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OLD TECHNOLOGY MEETS NEW TECHNOLOGY: COMPLEMENTARITIES, SIMILARITIES, AND ALLIANCE FORMATION

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Alliance formation is commonplace in many high-technology industries experiencing radical technological change, where established firms use alliances with new entrants to adapt to technological change, while new entrants benefit from the ability of established players to commercialize the new technology. Despite the prevalence of these alliances, we know little about how these firms choose to ally with specific firms given the range of possible partners they may choose from. This study explores factors that lead to alliance formation between pharmaceutical and biotechnology companies. We focus on the alliance tie as the unit of analysis and argue that dyadic complementarities and similarities directly influence alliance formation. We then introduce a contingency model in which the positive effect of complementarities and similarities on alliance formation is moderated by the age of the new technology firm. We draw theoretical attention to the intersection between levels of analysis, in particular, the intersection between dyadic and firm-level constructs. We find that a pharmaceutical and a biotechnology firm are more likely to enter an alliance based on complementarities when the biotechnology firm is younger. Another noteworthy finding is that proxies for broad capabilities appear to be at least as effective, if not more so, in predicting alliance formation compared to fine-grained science and technology-related indicators, like patent cross-citations or patent common citations. We conclude by suggesting that future studies on alliance formation need to take into account interactions across levels; for example, how dyadic capabilities interact with firm-level factors, and the advantages and disadvantages of more or less fine-grained measures of organizational capabilities. Copyright © 2007 John Wiley & Sons, Ltd.

INTRODUCTION

The formation of partnerships, alliances, and joint ventures between firms has increased at a dramatic rate over the last few decades (Hagedoorn, 2002). This phenomenon has inspired significant research into the question of *why* firms enter alliances. Extant research has suggested that firms are motivated to enter alliances to overcome market failures (Williamson, 1985), accrue market power (Porter and Fuller, 1986), learn from one another (Hamel, Doz, and Prahalad, 1989), share risks (Ohmae, 1989), access complementary assets (Arora and Gambardella, 1990; Rothaermel, 2001), enhance legitimacy (Baum and Oliver, 1991), build new competences (Hennart, 1991), enter new markets and technologies (Kogut, 1991), enhance innovativeness (Shan, Walker, and Kogut, 1994) and new product development (Rothaermel and Deeds, 2004), and improve early performance (Baum, Calabrese, and Silverman, 2000).

Keywords: alliance formation; technological change; measurement of capabilities; multilevel research; pharmaceutical biotechnology industry
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Others have suggested that a firm's propensity to form alliances depends on the firm's strategic and social position (Eisenhardt and Schoonhoven, 1996); technical, commercial, and social capital (Ahuja, 2000); and its resources and external environment (Park, Chen, and Gallagher, 2002). While we seem to have a fairly good understanding of why firms enter alliances, the *question of partner choice* has received less attention.

Yet, the importance of alliance partner choice has long been recognized (Harrigan, 1985). Pioneering research into the question of *who allies with whom* has drawn on resource dependence theory and suggested that organizations enter into relationships motivated by strategic interdependencies (Oliver, 1990). Scholars have also argued that status similarities (Podolny, 1994) and social networks (Gulati, 1995b) play an important role in predicting partner choice. More recent work has suggested that complementarities arising from different geographic locations combined with status similarity and social capital predict alliance formation (Chung, Singh, and Lee, 2000). Firms' participation in technical committees has also been found to explain subsequent alliance formation (Rosenkopf, Metiu, and George, 2001).

Extant empirical research that explains who partners with whom has focused predominantly on horizontal alliances between established firms (e.g., Gulati, 1995a, 1995b; Ahuja, 2000; Chung, *et al*., 2000; Garcia-Pont and Nohria, 2002). Rather than focusing on alliance formation between established firms, we focus on the evolution of technology fields in an industry and on the antecedents of alliances between firms imprinted under an old technology and firms imprinted under a new technology (Stinchcombe, 1965). Such a focus seems particularly salient given the theoretical emphasis researchers have placed on strategic alliances as a tool for established firms to adapt to technological change (Teece, 1992; Hill and Rothaermel, 2003). Prior work, with its focus on horizontal partnerships between established firms in existing technologies, has offered insights into the importance of alliance behavior for market power and market expansion, but has focused little attention on the manner in which firms ally to meet the needs of a dynamic and technologically complex external environment. The setting for this study is the intersection between the pharmaceutical and the biotechnology industry. Our focus is on the choice of alliance partner between incumbent technology firms and new technology firms. The incumbent technology firms in this study are the pharmaceutical companies founded under the technology paradigm of chemical screening, and the new technology firms are biotechnology firms founded under a new technology paradigm based on molecular biology.

Extant literature indicates that strategic interdependence and status similarities increase the probability of alliance formation (Oliver, 1990; Podolny, 1994; Gulati, 1995b; Chung *et al*., 2000). When investigating the effect of dyadic complementarities on alliance formation, we follow prior research and focus on complementarities arising from non-overlapping niches (Gulati, 1995b; Chung *et al*., 2000). In addition to non-overlapping niches, we develop a second measure to assess the potential for complementarities that combine different competences along the value chain. We combine a biotechnology firm's competence in drug development—an upstream value chain activity—with a pharmaceutical firm's competence in regulatory management, marketing, and distribution—all downstream value chain activities. Prior research has demonstrated that pharmaceutical firms possess distinctive competences along the value chain (De Carolis, 2003).

When analyzing the effect of dyadic similarities on alliance formation, we build on the pioneering work of Mowery, Oxley, and Silverman (1996, 1998), and use patent cross-citation and patent common citation rates to proxy technological similarities. In addition to these more fine-grained measures for science and technology relatedness, we develop a third measure that captures dyadic similarity, based on each firm's competence in innovation. In particular, we measure dyadic similarity through overall patenting propensity, which captures the firm's broad-based capabilities in generating innovation (Stuart, 2000).

Prior work has not considered that the probability of alliance formation might be contingent upon how *dyadic* constructs may interact with *firm-specific* factors. Here we focus on the age of the new technology firm, as a proxy for the firm's legitimacy, power, and credibility. We posit that alliance formation driven by complementarities between established and new technology firms is more likely when the new technology firm is younger. As the new technology firm ages, we argue that alliance formation between established

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and new technology firms is more likely to be based on similarities. Thus, we contend that the age of the new technology partner moderates the effect of complementarities in a negative fashion, while it moderates the impact of similarities in a positive fashion. We conclude that the dyadic effects of complementarities and similarities on alliance formation are contingent upon firm-level characteristics of the new technology venture.

THEORY AND HYPOTHESES DEVELOPMENT

Complementarities and alliance formation

Past research cites the pooling of complementary skills and resources to create added value as one of the primary motives for creating strategic alliances (Arora and Gambardella, 1990; Teece, 1992; Rothaermel, 2001). With the increased emphasis on core competences and the possession of 'best in class' capabilities over the last decade, strategic alliances have been promoted as an opportunity for two firms to combine and create a synergistic entity (Nohria and Garcia-Pont, 1991; Dyer and Singh, 1998). A strategic interdependence perspective on alliance formation suggests that dependencies create conditions that favor alliances, and that firms create alliances with those partners who can best provide the complementary assets and skills they need. Extant research examining resource interdependencies between specific firms has tied alliance formation to the availability of specific competences, typically functional capabilities within and across firms, such as research and development (R&D), production, marketing, and distribution.

The central perspective of these arguments is that each partner has certain areas of strength that may compensate for the weaknesses of their potential alliance partner—a perspective that has been supported by a number of empirical studies (Harrigan, 1985; Lorange and Roos, 1992; Burgers, Hill, and Kim, 1993). Prior research has provided consistent evidence across different industries that firms that occupied complementary niches were more likely to form alliances (Gulati, 1995b; Chung *et al*., 2000). One common example is the benefit of alliance formation between large, established firms and small firms (often recent entrants into the market) where the established manufacturing, sales, marketing, and distribution channels of the large firms can be utilized by the smaller partners, which may excel in product innovation or new product development. In these cases, firms attempt to leverage the critical knowledge available from another partner to build on their own set of capabilities. Teece (1986, 1992) goes so far as to argue that established competitors in emerging industries risk obsolescence if they are unable to form partnerships with innovative startups that can provide them with a steady stream of future ideas. Rothaermel (2001) found evidence of the importance of complementary assets in alliance formation by providing support for the notion that incumbents may benefit from radical technological change through allying with new entrants, if the incumbents possess specialized complementary assets necessary to commercialize the new technology. When applied in the context of the dyad, these arguments suggest that firms seek out partners that can help them manage strategic interdependencies by offering superior capabilities in areas where the focal firm may be weaker.

Within the empirical setting of our research, biotechnology represents a scientific base (molecular biology) that is significantly different from the knowledge base of pharmaceuticals (organic chemistry). Past work has indicated that a scientist who is trained in the framework of drug discovery and development based on chemical synthesis loses on the average around 80–100 percent of his or her skills when attempting to transition to the emerging framework of drug discovery and development based on molecular biology (Rothaermel, 2001). The new biotechnology is thus considered to be competence destroying for pharmaceutical companies (Powell, Koput, and Smith-Doerr, 1996; Stuart, Hoang, and Hybels, 1999). Biotechnology firms possess R&D competences and capabilities that traditional pharmaceutical companies can profitably draw upon to maintain their innovative presence. The fact that pharmaceutical companies marketed and distributed seven of the top-ten selling biotechnology drugs in the late 1990s, even though none of the drugs were developed by the pharmaceutical companies, demonstrates the importance of the distribution of biotechnology products by pharmaceutical companies (*Ernst & Young Biotechnology Reports*). Emerging industries such as biotechnology may offer significant opportunities for cooperation between small new

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entrants and large established firms that are seeking to exploit technological spillovers in an attempt to realize the potential for commercialization. Situations in which both parties can benefit usually occur when complementarities between partners allow them to compensate for each other's weaknesses while leveraging each other's comparative strengths.

Hypothesis 1: Complementarities between an incumbent technology firm and a new technology firm increase the probability of alliance formation.

Similarities and alliance formation

Although a focus on complementary assets, skills, and knowledge may provide a relatively straightforward explanation of the formation of alliances between some firms, such a perspective potentially ignores how firms overcome the uncertainties associated with such partnerships (Kale, Singh, and Perlmutter, 2000). Market risk and a high level of uncertainty typically characterize the initiation of any alliance or partnership (Hamel *et al*., 1989). The creation of an alliance involves a very careful assessment on the part of each partner as to what the partner and the alliance might offer and whether the benefits of the alliance exceed the potential downside risks.

To ameliorate some of the fears that the alliance represents, firms may focus on other characteristics and signals from their potential partners that they feel may increase the likelihood that the alliance will work. A preference to partner with firms of similar status, for example, has been found to consistently predict alliance formation in the investment banking industry (Podolny, 1994; Chung *et al*., 2000). In more technology- and science-intensive industries like biotechnology, patenting is often considered a signal of the quality for a firm, in particular in the absence of more tangible signals like the successful commercialization of new products.[1] In this industry, firms that patent more than their peers are considered to be on the technological frontier of their field (Sorensen and Stuart, 2000). Thus, highly innovative firms may search out each other as alliance partners based on similarities in overall technology strategy. This seems particularly pertinent in the pharmaceutical industry because it is characterized by distinct strategic groups, in which one group competes on drug discovery and development of patent-protected proprietary drugs, while a second strategic group competes on generic, me-too products, where the patent protection has expired (Cool and Schendel, 1987, 1988). In addition, work by Mowery *et al*. (1998) showed that firms with similarities in technological capabilities, proxied by patent cross-citation and patent common citations, were more likely to form an alliance. Similarly, work by Lane and Lubatkin (1998) demonstrated that pharmaceutical and biotechnology firms that draw from the same knowledge base and dominant logics were more likely to partner and create better-performing alliances. Their research adopted an organizational learning perspective to examine the role that absorptive capacity played in the dyad's ability to value, assimilate, and utilize external knowledge, showing that similarities in basic knowledge and organizational practices (e.g., compensation practices and levels of formalization and centralization) helped the partners operate together more effectively. Assuming that there are good strategic reasons to create an alliance, firms may be most interested in partnering with firms that they feel are similar in other dimensions, like innovation orientation or technological overlap, both of which seem to be particularly salient in high-technology industries.

