0030 (.002)
Alliance formed after 1995	−0.3593 (.000)	−0.3992 (.000)	−0.3214 (.000)	−0.5026 (.000)	−0.3188 (.000)
Observations	25,498	12,694	12,804	5,533	19,965
Log-likelihood	−12,280	−6,068	−6,206	−2,638	−9,611

Note: *p*-Values in parentheses. Our matching has Rubin's $B = 17.5\%$ (well below 25% threshold) and Rubin's $R = 0.9$ (within the [0.5, 2] interval).

In H4 and H5, we examine the heterogeneity in the *inherited effect* (discussed before) because of the heterogeneity in the interconnections between the alliance partners. Table 3 reports the results of the corresponding regressions. Model 1 includes only controls, Model 2 adds the indicator variable *target's alliance* (which equals 1 for inherited alliances and 0 for preexisting ones), Model 3 introduces the interaction with common partners, and Model 4 (the full model) introduces the interaction with unique partners. We base our inferences on Model 4.

We first note that the coefficient of the indicator variable *target's alliance* is positive (Model 4: $b = 0.7760$; $p = .000$). This observation is consistent with our earlier finding for H3 in the matched sample that, compared to the acquirer's preexisting alliances, the target's alliances inherited by the acquirer are more likely to be terminated following the acquisition.[21] In Model 4, the coefficient *target's alliance×#common partners* is negative ($b = -0.2858$; $p = .019$), suggesting that, as predicted by H4, the *inherited effect* is attenuated by the number of overlapping connections between the inherited alliance partner and the acquiring firm. However, since inferences based solely on the interaction coefficient can be problematic (e.g., Hoetker, 2007), we conduct two further sets of analyses. We confirm the validity of the interactions first with the Stata post-estimation command *inteff* (Norton et al., 2004), and then more extensively with marginal analysis plots (calculated using Stata's *margins* command) suggested by Hoetker (2007, p. 336) (Figure 4a).

The results of the *inteff* post-estimation analysis show that the mean value of the interaction effect across all observations (Norton et al., 2004) is also negative ($b = -0.0587$; $p = .029$), thus increasing our confidence that the results in Table 3 are indeed consistent with our predictions in H4. We then use the marginal analysis plots to capture how these interaction effects vary across three different representative scenarios, where each scenario corresponds to a specific part of the distribution from which the rest of the control variables are drawn (Hoetker, 2007, p. 336). For each scenario, we calculate and graph the likelihood of termination for alliances with low values of *#common partners* (=10th percentile; shown by dashed lines) and high values of *#common partners* (=90th percentile; represented by solid lines) to show the interaction effects. In the first representative scenario, we calculated the termination likelihood when *all* other variables are kept at their median values (the topmost lines in Figure 4a). This scenario effectively corresponds to a *high* alliance termination likelihood case. In the second scenario, all other independent variables are kept at their observed values (the middle set of lines in Figure 4a). This scenario represents an *ambivalent* or mid-range case where termination probabilities are neither very high nor very low. In the third scenario, to model a *low* alliance termination likelihood case, we changed only two variables from the second scenario: we fixed the dummy variable *rare-disease alliance* at 1 and the variable *alliance's activity breadth* at its maximum value in the distribution to represent alliances that are (arguably) the *most* valuable to acquirers because of their greater market impact, and are thus likely to have an extremely low probability of termination despite the acquisition event.

Examining the plots, we can first see that the likelihood of termination is greater when the alliances are inherited from the target—across all three scenarios, the termination likelihood increases (upward slope of both dashed and solid lines) as we move from preexisting alliances

[21]Although we employ acquisition fixed effects to account for unobserved heterogeneity across acquiring firms, one concern might be that these results represent a distribution where only a very small subset of acquirers retain any inherited alliances whereas a large majority terminate all of them. We explored this possibility in our data and found it not to be the case. We found that in a vast majority of acquisitions (~75%), acquirers do retain some inherited alliances. In the minority of cases where acquirers do not retain any inherited alliances, the number of inherited alliances is very small (~2). This represents a very small portion of inherited alliances.