Hypothesis 2: Similarities between an incumbent technology firm and a new technology firm increase the probability of alliance formation.

Complementarities, similarities, and new technology firm age

Biotechnology firms, as more recent market entrants, are frequently at the forefront of the introduction of radical new technologies (Tushman and Anderson, 1986). Given the high uncertainty that surrounds this field, however, a high failure rate of new entrants is a common occurrence, which is reflected in the theoretical notion of a liability of newness. Stinchcombe (1965) proposed that younger organizations experience a higher mortality rate because they lack accumulated production experience, well-developed internal processes and procedures, strong ties with customers and

[1] Very few biotechnology ventures have successfully commercialized new biotechnology drugs at this stage of industry evolution.

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suppliers, and experienced human resources. Evolutionary theorists posit that newer organizations are prone to higher mortality, because their routines have not yet developed to a point that they serve as sufficient repositories of organizational knowledge (Nelson and Winter, 1982; March, 1988).

Alliance choice and ultimate success are influenced by the capabilities of each partner. When an incumbent technology firm allies with a new technology firm, the incumbent technology firm is likely to be the member of the pair that is larger and more powerful, and thus the legitimacy of the incumbent technology (in this case pharmaceutical) partner is seldom questioned. The legitimacy and viability of the new technology (biotechnology) firm, conversely, may be much more uncertain. As Stinchcombe (1965) pointed out, development of trust and internal legitimation of the new firm's management and business model takes time, as does the acquisition of institutional identity. Younger firms, such as the new technology firms in this study, are likely to have a lower level of legitimation than older ones. In addition, as firms age, they accumulate innovation and production experience, and are thus able to build on prior knowledge when discovering and developing new products or when incorporating new external knowledge (Cohen and Levinthal, 1990).

As incumbent technology firms decide with whom to partner, they examine and assess the strengths and weaknesses of an array of potential new technology partners. The age of the new technology partner may be particularly instructive in such assessment when the quality of the new technology partner's potential products and markets is not well known, given its early stage of development. In this case, the new technology firm's age takes on an important role of signaling to others the quality of the firm (Sorensen and Stuart, 2000).

Processes of external legitimation also take time. Although an organization must have some minimal level of legitimacy to be attractive as an alliance partner, newer firms have comparatively weaker claims on support and interest from potential partners. Newer, younger firms may be less prominent and may have more difficulty attracting resources or partners. As firms with a new technology (in this case biotechnology companies) evolve, they gain credibility and legitimacy. They are also more likely to be perceived by the broader community of pharmaceutical firms that are interested in forming alliances as more reliable alliance partners. Older organizations tend to have a dense web of exchanges, to affiliate with centers of power, and to have increased status. External actors may also wait for an initial period of testing to be passed before making investments in exchange relations with new organizations.

Moderating effects of new technology firm age on alliance formation

A critical issue for the incumbent technology firm concerns the choice of when to partner with a new technology firm. Ideally, the incumbent firm would choose a new technology partner early in its development, before it becomes too established, too legitimate, too attractive to others, and too powerful. Choosing a partner early allows the incumbent firm to lock in partnerships with the best new technology firms before they begin to work with other, rival, incumbent firms. Waiting too long can create two problems: the window of opportunity for capitalizing on the new set of ideas and technologies may have passed, or its value may be undermined; and rival incumbent firms may be able to capitalize on their own opportunities to work with new technology partners—thus the potential competitive advantage presented by the new technology firm is ceded to a rival.

The age of the new technology firm is particularly important in alliances formed to exploit complementarities across partners. Complementarity involves the creation of immediate value for the combined entity. Speed of the alliance formation process is key, and at a premium. Under these conditions it is advantageous to form partnerships early with promising new technology partners. Forming a partnership early may also be in the best interest of the new technology firm because this can pave the way to market access (Shan *et al*., 1994), and enhance the new venture's legitimacy as the established partner's reputation spills over through affiliation (Stuart *et al*., 1999). It is also clear, however, that younger new technology firms are likely to have less power and influence, following the legitimacy and institutional arguments made above. Early after founding, the new technology firm may be in a relatively weaker position in the alliance compared to the larger, more established incumbent firm. Differences in age and legitimacy exacerbate power differences between

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the two potential partners, with the relative power differential inversely related to the new technology firm's age. Because of the new technology firm's relative youth and lack of legitimacy and influence, it is much more likely that the incumbent technology partner will play a more proactive role in setting the terms for the alliance in a manner that supports and facilitates its own business. The new technology firm, with less power, may be forced to accept less attractive terms than if it had more power relative to the incumbent technology firm.

Complementary technologies present a compelling and straightforward logic for entering into alliances, particularly between new technology and incumbent technology firms (Teece, 1992). Established technology firms are likely to be particularly vigilant and aggressive in uncovering new technology firms that appropriately fit their existing set of complementary assets and value chain positions (Kale, Dyer, and Singh, 2002). Because new technology firms may also find the prospect of an alliance with an established technology firm compelling, it is likely that the new technology firm will also be interested in such a venture. New technology ventures may have no choice but to enter an alliance if they desire market access, because forward integration is often difficult and both time and resource intensive (Rothaermel and Deeds, 2004). Added to this dynamic is the likely reality that the new technology firm has less power earlier in its development and thus is more willing to participate in an alliance initiated by the established technology partner. Given the importance of complementarities to the established technology firm trying to take advantage of the scientific advances of the new technology firm early in its development, it is likely that complementarities will drive alliances between young new technology firms and established technology firms.

Hypothesis 3: Incumbent and new technology firms are more likely to enter alliances based on complementarities when the new technology firm is younger.

Choosing relatively young partners because of their potentially complementary competences can create a successful alliance, but the alliance is also infused with uncertainty. As time passes, an incumbent technology firm finds it easier to assess the performance of the potential new technology partner and also to assess its ability to contribute to the value created by a potential alliance. As the new technology firm ages, critical external constituencies such as investors, suppliers, and customers are better able to form judgments about the quality of the firm.

The power, reputation, and status of the new technology firm increases as it ages, enhancing its attractiveness as a potential alliance partner. Because older new technology firms may be seen as more competent and more prominent, alliances with them can offer a better opportunity to benefit from their competences and skills, while also leading to a greater likelihood of alliance success. In addition to the direct benefits accorded through access to superior capabilities, affiliation with a longer-lived, more legitimate, and thus more established new technology firm can increase the perceived quality of the incumbent technology firm in the minds of other external actors.

Allying with successful new technology ventures may signal that the established technology firm is making headway in adapting to the new technology (Hill and Rothaermel, 2003; Rothaermel and Hill, 2005). In this case, reputation spillovers would flow from the older, and generally more successful new technology firm to the incumbent technology firm. For example, Lilly is seen as more likely to maintain its market leadership in insulin after it entered an alliance with the biotechnology firm Genentech and obtained exclusive rights to market and distribute a new biotechnology-based human insulin drug (Humulin). One could argue that Genentech bestowed legitimacy and reputation effects upon Lilly. The amount of power and influence that the new technology firm has relative to the incumbent technology firm is likely to increase over time, which in turn may influence its dealings with any potential partner. An alliance partnership with a more established new technology firm that has overcome the liability of newness is likely to represent less of an absolute difference in power between the two partners. The new technology firm has gained prominence, legitimacy, and influence, and is more likely to take a stronger role in deciding on its alliance partner and in setting the terms of the alliance.

Given the greater balance of power between the two potential partners, the new technology firm should have a more active voice in any alliance decision. It is likely that the new technology firm,

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while interested in complementarities, is also interested in similarities with the established firm. To the extent that both parties are similar, they may feel a greater comfort level, sense that they can work together more successfully, and more successfully manage the integration of competences and skills that must happen for the alliance to create value. Assuming a diminishment of the power differential between new and incumbent technology firms that occurs as a byproduct of the new technology firm's aging, we posit that these firms tend to ally with incumbent technology firms to which they are similar.

Hypothesis 4: Incumbent and new technology firms are more likely to enter alliances based on similarities when the new technology firm is older.

METHODOLOGY

Research setting

To empirically test the role of dyad-level capabilities and their interaction with the age of the new technology firm in predicting alliance formation, we chose the global biopharmaceutical industry as our research setting. The global biopharmaceutical industry consists of pharmaceutical and biotechnology firms such as Biogen and Chiron and traditional pharmaceutical companies such as Pfizer and Merck that focus on human therapeutics.

We chose this particular research setting for a number of reasons. The scientific foundation of the pharmaceutical companies is organic chemistry, while the sciences underlying biotechnology are molecular biology, immunology, and genetics, among others. The emergence of biotechnology is considered a radical process innovation in the way drugs are discovered and developed (Stuart *et al*., 1999). This radical process innovation in turn created the need for pharmaceutical firms to collaborate with new biotechnology firms to aid in transitioning from old to new methods of drug discovery and development. Conversely, new biotechnology firms also needed to collaborate with the pharmaceutical firms because the incumbent pharma firms controlled access to the market for human pharmaceuticals, in particular valuable and path-dependent capabilities in clinical trial management and drug marketing and distribution (De Carolis, 2003). Not surprisingly, the commercialization of biotechnology is characterized by extensive interfirm cooperation. The biotechnology industry exhibits high alliance intensity and accounts for about 20 percent of the observed strategic alliances in high-technology industries (Hagedoorn, 1993). Given the need of old and new technology firms to collaborate and the ensuing high propensity of alliance formation, the global biopharmaceutical industry seems an ideal setting to study antecedents to alliance formation.

Sample and data

To create the sample for this study, we identified all pharmaceutical and biotechnology firms active in *in-vivo* human therapeutics listed in various volumes of *BioScan*, a publicly available industry directory.[2] The biotech and pharma firms in the sample are engaged in the discovery, development, and commercialization of human therapeutics that are placed inside the human body (*in-vivo*). Applying this industry demarcation reflects the uniqueness of the human *in-vivo* segment of biotechnology in terms of its economic importance and potential, its regulatory environment, and its consumer market (Powell *et al*., 1996).

We examined factors that affect alliance formation between a pharmaceutical and a biotechnology firm, with the unit of analysis being the *dyad*. We identified 59 incumbent pharmaceutical firms and 548 new biotechnology firms engaged globally in human *in-vivo* therapeutics ($59 \times 548 = 32,332$ pharma–biotech dyads). The time frame in which we chose to investigate alliance formation between a pharmaceutical and biotechnology firm is the 4-year time window between 1998 and 2001.[3] We chose this specific time window for several reasons: it was characterized by sustained high alliance activity in the biopharmaceutical industry and was also far enough removed from the beginnings of commercialized biotechnology (marked by Genentech's founding in 1976 and successful initial public offering in 1980) to assess the impact of firm- and dyad-level characteristics

[2] *BioScan* provides comprehensive data about the worldwide biotechnology industry. The data contained in *BioScan* are cumulative (each subsequent issue includes the information of all prior versions), which enabled us to track alliance formation over time.

[3] The results remained robust to variations in the time window.

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on alliance formation between biotechnology and pharmaceutical companies. In addition, this time window covered both a bull and a bear market in public equity evaluations. This is salient in our investigation since the condition of the equity market has been shown to impact alliance formation between biotechnology and pharmaceutical companies (Lerner, Shane, and Tsai, 2003). Finally, the time window captures recent alliance activity in this industry. To construct the network measures and other independent variables, we drew on data documenting the alliance activity in this industry since the emergence of biotechnology in 1973, and were thus able to attenuate a problem of left censoring prevalent in prior alliance studies.

Our data sources are multiple issues of the *BioScan* industry directory and various databases provided by *Recombinant Capital*, an independent research firm specializing in the life sciences. *BioScan* and the *recap* database (by *Recombinant Capital*) appear to be the two most comprehensive publicly available data sources documenting alliance activity in the global biopharmaceutical industry. Prior research addressing different questions has relied on either *BioScan* or *recap* data, and thus their usefulness has been validated (Shan *et al*., 1994; Lane and Lubatkin, 1998; Lerner *et al*., 2003). To ensure accurateness and completeness of our data, we drew data from both *BioScan* and *recap*.[4] In addition, we obtained patent data from the U.S. Patent and Trademark Office (U.S. PTO), and patent citations data from the National Bureau of Economic Research (NBER) patent database (Hall, Jaffe, and Trajtenberg, 2001).

Dependent variable: alliance formation

We focus on bilateral dyadic relationships that are formalized as strategic alliances between independent organizations. A focus on bilateral dyadic alliances is appropriate because the biopharmaceutical industry is generally not characterized by group structures or alliance blocks. We consider all 32,332 dyads at an equal a priori risk of entering an alliance, because we do not believe that excluding certain dyads is theoretically justifiable. Including all possible dyads in the alliance opportunity risk set is the most conservative approach in assessing different variables' effect on the probability of alliance formation (Gulati, 1995a, 1995b). Table 1 provides an overview on how each variable was constructed and depicts the expected signs based on the hypotheses advanced. Below, we describe each variable in detail.

We measured alliance formation in two ways. We focused on the *event* of alliance formation and the *intensity* of alliance activity in any given dyad. A similar approach was taken by Park *et al*. (2002) when studying alliance formation of semiconductor start-ups at the firm level, rather than at the dyad level. The *event of alliance formation* between an old and a new technology firm is proxied by the probability of an alliance being formed in any possible dyad opportunity set between a pharmaceutical and a biotechnology firm. This dependent variable is coded 1 if the given dyad formed an alliance, and 0 otherwise.

Clearly, not all alliances are equal in terms of partner involvement and commitment. The most frequent distinction made in the literature is between equity and non-equity alliances (Gulati, 1995a). Non-equity alliances are contract-based cooperative agreements, whereas equity alliances are based on taking an equity stake in a partner, exchanging equity, or setting up a third organization as a joint venture. As a consequence, non-equity alliances are much more frequent, although equity alliances are considered to be stronger ties. To assess problems of unobserved heterogeneity that can arise when including different alliance types as indicators of alliance formation, we also applied the formation of *non-equity alliances* as a second dependent variable. This variable is coded 1 if the given dyad formed a non-equity alliance, and 0 otherwise.

We proxied the *alliance intensity* in a given dyad by a count of the total number of alliances formed within a pharmaceutical and a biotechnology dyad. Parallel to the distinction between all alliances and non-equity alliances when assessing the probability of alliance formation in a given dyad, we also assessed alliance intensity by both the total number of all alliances and the total number of non-equity alliances formed. During the 4-year time window between 1998 and 2001, 508 dyads had an alliance event, and a total of 580 alliances were formed.

[4] We found that these two data sources were quite consistent in their reporting. For example, the inter-source reliability was greater than 0.90 when documenting alliances.

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Table 1. Definition of variables and hypothesis prediction

Dependent variables	Definition
Alliance formation	1 = pharma–biotech dyad i formed an alliance; 0 otherwise
Alliance formation (non-equity)	1 = pharma–biotech dyad i formed a non-equity alliance; 0 otherwise
Alliance intensity	Total number of alliances formed in pharma–biotech dyad i
Alliance intensity (non-equity)	Total number of non-equity alliances formed in pharma–biotech dyad i

Independent variables		Hypothesis	Prediction
Dyadic complementarity			
Non-overlapping niches as proxy for strategic interdependence (Gulati, 1995b; Chung *et al*., 2000)	Count of each pharma-biotech dyad i's non-overlap in biotechnology subfields	H1	Positive
Biotech firm's competence in drug development combined with pharma firm's competence in marketing and distribution (complementarity index)	$\left(\frac{(\text{Drugs in development})_{\text{biotech}_i}}{\text{Mean (Drugs in development)}_{\text{biotech}_{i\ldots n}}}\right)+\left(\frac{(\text{SM\&A})_{\text{pharma}_i}}{\text{Mean (SM\&A)}_{\text{pharma}_{i\ldots n}}}\right)$	H1	Positive
Dyadic similarity			
Patent cross-citation rates (Mowery *et al*., 1996, 1998)	$\left(\frac{\text{Citations to biotech firm } i\text{'s patents in pharma firm } j\text{'s patents}}{\text{Total citations in pharma firm } j\text{'s patents}}\right)+\left(\frac{\text{Citations to pharma firm } j\text{'s patents in biotech firm } i\text{'s patents}}{\text{Total citations in biotech firm } i\text{'s patents}}\right)$	H2	Positive
Patent common citation rates (Mowery *et al*., 1998)	$\left(\frac{\text{Citations in biotech firm } i\text{'s patents to patents cited in pharma firm } j\text{'s patents}}{\text{Total citations in biotech firm } i\text{'s patents}}\right)+\left(\frac{\text{Citations in pharma firm } j\text{'s patents to patents cited in biotech firm } i\text{'s patents}}{\text{Total citations in pharma firm } j\text{'s patents}}\right)$	H2	Positive
Similarity in patenting propensity	$\text{Maximum Value}-\left\lvert\left(\frac{(\text{Patents})_{\text{biotech}_i}}{\text{Mean (Patents)}_{\text{biotech}_{i\ldots n}}}\right)-\left(\frac{(\text{Patents})_{\text{pharma}_j}}{\text{Mean (Patents)}_{\text{pharma}_{i\ldots n}}}\right)\right\rvert$	H2	Positive
Dyadic and firm-level interactions	Dyadic complementarity × Age biotech firm i	H3	Negative
	Dyadic similarity × Age biotech firm i	H4	Positive

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Table 1. (*Continued*)

Moderating variable	Definition
Biotech Firm Age	Age in years since founding of biotechnology firm *i*
Control variables	
Geographic Zone	1 = pharma–biotech dyad *i* is located in the same geographic zone, 0 otherwise
Time Elapsed	Time elapsed in months since latest alliance
Direct Ties	Count of each pharma–biotech dyad *i*'s total number of prior direct ties
Indirect Ties	Count of each pharma–biotech dyad *i*'s total number of indirect ties at degree distance two
Centrality Biotech	Total number of alliances the biotech firm has entered within the network (degree centrality)
Centrality Pharma	Total number of alliances the pharma firm has entered within the network (degree centrality)
Firm Size Biotech	Count number of employees in biotech firm *i*
Firm Size Pharma	Count number of employees in pharma firm *j*
Public Biotech	1 =biotech firm *i* is public, 0 otherwise
Public Pharma	1 = pharma firm *j* is pubic, 0 otherwise
Patents Biotech	Count number of patents assigned to biotech firm *i*
Patents Pharma	Count number of patents assigned to pharma firm *j*

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Independent variables: complementarities and similarities

We employ multiple measures for complementarities and similarities, utilizing measures used in past research and also developing new measures. We suggest that using multiple proxies enables researchers to detect which dimension is more critical when predicting alliance formation. This point is especially salient in this study because we develop more broad-based capability measures, while some of the measures employed in prior research tend to be more fine grained, especially when comparing patent measures. In the regression analysis, we are thus able to juxtapose broad-based and fine-grained types of capability relatedness to assess their respective merit in predicting alliance formation.[5]

Non-overlapping niches

We employed two different measures for a dyad's level of complementarities, with the first one derived from prior research. Following Gulati (1995a) and Chung *et al*. (2000) we used a count of each dyad's non-overlapping niches as a proxy for its strategic interdependence. Population ecology posits that firms competing in the same organizational niche possess similar resources and capabilities (Hannan and Freeman, 1977), which makes a potential resource combination through an alliance redundant and less complementary. On the other hand, firms active in non-overlapping niches are limited in their direct competition, which in turn enhances their potential strategic interdependence (Gulati, 1995b; Chung *et al*., 2000). The biopharmaceutical industry is characterized by a multitude of technological trajectories (Dosi, 1982), which can be represented as different organizational niches.

We developed the proxy for non-overlapping niches in four steps. First, we coded each firm's participation/non-participation in different biotechnology subfields. This resulted in 133 biotechnology fields across all firms in the sample. Second, because the descriptions of a firm's subfields are highly technical, we solicited the help of two industry experts (one a doctor of pharmacology, the other a research/laboratory scientist), to independently collapse the 133 different specific categories into broader areas. This resulted in 54 distinct biotechnology subfields, with an interrater reliability of 0.99.[6] In a third step, we calculated the absolute overlap in the 54 technology subfields for each biotech–pharma dyad. This measure represents a count of the overlapping biotechnology subfields that each biotech–pharma dyad competed in. In a final step, we subtracted this value for each pharma–biotech dyad from the maximum level of overlap (54 technology subfields) to obtain the measure for non-overlapping niches.[7]

Complementarity index

Prior research has argued that the emergence of biotechnology is competence destroying for the upstream R&D competences of incumbent pharmaceutical firms, but competence enhancing for their downstream commercialization competences (Powell *et al*., 1996; Rothaermel and Hill, 2005). Subsequently, access to mutually complementary assets has been invoked in explaining alliances between biotechnology and pharmaceutical companies (Teece, 1992; Rothaermel, 2001). In these alliances, gains can accrue due to economies of specialization as the biotechnology firm focuses on the upstream value chain activities of drug discovery and development, and the pharmaceutical firm focuses on the downstream value chain activities like regulatory approval, drug distribution, and marketing. Based on these conceptual arguments, we constructed a measure to proxy the extent of complementarities for each biotechnology–pharmaceutical dyad. We combined a biotechnology firm's competence in drug development with a pharmaceutical firm's competence in drug commercialization.

We proxied a biotechnology firm's competence in drug development by the number of biotechnology drugs the firm had in development. We counted only drugs that have entered clinical trials as being products in development since these products have overcome a major hurdle toward successful commercialization in the product development process (De Carolis and Deeds, 1999; Rothaermel

[5] Unless specific time windows are indicated, all independent variables were assessed at $t - 1$.

[6] A complete list of the 54 biotechnology subfields is available from the first author upon request.

[7] As a robustness check, we also employed the measure based on the total number of non-overlapping subfields (133). The results remained robust.

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and Deeds, 2006). It is important to note that the drug product development process is beset with high uncertainty, with only 1 percent of molecules screened making it into clinical trials (*Ernst & Young Biotechnology Reports*).

Following prior research, we proxied a pharmaceutical firm's competence in commercializing new drugs by its expenses allocated to selling, marketing, and administrative activities (SM&A) (Chatterjee and Wernerfelt, 1991; De Carolis, 2003). The vast majority of a pharmaceutical company's SM&A expenses are devoted to managing new drugs through the regulatory process and distributing them through sales forces ('detail people') that are frequently 15,000 people strong. While the downstream complementary assets necessary to commercialize new drugs are specialized resources, and thus partly explain the bargaining power of incumbent pharmaceutical firms *vis-à-vis* new biotechnology firms (Teece, 1986), these downstream assets also contain a generic component in the sense that the regulatory process and drug distribution are more or less identical regardless of whether the drug is based on biotechnology (large molecules) or organic chemistry (small molecules). This in turn makes this competence fungible across different drug commercialization projects (Hoang and Rothaermel, 2005). Consistent with past research (Chatterjee and Wernerfelt, 1991; De Carolis, 2003), we argue that a pharmaceutical company's SM&A expenses, holding everything else constant including firm size, are a reasonable proxy for its strength in the downstream complementary assets needed to commercialize new drugs. In support of this notion, prior research has identified the pharmaceutical industry as an industry where sales and marketing expenditures, besides R&D, are a prime competitive weapon (Matraves, 1999; De Carolis, 2003).