TABLE 3 Logistic regression results for H4 and H5

	Model 1 Controls	Model 2 Base	Model 3 H4	Model 4 H4 and H5 (full)
Target's alliance		0.8462 (.000)	0.9546 (.000)	0.7760 (.000)
Target's alliance × #common partners			−0.2073 (.065)	−0.2858 (.019)
Target's alliance × #unique partners				0.0179 (.046)
#Common partners			0.1358 (.001)	0.1387 (.001)
#Unique partners				−0.0056 (.343)
Acquisition's value	0.6418 (.014)	0.4039 (.145)	0.3915 (.158)	0.367 (.261)
Cross-border acquisition	−1.7979 (.000)	−1.4107 (.001)	−1.3850 (.001)	−1.3448 (.009)
Post-acquisition alliance portfolio size	0.0082 (.021)	0.0074 (.039)	0.0069 (.057)	0.0058 (.182)
Target's portfolio density	14.1199 (.051)	7.6995 (.315)	7.3085 (.342)	6.5831 (.465)
Acquirer's portfolio density	−9.4107 (.261)	−13.5646 (.111)	−15.2234 (.079)	−19.6224 (.027)
Partner's unique technological resources	−0.0005 (.058)	−0.0005 (.060)	−0.0005 (.055)	−0.0004 (.169)
Acquisition after 1995	−1.3719 (.018)	−0.9257 (.126)	−0.8915 (.149)	−0.7635 (.294)
Alliance's product-market breadth	−0.0974 (.270)	−0.1051 (.236)	−0.113 (.201)	−0.1157 (.194)
Rare-disease alliance	−0.4140 (.066)	−0.3708 (.099)	−0.3831 (.085)	−0.3809 (.090)
Exclusive alliance	−0.1526 (.279)	−0.2322 (.088)	−0.2406 (.083)	−0.2384 (.086)
Combinatorial chemistry alliance	−0.0502 (.779)	−0.0633 (.717)	−0.0638 (.713)	−0.0679 (.696)
Complex interdependence	0.3258 (.011)	0.3323 (.014)	0.3335 (.013)	0.3356 (.013)
Equity alliance	0.1385 (.356)	0.181 (.216)	0.1913 (.188)	0.1788 (.218)
Alliance's activity breadth	−0.1408 (.009)	−0.1287 (.019)	−0.1298 (.018)	−0.1280 (.019)
Alliance's age at acquisition	−0.0023 (.504)	−0.0028 (.418)	−0.0028 (.433)	−0.0028 (.429)
Alliance formed after 1995	−0.2193 (.328)	−0.2016 (.358)	−0.1881 (.393)	−0.1905 (.384)
Constant	1.2083 (.000)	0.8050 (.007)	0.7910 (.009)	0.8122 (.017)
Acquisition fixed effects	Y	Y	Y	Y
Observations	1,838	1,838	1,838	1,838
Log-likelihood	−1,140	−1,120	−1,115	−1,113

Note: *p*-Values in parentheses.