To proxy each dyad's level of complementarities, we summed the centered ratios of the biotechnology firm's drugs in development and the pharmaceutical firm's SM&A expenses. The centered ratios were developed as follows: first, we counted the number of drugs the biotechnology firm had in development. We then centered (or normalized) the firm's number of drugs in development around the mean value for all biotechnology firms (Cohen *et al*., 2003). A ratio of 1.0 implies that the biotechnology firm under consideration has exactly as many biotechnology drugs in development as the average biotechnology firm; a ratio of 1.2 implies that the firm has 20 percent more drugs in development than the average firm; whereas a ratio of 0.4 implies that the firm has 60 percent fewer drugs in development in comparison to the average firm. Likewise, we measured a pharmaceutical firm's competence in marketing and distribution by centering the firm's SM&A expenses around the SM&A mean for all pharmaceutical firms. The notion behind complementarities driving alliance formation is that the partners strive to combine assets in which they possess a comparative advantage. The sum of these two different competences is a reasonable proxy for the magnitude of the potential synergies realizable in an alliance.

Similarities

We constructed three different measures to proxy a dyad's level of similarity, with two derived from prior research. To develop proxies for dyadic similarity, we focused on patenting measures to reflect a firm's innovative competence (Shan *et al*., 1994; Stuart, 2000). Focusing on patenting measures as proxies for similarities is appropriate, because a firm's innovativeness has been shown to be a crucial competence in the pharmaceutical industry (Matraves, 1999). This industry is characterized by a winner-take-all scenario (Arthur, 1989), in which innovative firms create temporary monopolies based on proprietary drugs protected by patents, directly affecting firm performance (Roberts, 1999; De Carolis, 2003). Moreover, patents are a more appropriate measure for a firm's innovative capabilities than, for example, R&D expenditures, because patents more accurately capture the output of R&D activities (Griliches, 1990), which directly underlie a firm's technological capabilities (Mowery *et al*., 1996; De Carolis, 2003).

Following Mowery *et al*. (1996, 1998), we employ patent cross-citation and patent common citation rates. Each patent granted by the U.S. Patent and Trademark Office contains a section in which all prior patents are listed on which the current patent draws. Prior patent citations can be viewed as 'technological fossils' representing the intellectual lineage of new patents. In this sense, patent citations are somewhat comparable to references in academic research. The firms applying for a patent have an incentive to be forthcoming in providing a complete a list as possible of all 'prior

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art' not only to reduce the probability of interference being declared during the processing of the patent application, but also to clearly establish the scope of the patent under evaluation, because only novel aspects of the invention result in legally protected property rights. Before granting the patent, a patent examiner verifies the provided list of references to prior art, and thus serves as an institutional safeguard for the integrity of the citation process.

Given the importance of continued innovation in the biopharmaceutical industry (Roberts, 1999; Deeds, De Carolis, and Coombs, 2000; De Carolis, 2003), one area of similarities we focus on is the technological similarity between a pharmaceutical and a biotechnology firm. Our first proxy for technological similarity, *patent cross-citations*, measures the extent to which the pharma–biotech pair in each dyad cites each other's patents (Mowery *et al*., 1996, 1998). This dyad-level measure provides a proxy of how important the pharmaceutical firm's patents are among the biotech's external technology portfolio, and vice versa. The second proxy for technological similarity, *patent common citations*, measures the degree to which the pharma and biotech firm in a dyad draw from the same external technology base (Mowery *et al*., 1998). Dyads with higher cross-citation or common citation rates exhibit higher technological overlap, and thus are more likely to form alliances.

To construct the patent cross-citation and common citation measures, we used the NBER patent database (Hall *et al*., 2001), which contains detailed and fine-grained information on all utility patents granted by the U.S. PTO between 1963 and 1999. The database contains information on 175,115 companies, 2,923,922 patents, and 16,522,438 patent citations.[8] We constructed the patent cross-citation and patent common citation rates for the sample firms between 1994 and 1997. We chose a 4-year window for the patenting proxies, because it attenuates fluctuations in any given year, while at the same time it is short enough to have a reasonable influence on subsequent alliance formation. Further, using a 4-year time window is consistent with prior research attempting to proxy innovative capabilities (Stuart and Podolny, 1996; Ahuja, 2000). We focused on patents obtained in the United States because it represents worldwide the largest market for therapeutics, and thus firms generally patent first in the United States before patenting in any other country (Albert *et al*., 1991). Moreover, firms active in biotechnology have a strong incentive to patent, because intellectual property protection has been held up consistently in court and is thus considered to be quite strong (Levin *et al*., 1987).

During the 1994–97 time period, the pharma and biotech firms in our sample were granted a total of 17,565 patents, with pharma firms being granted 13,949 patents and the biotech firms 3,616 patents. These patents contained a total of 116,234 patent citations, with 89,819 patent citations in the pharma patents and 26,415 patent citations in the biotech patents. During the 1994–97 time period, the 59 pharmaceutical companies and the 548 biotechnology firms in the sample cited each other's patents 751 times (cross-citation rate). During the same time period, the sample firms cited the same patents 5,460 times (common citation rate).

Both patent cross-citations and patent common citations are fine-grained and accepted indicators of science and technology relatedness. Our third dyadic similarity proxy focuses on similarities in the absolute level of a firm's innovativeness by measuring the *patenting propensity* of each pharma–biotech dyad. First, we centered each biotechnology and pharmaceutical firm's patenting propensity by their respective industry average in the same manner in which we created the centered ratios for the complementarity index described above. Next, for each dyad, we created its patenting distance measure by taking the absolute difference of the centered patenting ratios. This procedure implies that a distance score of zero reflects complete similarity in patenting propensity between the two partners. Finally, we transformed this patenting distance measure by subtracting it from its maximum value so that the resulting measure represents similarity instead of distance.

Moderating variable

New technology firm age

We used the biotechnology firm's age since founding to proxy new technology firm age (*Biotech Firm Age*). All new technology firms in this sample are fully dedicated biotechnology firms, and

[8] Hall *et al*. (2001: 8, footnote 4) explain that 'in addition to utility patents, there are three other minor patent categories: Design, Reissue, and Plant patents. The overwhelming majority are utility patents: in 1999 the number of utility patents granted reached 153,493, versus 14,732 for Design patents, 448 Reissue, and 421 Plant.'

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thus age is measured beginning at incorporation (Sorensen and Stuart, 2000). While biotech firm age is the moderating variable of this study, the direct effect of firm age is included in all regression models. This approach makes moderated regression a conservative method for examining interaction effects, because the interaction terms are tested for significance after all lower-order effects have been entered into the regression equation (Jaccard, Wan, and Turrisi, 1990). This enables us to assess the interaction effects between biotech firm age and complementarities or similarities on alliance formation, above and beyond the direct effect of biotech firm age (Cohen *et al*., 2003). The average biotechnology firm in the sample is 15 years old.

Control variables

We included several variables to control for alternative factors that may influence the propensity of a biotech–pharma pair to enter into an alliance. Some of our control variables, like direct and indirect ties, were key independent variables in prior research (Gulati, 1995a, 1995b; Ahuja, 2000; Chung *et al*., 2000; Stuart, 2000; Rosenkopf *et al*., 2001). Aside from dyadic variables, we also included firm-level variables to control for firm-level heterogeneity.

Geographic zone

The biotechnology and pharmaceutical firms in the sample are globally dispersed. This implies that the firms are exposed to different institutional frameworks and cultures, which should affect their tendency to form alliances. Firms tend to be less likely to form alliances across cultural and institutional boundaries. Hagedoorn (2002), for example, studied international alliances across the Triad North America, Europe, and Asia, and has found that the companies in most high-tech industries prefer to partner with firms in their same geographic zone. To control for this effect, we divided the firms in our global sample into three geographic zones (North America, Europe, and Asia) based on the location of their headquarters. These three geographic zones capture the economic centers of the world in high technology and account for almost all alliance activity (Hagedoorn, 2002). Subsequently, we constructed an indicator variable for each dyad coded 1 if both firms were located in the same geographic zone, and 0 otherwise. About one third of all biotech–pharma pairs were located in the same geographic zone.

Time elapsed

Researchers have long argued that organizations are governed by routines (Cyert and March, 1963). Others have found evidence for the notion that organizations have short memories and thus are likely to repeat activities that they had undertaken in the recent past, with the likelihood of such an action taking place decreasing as more time elapses (Amburgey, Kelly, and Barnett, 1993). Forming alliances can be viewed as an example of firm routines, with the likelihood of a firm activating this routine decreasing with the time elapsed since latest use. Recent empirical work has found that the relationship between time elapsed and future alliance formation was characterized by diminishing returns (Gulati, 1995b). To control for this temporal dynamic, we included a variable capturing the time elapsed in months since latest alliance for each dyad and its squared term.

Direct and indirect ties

Social networks have been found to be reliable predictors of alliance formation in prior studies across different industries and time frames (Podolny, 1994; Gulati, 1995b; Eisenhardt and Schoonhoven, 1996; Ahuja, 2000; Chung *et al*., 2000). Social networks are conduits of information about the reliability and competence of potential alliance partners. Direct ties can create dyadic-specific alliance routines, capabilities, and reputation spillovers, while indirect ties provide access to information.

We controlled for a firm's social embeddedness through its direct and indirect ties. We proxied direct ties, indicating the level of partner-specific prior alliance experience in each dyad (Zollo, Reuer, and Singh, 2002; Hoang and Rothaermel, 2005), by the total number of prior alliances for each pair (Gulati, 1995a, 1995b; Ahuja, 2000). For dyads without prior direct ties, we assessed their level of indirect ties through a count number of common partners shared (Powell *et al*., 1996). Here we drew on the complete network in the biotechnology field, including research universities, nonprofit research organizations, and government agencies—such as the National Institutes of Health—and counted the number of indirect ties

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at degree distance two. For example, the pharmaceutical company Lilly was not directly tied to the biotechnology firm Apollon, but the two firms in this dyad were indirectly tied to one another because both firms had a direct tie to the biotechnology firm Biogen. We argue that Biogen can serve as a bridge between Lilly and Apollon and thus facilitate future alliance formation. Likewise, research universities and nonprofit research institutions can also serve as bridges between unconnected pharmaceutical and biotechnology firms.

Given the relatively short time span since the emergence of biotechnology and the longevity of alliances in this industry (successful new product development and commercialization can take up to 15 years and patents provide a 20-year protection), we considered all prior direct and indirect ties, consistent with prior research (Gulati, 1995a, 1995b; Singh, 1997). A total of 531 biotech–pharma dyads already had a prior alliance before we assessed future alliance formation. The biotech–pharma dyads that did not have a prior alliance were linked indirectly to one another through 2,472 indirect ties at degree distance two.

Network centrality

We proxied each firm's embeddedness in the industry network through a firm's degree centrality. We constructed the industry network for the biotechnology and pharmaceutical firms to assess each firm's level of embeddedness. We proxied a firm's centrality in the network by the total number of ties the firm had entered within the pharma–biotech network. We used this procedure for both the biotechnology and the pharmaceutical firm to construct a firm-level network centrality measure for new and old technology firms (*Centrality Biotech* and *Centrality Pharma*). Employing a count number of all alliances entered into within the local network as a proxy for firm network centrality is consistent with prior research (Powell *et al*., 1996; Ahuja, 2000). When constructing the network centrality measures, we were careful not to include direct ties between two dyad partners to ensure the independence of the network centrality and direct ties measures, and to reduce the threat of finding spurious results based on an inflated network centrality measure. To assess a potential diminishing returns effect, we included the linear and squared term of network centrality. Within the local biotech–pharma network, the average biotech firm had entered at least one alliance, while the average pharma firm had entered more than nine alliances.

Firm size

A critical control variable in isolating the dyadic effect of complementarities and similarities on alliance formation is firm size. Controlling for firm size helps to avoid finding spurious age effects due to the expected positive correlation between firm age and firm size, and thus controlling for firm size isolates the firm age effect and reduces the threat of unobserved heterogeneity (Barron, West, and Hannan, 1994). Controlling for new technology firm size is indicated when assessing how the new technology firm's age interacts with complementarities and similarities in predicting alliance formation. A similar approach was taken by Sorensen and Stuart (2000) when assessing the effect of organizational aging on firm-level innovation.

We proxied firm size through the number of employees for each biotechnology firm (*Firm Size Biotech*). Using the number of employees as a proxy of firm size is the preferred measure in this industry, because many biotechnology firms do not yet have any positive revenues that would allow the use of more traditional size measures like market share. Moreover, the assets of dedicated biotechnology firms are largely intangible. Accordingly, the number of employees as proxy for biotechnology firm size has been used in a number of prior studies (Powell *et al*., 1996; Sorensen and Stuart, 2000; Rothaermel and Deeds, 2004). In parallel, we proxied for the size of the pharmaceutical companies through the number of its employees (*Firm Size Pharma*). The difference in size between the two different partners is striking: the average biotechnology firm had 299 employees, while the average pharmaceutical company was more than 80 times larger, with approximately 25,000 employees.

Ownership status

We controlled for whether the firms were in public or in private ownership. Public biotechnology firms might have more similar business processes and procedures compared to pharmaceutical companies than private biotechnology firms have. We also controlled whether the ownership status of

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the pharmaceutical company might influence its propensity to enter alliances. To control for ownership effects, we included a firm-level dummy variable that takes the value 1 if the firm is public, and 0 otherwise (*Public Biotech* and *Public Pharma*).

Patenting

To test Hypothesis 2, we developed the dyadic similarity measures of patent cross-citations, patent common citations, and patenting propensity. To further isolate the effects of these patent-based similarity constructs on alliance formation, and thus to reduce the threat of unobserved heterogeneity, we additionally controlled for firm-level patenting effects. Through the inclusion of the firm-level patent propensities, we were able to assess the unique effect of the dyad-level patent constructs above and beyond firm-level patenting. We included a count number of the total patents assigned between 1994 and 1997 to the biotechnology and pharmaceutical firms in our sample (*Patents Biotech* and *Patents Pharma*). The average biotechnology firm was granted seven patents, while the average pharmaceutical company obtained 236 patents.

Estimation method

Because we focus on the *event* of alliance formation and the *intensity* of interfirm cooperation as two separate dependent variables, we needed to employ two different econometrical models (Greene, 1997). The first dependent variable measures the event of alliance formation and is binary in nature (0, 1), and thus for estimation we used a logit regression. The outcome variable, $\hat{Y}$, is the probability of alliance formation/non-formation based on a nonlinear function with two outcomes. The logit model is estimated with a maximum likelihood procedure with the following specification:

$$\ln\left(\frac{\hat{Y}}{1-\hat{Y}}\right) = \alpha + \sum \beta_j \mathrm{X}_{ij}$$

where X_{ij} is a vector of independent variables.

The second dependent variable proxies the alliance intensity in each dyad and is measured through a count number of the total number of alliances formed between each dyadic pair. Here the dependent variable is a non-negative integer count with a limited range, and a negative binomial regression is the preferred estimation technique (Greene, 1997). A negative binomial regression model relaxes the restrictive assumption of mean and variance equality inherent in the Poisson model and accounts for omitted variable bias, while estimating heterogeneity. We applied the following specification:

$$P(n_i/\varepsilon) = e^{-\lambda_i \exp(\varepsilon)} \lambda_i^{n_i} / n_i!$$

where n is a non-negative integer count variable capturing the alliance intensity in each dyad, and thus $P(n_i/\varepsilon)$ indicates the probability that dyad i will form n alliances.[9]

RESULTS

All of the bivariate correlations between the independent variables fall below the 0.70 threshold, thus indicating acceptable discriminant validity (Cohen *et al*., 2003). The bivariate correlations among the five variables to proxy complementarities and similarities are quite low, with the highest being between the complementarity index and patenting propensity ($r = -0.29$). It is important to note that the bivariate correlations between the broad-based capability measures (non-overlapping niches, complementarity index, patenting propensity), and the fine-grained technology relatedness measures (patent cross-citation and patent common citation rates) are all less than 0.092, and thus reflective of low or non-existing bivariate correlations (range: $-0.007 \leq r \leq 0.091$). This observation becomes pertinent when later assessing the utility of fine-grained vs. more broad-based capabilities in predicting alliance formation.[10] Table 2 depicts the descriptive statistics and the bivariate correlation matrix.

[9] To interpret the results in a meaningful manner, we standardized all independent variables before entering them into the various regression models. The variables contained in the cross-products of the interaction terms to test the moderating hypotheses were standardized before creating the respective cross-products. Standardizing the independent variables improves the robustness of the analysis without degrading the quality of the data or affecting the level of statistical findings. While this procedure allows the researcher to directly compare beta coefficients, the level of significance is not affected (Cohen *et al*., 2003).

[10] We are indebted to the anonymous reviewers for suggesting to employ existing fine-grained measures of science and technology relatedness, and to compare them to the more broad-based capability measures developed for this study.

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We assess the *event* of alliance formation and the *intensity* of allying in any given biotech–pharma dyad. In Models 1–3 we assess the probability of alliance formation, while in Models 4–6 we evaluate the probability for the formation of non-equity alliances to correct for potential unobserved heterogeneity due to different alliance types. In parallel, in Models 7–9 we assess alliance intensity, while in Models 10–12 we evaluate the alliance intensity for non-equity alliances. We used a hierarchical regression approach. The first model in each of the four blocks (Models 1, 4, 7, and 10) contains the control variables only and serves as a baseline model. In subsequent models, we entered the variables for complementarity and similarity (Models 2, 5, 8, and 11). In the final model of each regression block we added the hypothesized interaction effects (Models 3, 6, 9, and 12). In the four regression blocks, each model represents a significant improvement over the baseline model (at $p < 0.01$ or smaller). Tables 3 and 4 present the regression results.

Direct effect hypotheses

In Hypothesis 1 we postulated that complementarities between old technology and new technology firms increase the probability of alliance formation, while in Hypothesis 2 we argued that similarities enhance the chance of future allying. We find support for the two hypotheses across all four regression blocks when focusing on a dyad's complementarity index, patent cross-citation rates, and overall patenting propensity. When comparing the effects of the two complementarity measures on alliance formation, we find that the dyadic complementarity index, based on the biotech firm's competences in drug development and the pharma firm's competences in marketing and distribution, is positive and significant in all four direct effects models at $p < 0.01$ or smaller (Models 2, 5, 8, and 11);[11] non-overlapping niches are not significant in predicting alliance formation. When assessing the effects of the three similarity measures on alliance formation, we find that both a dyad's patent cross-citation rate as well as its overall patenting propensity are positive and significant in predicting alliance formation ($p < 0.05$ in Models 2, 5, and 11, and $p < 0.10$ in Model 8, for both variables). Contrary to our expectations, a dyad's patent common citation rate, however, is negative and significant, and thus reduces the probability of alliance formation ($p < 0.05$ in Models 2, 5, and 11).

To illustrate the findings, we use the coefficients from Model 2, the fully specified direct effects estimation, to evaluate the effect of the different complementarity and similarity measures on the probability of alliance formation. Holding all other variables constant, a dyad's complementarity index multiplies the rate of alliance formation by a factor of 1.160 ($\exp(\beta)$, here $\exp(0.1482)$). When considering the similarity measures, we find that a dyad's cross-citation rate multiplies the rate of alliance formation by a factor of 1.042, and a dyad's patenting propensity by a factor of 1.096. In contrast, a dyad's patent common citation rate reduces the rate of alliance formation by a factor of 0.879.

Taken together, the results suggest that the broad-based capability measures developed for this study, the complementarity index and the overall patenting propensity, perform well in predicting alliance formation across different dependent variables and estimation procedures. Both dyadic complementarity across different competences in the value chain and a similar overall orientation towards innovation predict the *event* of alliance formation as well as the *intensity* of allying in the biotech–pharma dyads under investigation. On the other hand, only a dyad's patent cross-citation rates behave as expected, while a dyad's patent common citations behave opposite to the hypothesized direction.

Interaction hypotheses

In the interaction hypotheses we predicted that incumbent and new technology firms are more likely to enter an alliance based on complementarities when the new technology firm is younger (Hypothesis 3), while alliance formation based on similarities is more likely when the new technology firm is older (Hypothesis 4). When applying a dyad's complementarity index, we find consistent support for Hypothesis 3 across the four models

[11] These results cannot be attributed reasonably to outliers, since the coefficient of variance (= S.D./mean) is only 0.75, and thus indicates that overdispersion is not a problem. This is important because it highlights the notion that the positive effect of the complementarity index on alliance formation is driven by both the new and old technology firms scoring high on their respective dimensions proxying for upstream and downstream competences, rather than by outliers of one firm in the dyad.

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Table 2. Descriptive statistics and bivariate correlation matrix

	Mean	S.D.	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.	16.	17.	18.	19.	20.	21.
1. Alliance formation (%)	1.571	12.436																					
2. Alliance formation (non-equity) (%)	1.546	12.339	0.992																				
3. Alliance intensity (%)	1.794	15.468	0.701	0.705																			
4. Alliance intensity (non-equity) (%)	1.775	15.411	0.912	0.919	0.778																		
5. Geographic zone	0.340	0.474	0.035	0.033	0.016	0.026																	
6. Time elapsed	0.589	6.079	0.084	0.085	0.087	0.108	0.021																
7. Direct ties	0.024	0.219	0.091	0.090	0.088	0.126	0.025	0.695															
8. Indirect ties	0.076	0.305	0.069	0.069	0.043	0.059	0.020	−0.006	−0.002														
9. Centrality biotech	0.998	1.473	0.081	0.079	0.076	0.076	−0.006	0.157	0.174	0.302													
10. Centrality pharma	9.220	8.456	0.099	0.099	0.067	0.090	0.284	0.091	0.100	0.143	0.000												
11. Firm size biotech	299.06	989.18	0.031	0.031	0.033	0.033	−0.002	0.041	0.028	0.106	0.126	0.000											
12. Firm size pharma	24676.71	25758.27	0.071	0.071	0.063	0.065	0.214	0.049	0.056	0.057	0.000	0.532	0.000										
13. Public biotech	0.578	0.494	0.052	0.052	0.051	0.050	0.001	0.054	0.057	0.101	0.323	0.000	0.092	0.000									
14. Public pharma	0.814	0.389	0.016	0.016	0.014	0.018	0.049	0.014	0.017	0.009	0.000	0.090	0.000	0.191	0.000								
15. Patents biotech	6.599	19.674	0.059	0.057	0.069	0.068	0.001	0.058	0.059	0.141	0.257	0.000	0.393	0.000	0.074	0.000							
16. Patents pharma	236.44	285.54	0.021	0.019	0.025	0.014	0.219	0.023	0.022	0.025	0.000	0.264	0.000	0.516	0.000	−0.022	0.000						
17. Biotech firm age	15.135	5.784	0.012	0.011	0.017	0.016	0.001	0.034	0.017	0.037	0.071	0.000	0.152	0.000	0.163	0.000	0.103	0.000					
18. Non-overlapping niches	51.691	1.884	−0.032	−0.031	−0.030	−0.032	−0.022	−0.052	−0.047	−0.063	−0.100	−0.130	−0.162	−0.106	0.029	−0.125	−0.112	−0.034	−0.092				
19. Complementarity index	2.015	1.518	0.093	0.093	0.081	0.087	0.192	0.085	0.087	0.155	0.271	0.391	0.101	0.535	0.246	−0.030	0.150	0.334	0.043	−0.144			
20. Patent cross-citation rate (%)	0.068	0.953	0.021	0.021	0.014	0.018	0.044	0.017	0.017	0.034	0.020	0.047	0.011	0.018	0.016	0.016	0.042	0.027	0.016	−0.018	0.037		
21. Patent common citation rate (%)	2.540	10.177	0.000	0.000	0.006	0.000	−0.012	0.024	0.026	0.052	0.121	0.001	0.012	−0.015	0.096	−0.042	0.100	0.011	−0.003	−0.007	0.091	0.054	
22. Patenting propensity	23.026	2.172	−0.043	−0.041	−0.053	−0.045	−0.091	−0.069	−0.072	−0.144	−0.249	−0.087	−0.403	−0.212	−0.058	0.015	−0.600	−0.424	−0.095	0.170	−0.290	−0.013	−0.067