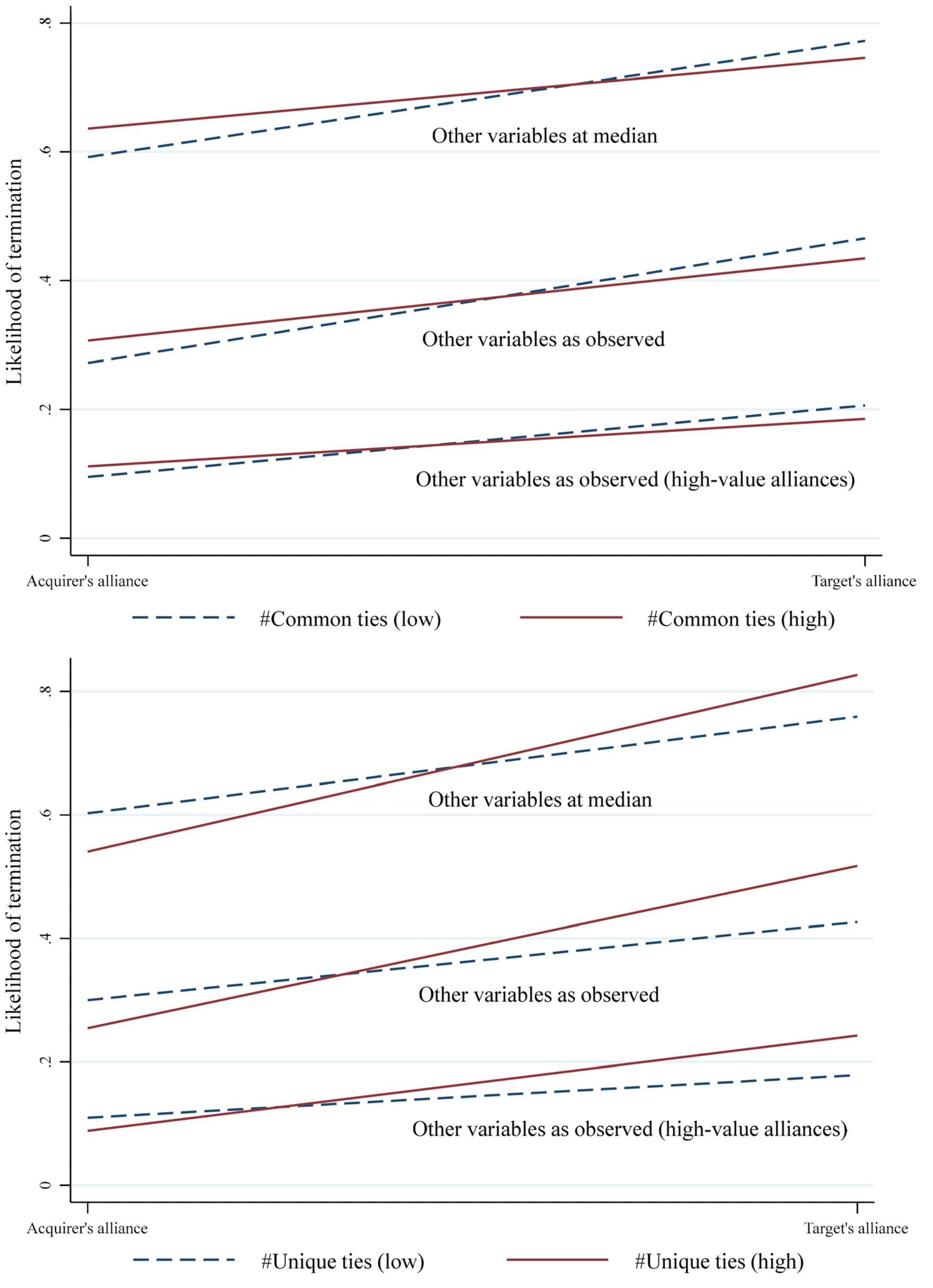

FIGURE 4 (a) The effect of number of common partners at different representative values. (b) The effect of number of unique partners at different representative values

on the left of the chart to the inherited alliances on the right of the chart. Next, we can visually observe the interaction effect by comparing the slopes of the dashed lines (low *#common partners*) with the slopes of the solid lines (high *#common partners*).

In Figure 4a, across all three scenarios, we find that the solid lines (high *#common partners*) are flatter than the dashed lines (low *#common partners*). In the topmost section (where other variables are at their median), as we go from left to right (i.e., from the acquirer's preexisting alliance to the target's alliance), the alliance termination likelihood increases by 13% (with respect to the preexisting alliance's termination likelihood) for the solid line (i.e., high values of *#common partners*). This proportional increase is greater (21%) for the dashed line (i.e., low value of *#common partners*). Similarly, in the middle section of the graph (where other variables are at observed values), the proportional increase is 39% for the solid line and 58% for the dashed line. Finally, in the bottom portion, the proportional increase is 60% for the solid line and 93% for the dashed line. These observations show that in all three scenarios, the increase in termination likelihood of inherited alliances is greater for low values of #common partners (dashed line). Thus, a greater number of common partners attenuates the vulnerability of inherited alliances (i.e., it dampens the inheritance effect). Overall, these plots verify the robustness of the effect across different scenarios and confirm that the results are unlikely to be an artifact of the nonlinear functional form (Hoetker, 2007).

In Model 4, the coefficient of *target's alliance* × *#unique partners* is positive ($b = 0.0179$; $p = .046$), suggesting that the number of unique connections of the alliance partners of inherited alliances amplifies the vulnerability of inherited alliances compared to preexisting alliances. While consistent with H5, this effect is validated by following an approach identical to the one described for H4. Using the *inteff* command, we find the mean value of this interaction effect is indeed positive ($b = 0.004$; $p = .056$). We then plot the interaction effect for low and high values of *#unique partners* across the same three representative scenarios discussed for H4 (see Figure 4b).

Figure 4b validates our findings by showing that the solid lines (high *#unique partners*) are steeper than the dashed lines (low *#unique partners*) across all three scenarios. In the topmost section (where other variables are at their medians), as we go from preexisting to inherited alliances (i.e., from left to right), the alliances' termination likelihood increases by 32% (with respect to the termination likelihood of preexisting alliances) for the solid line; this proportional increase is lower (18%) for the dashed line. Similarly, in the graph's middle portion (where other variables are at observed values), the proportional increase is 79% for the solid line and 39% for the dashed line. Finally, in the bottom portion, the proportional increase is 131% for the solid line (high values of *#unique partners*) and 59% for the dashed line (low value of *#unique partners*). This shows that across all three scenarios, the inheritance effect (i.e., increased vulnerability of inherited alliances compared to preexisting alliances) is amplified at higher values of *# unique partners*. These plots, therefore, demonstrate that our findings are unlikely to be an artifact of nonlinear functional form and add confidence to our conclusions.