N = 32, 332 pharma-biotech dyads

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Table 3. Logistic regression estimates of dyad-level alliance formation

	Alliance formation			Alliance formation (non-equity)		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Constant	−4.4309***	−4.4704***	−4.4780***	−4.4643***	−4.5049***	−4.5114***
	(0.0727)	(0.0746)	(0.0751)	(0.0737)	(0.0756)	(0.076)
Geographic zone	0.0824*	0.0663†	0.0647†	0.0718†	0.0556	0.0539
	(0.0469)	(0.0472)	(0.0473)	(0.0473)	(0.0477)	(0.0477)
Time elapsed	0.1865**	0.1782**	0.1839**	0.1910**	0.1826**	0.1895**
	(0.0645)	(0.0648)	(0.0647)	(0.0646)	(0.0649)	(0.0648)
(Time elapsed)^2	−0.0079*	−0.0075*	−0.0077*	−0.0080*	−0.0076*	−0.0078*
	(0.0037)	(0.0037)	(0.0037)	(0.0037)	(0.0037)	(0.0037)
Direct ties	0.0438†	0.0495*	0.0475*	0.0425†	0.0482*	0.0459*
	(0.0273)	(0.0272)	(0.0273)	(0.0275)	(0.0274)	(0.0275)
Indirect ties	0.1766***	0.1762***	0.1796***	0.1774***	0.1768***	0.1807***
	(0.0526)	(0.0527)	(0.0528)	(0.0528)	(0.0529)	(0.0529)
(Indirect ties)^2	−0.0130*	−0.0127*	−0.0127*	−0.0126*	−0.0123*	−0.0124*
	(0.0074)	(0.0075)	(0.0075)	(0.0074)	(0.0075)	(0.0075)
Centrality biotech	0.3379***	0.2985***	0.3147***	0.3473***	0.3069***	0.3255***
	(0.0685)	(0.0704)	(0.0715)	(0.0693)	(0.0712)	(0.0725)
(Centrality biotech)^2	−0.0440**	−0.0322*	−0.0347*	−0.0484**	−0.0361*	−0.0401*
	(0.0176)	(0.0188)	(0.0199)	(0.0179)	(0.0192)	(0.0205)
Centrality pharma	0.7092***	0.6696***	0.6678***	0.6936***	0.6541***	0.6521***
	(0.0895)	(0.0905)	(0.0906)	(0.0904)	(0.0913)	(0.0915)
(Centrality pharma)^2	−0.1436**	−0.1252**	−0.1246**	−0.1235**	−0.1043*	−0.1037*
	(0.0497)	(0.0503)	(0.0503)	(0.0499)	(0.0505)	(0.0506)
Firm size biotech	0.0127	0.0317	0.0407	0.0192	0.0383	0.0477
	(0.0380)	(0.0418)	(0.0413)	(0.0378)	(0.0416)	(0.0412)
Firm size pharma	0.1924***	0.1099*	0.1029*	0.2056***	0.1221*	0.1151*
	(0.0538)	(0.0601)	(0.0603)	(0.0543)	(0.0607)	(0.0609)
Public biotech	0.3374***	0.3199***	0.3116***	0.3307***	0.3115***	0.3032***
	(0.0586)	(0.0602)	(0.0601)	(0.0589)	(0.0605)	(0.0604)
Public pharma	0.0054	0.0172	0.0175	−0.0135	−0.0006	−0.0003
	(0.0569)	(0.0585)	(0.0585)	(0.057)	(0.0585)	(0.0586)
Patents biotech	0.1424***	0.1648***	0.1654***	0.1384***	0.1603***	0.1605***
	(0.0284)	(0.0287)	(0.0287)	(0.0289)	(0.0293)	(0.0293)
Patents pharma	−0.0689†	−0.0436	−0.0324	−0.0865*	−0.0619	−0.0476
	(0.0502)	(0.0526)	(0.0551)	(0.051)	(0.0534)	(0.0559)
Biotech firm age	−0.0286	−0.0386	0.0187	−0.0302	−0.0398	0.0188
	(0.0503)	(0.0506)	(0.0553)	(0.0507)	(0.0510)	(0.0557)
Dyadic complementarities						
Non-overlapping niches		−0.0151	−0.0200		−0.0084	−0.0134
		(0.0449)	(0.0464)		(0.0454)	(0.0467)
Complementarity index		0.1482**	0.1654***		0.1510**	0.1681***
		(0.0496)	(0.0502)		(0.0499)	(0.0506)
Dyadic similarities						
Patent cross-citation rate		0.0408*	0.0398*		0.0419*	0.0411*
		(0.0228)	(0.0238)		(0.0226)	(0.0237)
Patent common citation rate		−0.1293*	−0.1349*		−0.1230*	−0.1280*
		(0.0599)	(0.0616)		(0.0592)	(0.0610)
Patenting propensity		0.0919*	0.1139*		0.0911*	0.1209*
		(0.0467)	(0.0612)		(0.0473)	(0.0621)
Dyadic and firm-level interactions						
Non-overlapping niches			0.0072			0.009
× Biotech firm age			(0.0433)			(0.0438)
Complementarity index			−0.1310**			−0.1294**
× Biotech firm age			(0.0458)			(0.0461)
Patent cross-citation rate			0.0002			0.0010
× Biotech firm age			(0.0302)			(0.0302)

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Table 3. (*Continued*)

	Alliance formation			Alliance formation (non-equity)		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Patent common citation rate × Biotech firm age			−0.0056 (0.1037)			0.0009 (0.1029)
Patenting propensity × Biotech firm age			−0.0406 (0.0425)			−0.0491 (0.0432)
Log-likelihood	−2325.17	−2316.01	−2311.30	−2294.24	−2285.28	−2280.65
Likelihood ratio test (χ^2)	577.42***	595.74***	605.16***	572.95***	590.87***	600.14***
Improvement over base model ($\Delta\chi^2$)		18.32**	27.74**		17.92**	27.19**
N	32,332	32,332	32,332	32,332	32,332	32,332

†$p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$; standard errors in parentheses.

Table 4. Negative binomial regression estimates of dyad-level alliance intensity

	Alliance intensity			Alliance intensity (non-equity)		
	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
Constant	−4.2830*** (0.0687)	−4.3078*** (0.0703)	−4.3211*** (0.0709)	−4.3545*** (0.0692)	−4.3991*** (0.0712)	−4.4149*** (0.0719)
Geographic zone	−0.0226 (0.0442)	−0.0372 (0.0446)	−0.0378 (0.0447)	0.0486 (0.0444)	0.0317 (0.0448)	0.0299 (0.0449)
Time elapsed	0.1877*** (0.0604)	0.1792** (0.0608)	0.1819** (0.0605)	0.1933*** (0.0559)	0.1850*** (0.0564)	0.1889*** (0.0563)
(Time elapsed)^2	−0.0070* (0.0033)	−0.0068* (0.0034)	−0.0067* (0.0033)	−0.0076** (0.0031)	−0.0073* (0.0032)	−0.0073** (0.0031)
Direct ties	0.0174 (0.0245)	0.0231 (0.0246)	0.0224 (0.0247)	0.0525** (0.0209)	0.0579** (0.0208)	0.0560** (0.0209)
Indirect ties	0.1579** (0.0589)	0.1554** (0.0590)	0.1578** (0.0590)	0.1805*** (0.0514)	0.1792*** (0.0516)	0.1832*** (0.0518)
(Indirect ties)^2	−0.0202* (0.0101)	−0.0199* (0.0101)	−0.0194* (0.0101)	−0.0142* (0.0075)	−0.0138* (0.0075)	−0.0137* (0.0076)
Centrality biotech	0.3301*** (0.0633)	0.2929*** (0.0651)	0.3049*** (0.0660)	0.3068*** (0.0651)	0.2617*** (0.0669)	0.2754*** (0.0679)
(Centrality biotech)^2	−0.0451** (0.0160)	−0.0362* (0.0172)	−0.0352* (0.0181)	−0.0525*** (0.0166)	−0.0387* (0.0178)	−0.0381* (0.0188)
Centrality pharma	0.3854*** (0.0765)	0.3498*** (0.0773)	0.3480*** (0.0774)	0.6337*** (0.0848)	0.5948*** (0.0857)	0.5942*** (0.0858)
(Centrality pharma)^2	−0.0611† (0.0460)	−0.0494 (0.0466)	−0.0492 (0.0467)	−0.1085* (0.0468)	−0.0895* (0.0473)	−0.0895* (0.0474)
Firm size biotech	0.0075 (0.0347)	0.0176 (0.0391)	0.0257 (0.0385)	0.0107 (0.0351)	0.0326 (0.0391)	0.0405 (0.0384)
Firm size pharma	0.2642*** (0.0472)	0.2021*** (0.0524)	0.1979*** (0.0525)	0.1991*** (0.0514)	0.1092* (0.0575)	0.1027* (0.0577)
Public biotech	0.3825*** (0.0562)	0.3657*** (0.0577)	0.3577*** (0.0577)	0.3685*** (0.0564)	0.3497*** (0.0580)	0.3416*** (0.0579)
Public pharma	0.0111 (0.0517)	0.0205 (0.0528)	0.0212 (0.0529)	0.0180 (0.0544)	0.0300 (0.0558)	0.0299 (0.0558)
Patents biotech	0.1598*** (0.0237)	0.1718*** (0.0247)	0.1736*** (0.0246)	0.1528*** (0.0246)	0.1740*** (0.0249)	0.1759*** (0.0249)
Patents pharma	0.0047 (0.0442)	0.0261 (0.0464)	0.0305 (0.0483)	−0.1140* (0.0497)	−0.0856* (0.0517)	−0.0795† (0.0537)
Biotech firm age	0.0166 (0.0461)	0.0082 (0.0465)	0.0667† (0.0488)	0.0149 (0.0467)	0.0059 (0.0469)	0.0792† (0.0506)

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Table 4. (*Continued*)