4.1 | Robustness checks

We performed several additional tests to examine the sensitivity of our assumptions regarding measure construction, model specification, and other confounding factors. First, we ran all our tests with the dependent variable reconstructed for shorter termination time windows (18 and 12 months). In other words, the dependent variable was coded as 1 if we observed termination within the alternate window and 0 otherwise. The findings of this test for Hypotheses H1–H3, provided in Table A1 (18 months) and Table A2 (12 months), are consistent with our main results. A similar sensitivity test (Table A3, Models 1 and 2) shows that our results for H4 and H5 remain consistent if we use shorter termination time intervals.

Second, though unlikely, it is possible that acquirers' termination decisions are influenced by their decisions to integrate or give autonomy to the target. Unfortunately, data limitations do not allow us to measure the extent of attempted integration of the target directly. However, we could construct a proxy for this unobserved mechanism using press releases covering the acquisition event. For 20 acquisitions in our sample, we observed that several post-acquisition press releases on the target's alliances not only mentioned the acquiring firm but also *continued* to mention the target firm. We interpreted this to mean that in these acquisitions, the acquirer did not fully integrate the target firms but allowed them some autonomy after the acquisition was completed. We created a dummy variable (*target not fully integrated*) equal to 1 for these 20 acquisitions. Including this variable yielded consistent results (shown in Table A3, Model 3).[22]

Finally, we examined the robustness of our results to a different specification of fixed effects. As discussed before, our main models included the acquisition-specific unconditional fixed-effect dummies to control for unobserved heterogeneity across acquisitions. We tested the sensitivity of this specification by running a conditional fixed-effect model instead. Model 4 in Table A3 shows that the results remained consistent.

4.2 | Examining possible endogeneity issues

An endogeneity concern in our analysis relates to the possibility that under-performing alliances may cause firms to become acquisition targets, presumably by reducing the firms' market value. As a result, alliances of such targets are more likely to be terminated post acquisition. Note that our analyses with acquisition fixed effects already account for time-invariant unobserved heterogeneity in alliance termination across all alliances that are subject to the same acquisition, in addition to controlling for several measures that capture the potential value (performance) of each alliance. Nevertheless, there could still be an issue if deals in this industry are largely spurred by alliances' under-performance. Because this alternate explanation relies on the notion that a firm's market value is reduced when it undertakes poor alliances, we investigated whether the target firms in our sample are indeed inferior, on average, in market value compared to their industry peers—if poor alliances cause firms to become targets, we might expect the target firms to be inferior to their industry peers (Kale et al., 2002). For our comparison, we use the firms' Tobin's q measured as the ratio of the firm's market value to its book value (Anand & Singh, 1997). Tobin's q is appropriate for the comparison since it "captures [a] firm's past performance as well as its growth potential" (Ma & Khanna, 2016, p. 1551). The results[23] in Table A4 indicate that the target firms in our sample are either similar or superior to the rest of the industry. If the alternate explanation was true, we would expect the reverse: Tobin's Q of target firms would be lower than their industry peers. Our finding is, therefore, inconsistent with this alternate explanation assuring that, in this industry, acquisitions were not typically used to correct alliance failures.

[22]Because this variable is only an approximation of the unobserved post-acquisition integration, we have taken the conservative approach of including it in our robustness analyses and not in our main tests.

[23]This specific analysis is restricted to acquisitions where the target firms are public and data to calculate Tobin's q is available (about 55% of our sample).

4.3 | Additional post hoc analyses

We conducted additional analyses to explore our theoretical mechanisms more deeply. Our theory is rooted in the relational view of rents from alliances. Recent extensions of this view argue that an alliance's age plays a complex role in determining its value (Dyer et al., 2018). Therefore, we explore how an alliance's age at acquisition affects the impact of common and unique partners, respectively (as per H4 and H5). We expect to see a stronger interaction effect for older inherited alliances compared to younger ones because they are more likely to have well-established knowledge exchange routines and better-codified alliance management systems (Zollo & Winter, 2002). The greater overlap across better-developed processes and systems will likely enhance the compatibility and benefits fostered by common partners. Yet, older inherited alliances are also more entrenched and less adaptable, therefore increasing the misalignment costs when they are associated with several unique partners. Older alliances are also likely to involve deeper and more extensive knowledge flows—the knowledge flow "pipes" are likely to be thicker (Podolny, 2001). As a result, the exchange hazards posed due to the alliance partners' unique partners are also likely to be accentuated.

We test these conjectures by estimating the moderation equations on two subsamples: one comprising older alliances (alliance age at acquisition is greater than the median) and the other comprising younger alliances (alliance age is less than or equal to the median). We find that the coefficient of interaction with common partners in older alliances is negative (−0.3170) with a p-value of .036. For younger alliances, the coefficient is negative (−0.3262) but with a p-value of .220, making it difficult to reject the null that it is zero, suggesting that the moderation effect of common partners is weaker in younger alliances. Examining the interaction with unique partners in the same subsamples reveals no meaningful difference between the coefficient for older ($b = 0.021$; $p = .101$) and younger alliances ($b = 0.015$; $p = .387$). While deeper examination of the alliance age effect is out of this study's scope, further exploration of the trade-off associated with alliance age (better alliance management systems vs. adaptability) would be valuable (Dyer et al., 2018).

5 | DISCUSSION

Acquisitions are widely used as an external corporate development strategy, particularly in technologically intensive settings where firms seek to obtain novel resources and capabilities that are challenging to build internally (Kale & Puranam, 2004; Puranam et al., 2009). In a similar vein, relational assets, created through firms' alliances with other organizations, can be sources of superior advantage (Dyer & Singh, 1998; Kale & Singh, 2009; Zollo et al., 2002). In this study, we examine whether and how acquisitions affect the stability of these alliances, particularly as asset restructuring and divestment frequently accompany acquisitions (Karim & Capron, 2016). We apply a counterfactual analysis (Angrist & Pischke, 2009) to a sample of global biopharmaceutical firms and find that alliances are indeed more likely to be terminated following acquisitions. A closer examination of the mechanisms shows that this higher termination likelihood is accentuated both when the acquirer's capacity to manage an alliance portfolio is excessively stressed and in alliances that are inherited from targets. The latter "inheritance" effect is more pronounced when the target's partner has unique connections outside the merging firms' alliance portfolios but attenuated when it shares common partners with the acquirer.

These findings are consistent with our relational view-based theorizing on the post-acquisition challenges of retaining relational assets.

Our study contributes to several streams of strategy research. First, by examining relational assets that span firm boundaries, we contribute to the post-acquisition restructuring literature, which has (by default) focused on the divestment of internal assets that reside wholly within the acquirer's organization (e.g., Capron et al., 2001; Karim, 2006). Our findings in this regard both echo and contrast internal asset divestment research. On the one hand, our discovery that the target's relational assets are more likely to be divested compared to those of the acquirer aligns with the existing theory that "the target is very likely to bear the burden of post-acquisition asset divestiture" (Capron, 1999, p. 992). However, in contrast to prior research that has found the retention of the target's assets is "more worthwhile when the resources are far from a[n] [acquiring] firm's existing set of resource[s]" (Karim & Mitchell, 2000, p. 1076), we show that the target's alliances become *more* unstable when partners have connections to unique firms outside the existing alliance portfolio.

This divergent finding likely underscores the novel mechanisms that undergird the sources of value and gains from relational assets. Whereas with internal assets the acquirer controls both its own resources and those of the target after the acquisition, it must share the control of alliance-based assets with the corresponding alliance partners. Consequently, the retention of an alliance following an acquisition depends on the future value the acquirer can derive from the relationship post acquisition, which in turn is affected by how the acquisition alters the nature and risks of interfirm exchange (Dyer & Singh, 1998). Importantly, this creates retention and integration challenges that are different from those involving internal assets.

Second, we also contribute to the scholarship on alliances (e.g., Asgari & Singh, 2017; Ghosh, Ranganathan, & Rosenkopf, 2016), where extant studies have assumed that the firms which initially form the alliance are the same ones deciding its renewal or dissolution (e.g., Asgari et al., 2018; Greve et al., 2010). This assumption has driven much of the theorizing on what causes or prevents alliance termination, such as the competitive tensions between firms in a network (e.g., Polidoro et al., 2011), within a portfolio (e.g., Asgari et al., 2018) or in overlapping product-markets (e.g., Greve et al., 2010). Our distinctive focus on how ownership change at one end of a partnership triggers alliance termination uncovers novel antecedent mechanisms that affect interfirm collaborations' longevity, thus expanding the theoretical toolkit for alliance scholars.

Moreover, because acquisitions discontinuously augment alliance portfolios, they provide natural contexts to observe increased stress on a firm's alliance management capacity and measure its effect on partnership continuity. While the nature of alliance capabilities and their relationship to firm performance have been central themes in corporate strategy research (e.g., Kale et al., 2002; Kale & Singh, 2007), the notion that such capabilities may be subject to capacity constraints (Levinthal & Wu, 2010) has not been systematically explored. In examining this mechanism, we complement emerging empirical work that has begun to highlight the opportunity costs associated with allocating scale-constrained alliance resources across different partnerships (Aggarwal, 2020).