	Alliance intensity			Alliance intensity (non-equity)		
	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
Dyadic complementarities						
Non-overlapping niches		−0.0319	−0.0402		−0.0129	−0.0249
		(0.0424)	(0.0439)		(0.0426)	(0.0440)
Complementarity index		0.1225**	0.1422**		0.1589***	0.1809***
		(0.0466)	(0.0471)		(0.0467)	(0.0473)
Dyadic similarities						
Patent cross-citation rate		0.0349†	0.0299		0.0420*	0.0419*
		(0.0247)	(0.0269)		(0.0220)	(0.0228)
Patent common citation rate		−0.0430	−0.0408		−0.1310*	−0.1337*
		(0.0438)	(0.0450)		(0.0576)	(0.0591)
Patenting propensity		0.0644†	0.0676		0.0972*	0.1035*
		(0.0415)	(0.0533)		(0.0432)	(0.0561)
Dyadic and firm-level interactions						
Non-overlapping niches			0.0164			0.0267
× Biotech firm age			(0.0405)			(0.5041)
Complementarity index			−0.1334***			−0.1508***
× Biotech firm age			(0.0418)			(0.0428)
Patent cross-citation rate			−0.0169			0.0019
× Biotech firm age			(0.0329)			(0.0294)
Patent common citation rate			0.0574			0.0521
× Biotech firm age			(0.0742)			(0.0961)
Patenting propensity × Biotech			−0.0182			−0.0273
firm age			(0.0373)			(0.0399)
Log-likelihood	−2655.371	−2649.81	−2643.48	−2558.33	−2547.22	−2539.57
Likelihood ratio test (χ^2)	523.71***	534.83***	547.50***	669.26***	691.49***	706.78***
Improvement over base model ($\Delta\chi^2$)		11.12*	23.79**		22.23***	37.52***
N	32,332	32,332	32,332	32,332	32,332	32,332

† $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$; standard errors in parentheses.

assessing the interaction effects (Models 3, 6, 9, and 12). In each of these models, the interaction between a dyad's complementarity index and the age of the biotechnology firm is negative and significant ($p < 0.01$ in Models 3 and 6, and $p < 0.001$ in Models 9 and 12), implying that the rate and intensity of alliance formation motivated by complementarities decrease as the new technology firm ages. Holding all else constant, when the biotechnology firm has reached the mean age of the sample firms (15.135 years), alliance formation between an incumbent pharmaceutical and a new biotechnology firm based on complementarities is reduced by a multiplier factor of 0.138 ($\exp(-0.131 \times 15.135)$ in Model 3); one standard deviation below the mean of biotech firm age (9.351 years) it is reduced by a factor of 0.294; and one standard deviation above the mean of biotechnology firm age (20.919 years) it is reduced by a factor of 0.065. Figure 1 graphically depicts how the odds of forming an alliance based on complementarities between a pharma and a biotech firm decreases non-monotonically with the age of the new biotechnology firm. Very young biotechnology firms are highly likely to enter an alliance with a pharmaceutical firm based on complementarities; however, this effect wanes drastically as the biotechnology firm ages, thus providing visual support for Hypothesis 3.

The regression results also reveal that none of the other interaction effects reach statistical significance. Thus, we fail to find support for Hypothesis 4.

Effects of control variables

The results for the control variables are consistent with the key findings of prior studies conducted in different industries and at different time frames (Gulati, 1995a, 1995b; Ahuja, 2000; Chung *et al.*,

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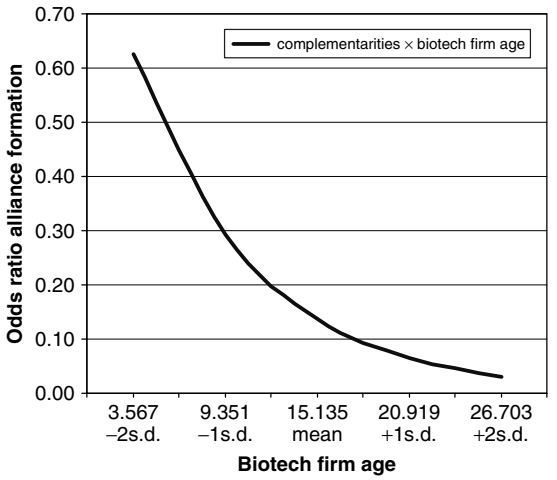

Figure 1. Moderating effect of biotechnology firm age on the relationship between dyadic complementarities and alliance formation

2000; Stuart, 2000; Rosenkopf *et al*., 2001). When considering the probability of alliance formation, the regression models reveal a (marginally) significant relationship for location—new and old technology firms are more likely to enter an alliance if they are located in the same geographic zone.

We also find that the relationship between time elapsed and future alliance formation appears to be characterized by diminishing returns based on the significance of the linear (positive sign) and square term (negative sign) of time elapsed since last alliance in dyads with prior ties. The number of prior direct ties has a positive impact on future alliance formation when considering the probability of alliance formation and the intensity of allying using non-equity alliances.[12] Prior ties enable firms to be familiar with one another and to build trust (Gulati, 1995a). The results also reveal that the number of prior indirect ties that a firm pair shares is related to future alliance formation and alliance intensity in a non-monotonic manner. The marginal informational value about a potential partner appears to decrease after more than a couple of indirect ties.

At the firm level, we find that centrality in the local network, for both the biotech and the pharma firm, is related to alliance formation and alliance intensity in a non-monotonic manner. Both the smaller biotechnology firms and the larger pharmaceutical companies may be exposed to a potential overembeddedness in the local network. Consistently, we also find that the larger the pharmaceutical company, the more likely it is to enter alliances with biotechnology firms. Pharmaceutical firms like Merck or Pfizer that compete in the proprietary drug development arena tend to be larger, and thus have more at stake when confronted with a discontinuity like biotechnology. Results of the control variables also reveal that public biotechnology firms are more active in forming alliances with pharmaceutical companies. At the dyad level, we found that similarities in patent cross-citation rates and patenting propensity increased the probability of alliance formation, which provided supported for Hypothesis 2. This result held while controlling for firm-level heterogeneity in patenting propensity. We found that biotech firms that patent more are more likely to form alliances.

Post hoc analysis

Biotechnology firm age is the moderator variable of this study, and we suggested that aging enhances a biotechnology firm's credibility, legitimacy, and power. These theoretical constructs can arguably also be captured by alternative measures such as whether the biotechnology firm is public or through biotechnology firm size.[13] Preliminary evidence for this notion can be found in the positive and significant bivariate correlations between biotechnology firm age and biotechnology firm public ($r = 0.163$; $p < 0.01$) and between biotechnology firm age and biotechnology firm size ($r = 0.152$; $p < 0.01$). A biotechnology firm that has successfully completed an initial public offering has transformed itself from a privately owned entrepreneurial venture into a publicly owned company, increasing its standing *vis-à-vis* potential alliance partners. Likewise, the power differential between biotech and pharma firms decreases as the biotechnology firm grows in size. Thus, one would expect that biotechnology firms that are privately held or are smaller in size are more likely to enter alliances with pharma firms based on complementarities (Hypothesis 3), while biotechnology firms that are public or are larger in size would be more

[12] We also tested for a non-monotonic effect of direct ties on alliance formation and alliance intensity through inclusion of the squared term of direct ties. We found no support for diminishing returns to prior allying.

[13] We thank an anonymous reviewer for suggesting these alternative model specifications.

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likely to enter alliances with pharma firms based on similarities (Hypothesis 4).

Models 13–16 in Table 5 display the results when using public firm status (biotech firm public = 1) as a moderator. Model 16 indicates that the interaction between a dyad's complementarity index and public biotech is negative and significant, thus providing some support for Hypothesis 3. Models 13–15 reveal a positive and significant interaction between a dyad's patenting propensity and biotech firm public ($p < 0.05$ or smaller), thus providing support for Hypothesis 4. Taken together, when applying public status as moderator of the relationship between complementarities, similarities, and alliance formation, we found support for both interaction hypotheses advanced above. When applying biotechnology firm size as moderator, we found some support for Hypothesis 3: the interaction between a dyad's complementarity index and biotech firm size was negative and significant ($p < 0.05$) when predicting the formation of non-equity alliances.[14] In sum, the results for the interaction hypotheses are robust, and even provide support for Hypothesis 4. As in the regression models presented earlier, it is the more broad-based complementarity and similarity measures that reach statistical significance when interacting them with biotech firm public or biotech firm size, and not the more fine-grained science and technology indicators.

Our theoretical assumption, which is borne out by the empirical findings of our study, is that both complementarities and similarities between biotechnology and pharmaceutical firms lead to a greater probability of alliance formation. We cannot definitively determine from our data, however, the specific motivations that lead individual companies to form alliances. To address this shortcoming, we performed some additional qualitative analyses.[15] First, we analyzed the top-ten selling biotechnology drugs at the end of our study period (2001) (*Standard & Poor's*, 2002). The number one (Procrit, $3,430 million), number three (Intron A, $1,447 million), and number five (Humulin, $1,061 million) best-selling drugs were all commercialized through an alliance formed by a biotechnology company and a pharmaceutical company.[16] Moreover, each of these three alliances was based on complementarities, because in each case the new biotechnology firm developed the drug, while the existing pharmaceutical company commercialized the new drug. This provides additional qualitative support for Hypothesis 1.

To assess whether the motivations of these complementarity alliances were in line with Hypothesis 3, suggesting that complementarity alliances are more likely to form when the biotechnology firm is younger, we assessed the age of the three biotechnology firms when forming these alliances. Amgen was founded in 1980, and formed the Procrit alliance with Johnson & Johnson in 1985. Biogen was founded in 1979, and entered the Intron A alliance with Schering-Plough in 1979. Genentech was founded in 1976, and the entered the Humulin alliance with Lilly in 1978. All three biotechnology firms formed these complementarity alliances very early in their lives, with their average age at alliance formation being 2.33 years. This average age lies more than two standard deviations below the mean age of the biotechnology firms (15.135 years) in this sample (see Figure 1). This provides qualitative support for Hypothesis 3, suggesting that complementarity alliances are indeed formed when biotechnology firms are younger.

In addition, we drew a random sample of 58 alliances (10% of all alliances formed). We then had these alliances independently coded for the age of the biotechnology firm at alliance formation as well as the various complementarity and similarity measures described above. A research assistant then tracked newspaper articles describing each alliance from Lexis-Nexis, content coding each article. Two different indicator variables were applied: 1 = complementarities are mentioned as motivation for alliance formation; 1 = similarities are mentioned as motivation for alliance formation. A second researcher then independently coded a subsample of these articles, and we found the interrater reliability to be satisfactory. We then ran the bivariate correlations among these variables, and found that the age of the biotechnology firm at alliance formation was negatively correlated with the number of non-overlapping niches, a complementarity measure ($r = -0.392$, $p < 0.01$), and positively correlated with patenting propensity ($r = 0.289$, $p < 0.01$), a similarity

[14] These results are available upon request from the first author.

[15] We thank an anonymous reviewer for suggesting additional qualitative analyses.

[16] The alliance partners are: Amgen–Johnson & Johnson; Biogen–Schering-Plough; Genentech–Lilly.