Finally, our study complements recent research on alliance networks, which has advanced the intriguing idea that an acquirer chooses a specific target in part to enhance its alliance network position (Hernandez & Menon, 2019; Hernandez & Shaver, 2018). However, realizing such benefits requires acquirers to maintain the stability of their post-acquisition portfolios. Our evidence suggests that this stability is affected by challenges arising after acquisitions.

Obtaining a superior network position, therefore, may also involve assessing the risks of alliance termination after acquisitions.

The above insight is also crucial for managers. It is well established that many (if not a majority of) acquisitions fail to yield expected results (Chaudhuri & Tabrizi, 1999). Moreover, the target's valuable assets or capabilities that trigger the acquisition are often the same ones that are eroded in the post-acquisition integration (Puranam et al., 2009; Ranft & Lord, 2000, 2002). In our case, the post-acquisition instability of target alliances likely reflects their increased coordination, integration, and governance costs that are ostensibly difficult to estimate before the acquisition. While we do not measure the extent of integration or address the performance consequences of alliance divestment, our study's findings are obtained *after* controlling for several different indicators of an alliance's potential value. Thus, while the acquiring firm's managers may indeed value a target's alliances for the market or technology access they provide or for the synergies that accrue from combining two alliance network positions, such valuations are incomplete unless they can account for the increased termination likelihood of these alliances.

5.1 | Limitations and future directions

Our paper, like most studies that are carried out in a single industry context and during a specific time period, can be limited in its generalizability. For instance, idiosyncratic features of the pharmaceutical industry that impede the transfer of competitive advantage from inherited alliances, thus diminishing their perceived value, or broader economic effects of the period of our study could, in principle, have affected corporate transactions. Future studies should attempt to examine these questions in a variety of other contexts and time periods.

With regard to theory, our arguments assume that firms cannot expand their alliance management capacity in the short run to accommodate the target's alliances. This assumption is based on the idea that effective alliance functioning requires skilled managerial, scientific, or engineering expertise, which is likely to be scarce posing opportunity costs in its allocation. While this is certainly true in our focal biopharmaceutical context, it does present an important boundary condition. Similarly, our theoretical arguments about the retention challenges for target alliances rely on the importance of informal governance and relationship-specific commitments (both of which are foundational in the relational view) and the importance of the portfolio approach in managing alliances. These are, in turn, premised on the incompleteness of alliance agreements and the potential for valuable recombinations across alliances in a portfolio. While these assumptions are also true in our setting, in contexts where value-generation activities are limited to dyads (e.g., client-supplier exchanges in professional services firms) or where contracts are more well defined and verifiable (arm's-length relationships), our mechanisms may be less applicable.

Similarly, in technology-intensive industries such as pharmaceuticals and semiconductors, alliances are most frequently used to access external knowledge. Therefore, our arguments, elaborating the importance of knowledge-sharing routines, compatibility of management systems, and informal governance mechanisms, are pertinent. However, in industries such as airlines, alliances are primarily used to coordinate downstream market arrangements and extend the regional market reach of firms (e.g., Gimeno, 2004). In such industries, alliance governance is likely to be more formal and contractual, and knowledge exchange concerns or target partner congestion issues are less likely to be essential drivers of post-acquisition alliance termination.

In conclusion, this article sheds light on a novel, unexplored outcome of acquisitions—they trigger the restructuring and divestment of the merging firms' relational assets, with a marked effect on those assets inherited from targets. Our findings expose both the capacity issues that constrain acquirers in managing substantial additions to their alliance portfolios and the types of alliances that conserve or stress this capacity. Future studies capable of capturing more granular data can extend our framework to test more nuanced arguments and potentially uncover new mechanisms that counter the inheritance effect documented here. For instance, while our study provided considerable evidence for our theorized mechanisms of alliance termination, data limitations prevented us from further examining the rich gamut of options that acquirers could exercise in integrating target alliances—from according them full autonomy on the one extreme to fully integrating them on the other. Similarly, while the effect of alliance age suggests that older alliances are less likely to be terminated, we could not pinpoint the specific mechanisms involved (e.g., the possibility that older alliances may already have well-established routines that make them less unstable after an acquisition). Analogously, we could not observe whether and how acquirers orchestrate new knowledge and resource transfers between their existing and inherited partners after acquisition. Indeed, the next logical step in extending our research would be to examine the specific kinds of practices and capabilities that allow acquirers to overcome the post-acquisition challenges of retaining inherited alliance-based assets. Similarly, because we rely on archival sources to identify terminations, data limitations preclude us from observing which party actually initiated the alliance termination for a majority of our alliances. Teasing apart these nuances may be a worthwhile avenue for future researchers who are able to gather primary data by interviewing alliance managers.

Finally, the divestment of relational assets can affect the acquiring firm's subsequent alliance formation choices and its performance. Our paper provides both a theoretical and an empirical foundation to further develop and test these linkages, thereby shaping the research conversation and scholarship at the intersection of alliances and acquisitions.

ACKNOWLEDGEMENTS
The authors appreciate the constructive comments and suggestions from their editor and the two anonymous reviewers. Gwendolyn Lee, John Chen, Kulwant Singh, Siddharth Natarajan, Salman Bokhari, Pek-Hooi Soh, David Clough, Hans Frankort, Elena Novelli, seminars participants at the University of Florida, National University of Singapore, Simon Fraser University, University of British Columbia, and the City University of London provided valuable suggestions.

DATA AVAILABILITY STATEMENT
Authors elect to not share data.

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How to cite this article: Tandon, V., Asgari, N., & Ranganathan, R. (2023). Divestment of relational assets following acquisitions: Evidence from the biopharmaceutical industry. *Strategic Management Journal*, *44*(4), 1013–1052. https://doi.org/10.1002/smj.3456

APPENDIX A

TABLE A1 Conditional logit models for the tests of Hypotheses H1–H3 on alliance termination (DV based on an 18-month window)

Variables	Model 1 H1 (All alliances)	Model 2 H2 Stress on acquirer's alliance capacity > median	Model 3 Stress on acquirer's alliance capacity ≤ median	Model 4 H3 T-TP	Model 5 F-FP
Tie exposed to acquisition = 1	0.1327 (.005)	0.2416 (.000)	0.0248 (.713)	0.7039 (.000)	−0.0370 (.500)
Alliance's product-market breadth	−0.1295 (.000)	−0.1368 (.000)	−0.1206 (.000)	−0.1915 (.000)	−0.1145 (.000)
Rare-disease alliance	−0.2077 (.001)	−0.3042 (.001)	−0.1347 (.110)	−0.3504 (.015)	−0.1794 (.009)
Exclusive alliance	−0.2897 (.000)	−0.2483 (.000)	−0.3311 (.000)	−0.1662 (.090)	−0.3265 (.000)
Combinatorial chemistry alliance	0.0776 (.219)	0.0922 (.269)	0.0482 (.621)	0.1996 (.142)	0.0420 (.557)
Complex interdependence	0.1929 (.000)	0.1436 (.018)	0.2237 (.000)	0.1004 (.284)	0.2100 (.000)
Equity alliance	−0.1541 (.002)	−0.2164 (.002)	−0.0977 (.151)	−0.1316 (.233)	−0.1597 (.003)
Alliance's activity breadth	0.0069 (.680)	0.0458 (.057)	−0.0251 (.283)	0.0364 (.340)	0.0018 (.922)
Alliance's age at acquisition	−0.0039 (.000)	−0.0057 (.000)	−0.0023 (.075)	−0.0077 (.000)	−0.0030 (.004)
Alliance formed after 1995	−0.3972 (.000)	−0.3553 (.000)	−0.4312 (.000)	−0.4236 (.001)	−0.3913 (.000)
Observations	24,849	12,386	12,463	5,357	19,492
Log-likelihood	−11,071	−5,461	−5,597	−2,380	−8,661

Note: *p*-Values in parentheses.

TABLE A2 Conditional logit models for the tests of Hypotheses H1–H3 on alliance termination (DV based on a 12-month window)

	Model 1	Model 2	Model 3	Model 4	Model 5
	H1	H2		H3	
Variables	**(all alliances)**	**Stress on acquirer's alliance capacity > median**	**Stress on acquirer's alliance capacity ≤ median**	**T-TP**	**F-FP**
Tie exposed to acquisition	0.1169 (.027)	0.1652 (.027)	0.0676 (.370)	0.7026 (.000)	−0.0680 (.276)
Alliance's product-market breadth	−0.1403 (.000)	−0.1895 (.000)	−0.0867 (.016)	−0.2355 (.000)	−0.1158 (.000)
Rare-disease alliance	−0.2383 (.001)	−0.4438 (.000)	−0.0633 (.521)	−0.3630 (.031)	−0.2125 (.009)
Exclusive alliance	−0.2754 (.000)	−0.2514 (.000)	−0.2931 (.000)	−0.2567 (.022)	−0.2826 (.000)
Combinatorial chemistry alliance	0.1703 (.017)	0.1683 (.075)	0.1697 (.127)	0.3617 (.019)	0.1193 (.142)
Complex interdependence	0.1544 (.001)	0.1036 (.131)	0.1942 (.003)	0.0889 (.402)	0.1670 (.002)
Equity alliance	−0.1873 (.001)	−0.2540 (.002)	−0.1180 (.133)	−0.1694 (.185)	−0.1883 (.003)
Alliance's activity breadth	0.0046 (.812)	0.0371 (.178)	−0.0254 (.353)	0.0360 (.410)	−0.0029 (.893)
Alliance's age at acquisition	−0.0032 (.002)	−0.0054 (.000)	−0.0012 (.422)	−0.0080 (.001)	−0.0020 (.097)
Alliance formed after 1995	−0.4132 (.000)	−0.4011 (.000)	−0.4161 (.000)	−0.4977 (.001)	−0.3887 (.000)
Observations	23,243	11,616	11,627	4,950	18,293
Log-likelihood	−8,894	−4,412	−4,471	−1,910	−6,958

Note: *p*-Values in parentheses.

TABLE A3 Logistic regression results of robustness tests for H4 & H5

Variables	Model 1 18 months	Model 2 12 months	Model 3 Target integration	Model 4 Fixed effect
Target's alliance	0.7419 (.000)	0.7602 (.000)	0.7760 (.000)	0.7408 (.000)
Target's alliance × #common partners	−0.3383 (.012)	−0.4876 (.001)	−0.2858 (.019)	−0.2675 (.027)
Target's alliance × #unique partners	0.0202 (.024)	0.0269 (.011)	0.0179 (.046)	0.0165 (.066)
#Common partners	0.1881 0.000	0.2878 0.000	0.1387 (.001)	0.1340 (.009)
#Unique partners	−0.0075 (.173)	0.0044 (.494)	−0.0056 (.343)	−0.0055 (.281)
Acquisition's value	0.4777 (.151)	−0.2126 (.149)	0.5512 (.025)	
Cross-border acquisition	−1.3829 (.008)	−0.1562 (.462)	−1.2492 (.025)	
Post-acquisition alliance portfolio size	0.0075 (.098)	−0.0211 0.000	0.0090 (.004)	
Target's portfolio density	12.1167 (.186)	−10.8764 (.008)	14.6870 (.009)	
Acquirer's portfolio density	−4.9118 (.634)	−47.5351 0.000	46.532 (.127)	
Partner's unique technological resources	−0.0005 (.111)	−0.0008 (.037)	−0.0004 (.169)	−0.0004 (.115)
Acquisition after 1995	−1.3174 (.077)	0.9021 (.010)	−1.8169 0.000	
Alliance's product-market breadth	−0.0337 (.743)	−0.0113 (.911)	−0.1157 (.194)	−0.1122 (.095)
Rare-disease alliance	−0.5381 (.052)	−0.7058 (.016)	−0.3809 (.090)	−0.3622 (.049)
Exclusive alliance	−0.0939 (.593)	−0.3343 (.073)	−0.2384 (.086)	−0.2263 (.094)
Combinatorial chemistry alliance	−0.1006 (.620)	0.1017 (.700)	−0.0679 (.696)	−0.0659 (.712)
Complex interdependence	0.4272 (.005)	0.3012 (.068)	0.3356 (.013)	0.3246 (.013)
Equity alliance	0.0478 (.764)	0.0934 (.641)	0.1788 (.218)	0.1735 (.291)
Alliance's activity breadth	−0.1669 (.003)	−0.1274 (.066)	−0.1280 (.019)	−0.1237 (.024)
Alliance's age at acquisition	−0.0015 (.680)	−0.001 (.788)	−0.0028 (.429)	−0.0027 (.313)
Alliance formed after 1995	−0.3057 (.217)	−0.4627 (.092)	−0.1905 (.384)	−0.1839 (.342)
Target not fully integrated			0.6680 (.053)	
Constant	0.7520 (.038)	0.1606 (.408)	0.6146 (.142)	
Observations	1,838	1,814	1,838	1,838
Log-likelihood	−1,035	−849.4	−1,113	−997.7

Note: *p*-Values in parentheses.

TABLE A4 Comparing Tobin's q value of the target firms and the rest of the industry

Year	Targets' Tobin's q	Rest of the industry's Tobin's q	p-Value (two-tailed t test of difference)
1989	2.4526	2.2149	.477
1990	2.2457	2.0205	.471
1991	4.4607	2.6614	.000
1992	2.9740	2.6609	.323
1993	2.5417	2.5185	.936
1994	2.2479	2.2021	.863
1995	3.6715	2.6612	.001
1996	3.8665	2.7249	.000
1997	3.6312	2.5757	.001
1998	3.7085	2.3743	.000
1999	3.3645	2.7429	.265
2000	2.6792	2.7334	.953