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Table 5. Binary logit and negative binomial regression estimates of dyad-level formation and alliance intensity

	Alliance formation		Alliance intensity	
	Model 13	Model 14 (non-equity)	Model 15	Model 16 (non-equity)
Constant	−4.8873***	−4.9122***	−4.7847***	−4.8658***
	(0.1242)	(0.1247)	(0.1145)	(0.1184)
Geographic zone	0.0639†	0.0531	−0.0419	0.0252
	(0.0473)	(0.0477)	(0.0447)	(0.0449)
Time elapsed	0.1763**	0.1805**	0.1718**	0.1760***
	(0.0647)	(0.0649)	(0.0606)	(0.0562)
(Time elapsed)^2	−0.0074*	−0.0075*	−0.0064*	−0.0069*
	(0.0037)	(0.0037)	(0.0033)	(0.0031)
Direct ties	0.0503*	0.0491*	0.0262	0.0609**
	(0.0271)	(0.0273)	(0.0245)	(0.0207)
Indirect ties	0.1736***	0.1741***	0.1507**	0.1728***
	(0.0527)	(0.0529)	(0.0592)	(0.0516)
(Indirect ties)^2	−0.0122†	−0.0118†	−0.0189*	−0.0126*
	(0.0075)	(0.0075)	(0.0102)	(0.0075)
Centrality biotech	0.2959***	0.3037***	0.2845***	0.2517***
	(0.0705)	(0.0713)	(0.0650)	(0.0668)
(Centrality biotech)^2	−0.0295†	−0.0331*	−0.0296*	−0.0307*
	(0.0188)	(0.0192)	(0.0171)	(0.0177)
Centrality pharma	0.6672***	0.6518***	0.3464***	0.5922***
	(0.0905)	(0.0914)	(0.0773)	(0.0857)
(Centrality pharma)^2	−0.1235**	−0.1025*	−0.0458	−0.0854*
	(0.0503)	(0.0506)	(0.0466)	(0.0473)
Firm size biotech	0.0373	0.0441	0.0291	0.0458
	(0.0415)	(0.0413)	(0.0384)	(0.0383)
Firm size pharma	0.1016*	0.1137*	0.1907***	0.0922†
	(0.0605)	(0.0611)	(0.0526)	(0.0579)
Public biotech	0.6940***	0.6765***	0.7892***	0.7641***
	(0.1330)	(0.1334)	(0.1218)	(0.1263)
Public pharma	0.0194	0.0016	0.0243	0.0347
	(0.0586)	(0.0587)	(0.0529)	(0.0559)
Patents biotech	0.1697***	0.1654***	0.1733***	0.1781***
	(0.0299)	(0.0305)	(0.0253)	(0.0259)
Patents pharma	−0.0584	−0.0773†	0.0085	−0.1075*
	(0.0532)	(0.0539)	(0.0463)	(0.0516)
Biotech firm age	−0.0388	−0.0402	0.0044	0.0016
	(0.0507)	(0.0512)	(0.0467)	(0.0473)
Dyadic complementarities				
Non-overlapping niches	0.0473	0.0499	0.0359	0.0595
	(0.0889)	(0.0892)	(0.0840)	(0.0845)
Complementarity index	0.2248*	0.2250*	0.2020*	0.2788**
	(0.1147)	(0.1152)	(0.1091)	(0.1097)
Dyadic similarities				
Patent cross-citation rate	0.0415	0.0423	0.0380	0.0378
	(0.0356)	(0.0353)	(0.0352)	(0.0360)
Patent common citation rate	−0.3442	−0.3345	−0.0604	−0.2194
	(0.2731)	(0.2702)	(0.1457)	(0.2157)
Patenting propensity	−0.0765	−0.0839	−0.1839*	−0.1887
	(0.1042)	(0.1042)	(0.0836)	(0.0847)
Dyadic and firm-level interactions				
Non-overlapping niches × Public biotech	−0.0779	−0.0725	−0.0826	−0.0891
	(0.1008)	(0.1012)	(0.0951)	(0.0956)
Complementarity index × Public biotech	−0.0808	−0.0774	−0.0768	−0.1200***
	(0.1162)	(0.1167)	(0.1101)	(0.1107)
Patent cross-citation rate × Public biotech	0.0029	0.0035	−0.0055	0.0094
	(0.0473)	(−0.047)	(0.0489)	(0.0467)

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Table 5. (*Continued*)

	Alliance formation		Alliance intensity	
	Model 13	Model 14 (non-equity)	Model 15	Model 16 (non-equity)
Patent common citation rate × Public biotech	0.2292	0.2256	0.0182	0.0925
	(0.2791)	(0.2762)	(0.1526)	(0.2234)
Patenting propensity × Public biotech	0.1925*	0.2004*	0.2862***	0.3332
	(0.1083)	(0.1084)	(0.0881)	(0.0904)
Log-likelihood	−2313.862	−2283.08	−2644.57	−2540.42
Likelihood ratio test (χ^2)	600.04***	595.27***	545.32***	705.09***
N	32,332	32,332	32,332	32,332

†$p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$; standard errors in parentheses.

measures. Here again, it is the broad-based capability measures that reach significance. These correlations are also in line with our expectations based on Hypotheses 1 and 2. Additionally, the complementarity and similarity proxies derived from the coding of the newspaper articles revealed that these two dimensions were negatively correlated ($r < -0.346$, $p < 0.01$). While these qualitative data are far from conclusive, they lend support to our deductively derived theoretical model.

DISCUSSION

Past research on alliance formation has noted critical differences between the complementary competences, skills, and capabilities that each partner brings to an alliance, and it has addressed the need for some level of institutional, structural, or social similarity to lower the risk and create trust in alliance building. Prior work has paid less attention, however, to the manner in which both complementarities and similarities across potential partners interact with firm-level characteristics to affect partner choice.

Whereas most past research explaining who partners with whom has focused on horizontal alliances between established firms, our study examines the antecedents of alliances between incumbent firms founded under an old technology and firms founded under a new technology. Such a focus is particularly critical given the importance of alliances as a mechanism for established firms to adapt to technological change. Moreover, prior work has not considered that the probability of alliance formation might be contingent upon how *dyadic* constructs such as complementarity and similarity may interact with *firm-specific* factors. Our research addresses this issue by arguing that alliance formation between an old and a new technology firm motivated by complementarities is more likely when the new technology firm is younger, while alliance formation driven by similarities is more likely when the new technology firm is older. Thus, we argue that firm age of the new technology partner moderates the impact of complementarities in a negative fashion, while it moderates the impact of similarities in a positive fashion. Our results provide support for the notion that the age of the new technology firm moderates the relationship between complementarities and alliance formation in a negative fashion.

We did not find support for a positive interaction effect of firm age on the relationship between similarities and alliance formation. In *post hoc* analyses, we did, however, find support for this hypothesis when operationalizing a biotechnology firm's enhanced legitimacy, credibility, and power by its public ownership status. Here, the positive effect of dyadic similarities on alliance formation and alliance intensity was reinforced when the biotechnology firm was public. Taken together, our results indicate that the effects of complementarities and similarities on alliance formation appear to be contingent upon certain firm characteristics of the new technology venture.

Our findings point to two sets of causal factors that directly affect alliance formation in specific ways. First, complementarities in skills, capabilities and competences create opportunities for firms to seek out partners that can provide valuable organizational resources not found in the focal firm. Second, the search for alliance partners that have different capabilities is tempered by a preference to

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affiliate with firms that share similarities in terms of firm characteristics. The challenge of managing alliance relationships focuses on maintaining this balance between differences and similarities—the yin and yang of successful alliance formation.

The additional contribution of this research is in the examination of specific qualities of the new technology partner. We identified the problems of legitimacy, credibility, and power, all linked to the liability of newness and the age of the firm. We argued that the new technology firm would gain credibility, legitimacy, and market power as it grew older and became more established. This, in turn, would permit it to have a greater say in the terms of the alliance with its more established potential partner. Alliances involving complementarities can focus on quick value creation through combining new technology firms that are just beginning (young firms) and more established, incumbent technology partners. Thus, age of the new technology firm has an inverse moderating effect on the relationship of complementarities between the established technology firm and the new technology firm. Younger new technology firms that have complementarities with established technology firms are even more likely to form alliances.

As new technology firms age, they become more independent and established. They are also likely to become more powerful. These (older) new technology firms can afford to be more selective in choosing alliance partners, and may be more interested in partners to which they are similar and with whom they feel a comfort level. In this case, similarities between the established technology firm and the new technology firm may be more likely to drive alliance formation when the new technology firm is older and more established. The age of the new technology firm might play an opposing role on complementarities and similarities—younger new technology firms create alliances with established firms that are complementary, whereas older new technology firms might create alliances with firms that are more similar.

The results demonstrated support for the hypothesized effects of complementarities and similarities, and some support for interactive effects of the new technology firm age in influencing alliance behavior. The results for the complementary hypothesis are based upon a novel approach to assess the potential of synergistic gains at the dyad level. The central perspective of these arguments is that each partner has certain areas of strength that may compensate for the weaknesses of their potential alliance partner. The results of our research indicate that alliance formation is enhanced when new technology partners focus on drug discovery and development, while incumbents offer downstream expertise as well as marketing and distribution systems for the commercialization of new products.

Somewhat surprisingly, the second measure employed to proxy complementarities—non-overlapping niches—was not significant in predicting alliance formation. One explanation for why prior research found significance for non-overlapping niches predicting alliance formation (Gulati, 1995b; Chung *et al*., 2000) while we did not could be that the prior work focused on horizontal alliances between established firms in more mature industries (e.g., new materials, industrial automation, automotive products, and investment banking), while we focused on vertical alliances between new and old technology firms in an emerging science-driven industry. Another reason might be that proxying complementarities based on non-overlapping niches is not a suitable measure, as pointed out recently by Gimeno (2004). Firms can occupy non-overlapping niches without being complementary to one another. This is the case when firms occupy dissimilar niches that are not complementary. Thus, while occupying non-overlapping niches might be a necessary condition for complementarity, it is not sufficient. Taken together, it appears that in newly emerging high-tech industries the level of (vertical) strategic interdependence between potential alliance partners can be effectively captured by measuring each partner's capability in complementary value chain activities.

Similarities between potential partner firms also appear to promote alliance formation. In this study, we focused on similarities arising from technological overlap in patent cross-citation and patent common citation rates as well as from a firm's general orientation toward technology and innovation that may imply similarities in terms of overall strategic approach. Mowery *et al*. (1998) were the first to use patent cross-citation and patent common citation rates as dyad-level proxies for technological similarities, albeit in a smaller sample of horizontal alliances among established firms over a 2-year period in the mid 1980s. They found

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that both patent cross-citation and patent common citation rates predicted alliance formation. In line with their result, we too find that a dyad's cross-citation rate consistently predicted alliance formation. Arguably, a dyad's patent cross-citation rate is a strong indicator not only of how familiar each partner is with one another, but also how similar they are in their technological overlap. Moreover, a dyad's overall patenting propensity, reflective of each partner firm's innovative competence, consistently predicted alliance formation. Taken together, we found that similarities along these dimensions enhance the probability of alliance formation. Some of our control variables also lend support to the notion that similarities attract. For example, new and established technology firms that are located closer geographically are more likely to cooperate. These firms are exposed to a similar cultural and institutional environment, which appears to facilitate interfirm cooperation.

Contrary to our expectations, however, we found a dyad's patent common citation rate had a significant negative effect on alliance formation. Why would firms that are similar in their technological overlap through drawing on the same external technology pool be less likely to form an alliance? We speculate that in this industry setting complementarities are a powerful predictor of alliance formation, and thus the complementarity effect may crowd out the similarity effect based on patent common citation rates. Firms that draw on the same external technological pool as proxied by patent common citation rates may not exhibit the threshold level of complementarities that is necessary to initiate the search for an alliance partner in the first place. While Mowery *et al*. (1998: 519) argue that patent cross-citation and patent common citation rates can be seen as 'fairly close substitutes in terms of their performance as measures of technological overlap,' an important distinction to the patent common citation rate is that dyads that score high on patent cross-citation rates can still draw on very different external technological pools, thus enabling complementarities to emerge that propel them to form alliances. This effect seems to be particularly pronounced when studying alliances between old and new technology firms in emerging industries.

We controlled for several of the variables that were the focus of attention in prior studies (e.g., Podolny, 1994; Gulati, 1995a, 1995b; Ahuja, 2000; Chung *et al*., 2000). Here, most of our results are broadly consistent with this prior work conducted in different industries with different time frames, and focusing predominantly on horizontal alliances between established firms. For example, we found that the relationship between time elapsed since last and subsequent alliance was non-monotonic. A similar relationship was found for indirect ties. On the other hand, we found that a dyad's number of direct ties is related to future alliances in a positive linear fashion. Perhaps our research setting is somewhat unique in a way that prior direct ties do not exhibit the dampening effect they have found to have in other industries. To make more sense of this finding, we interviewed Anton Gueth, former director of the Office of Alliance Management at Lilly. He stated that multiple direct ties with one partner build an ecosystem of alliances, which in turn is less likely to collapse in comparison to stand-alone binary alliances. This may explain why we find a positive and linear effect of direct ties on alliance formation.

This study also makes methodological contributions. While we build on prior research in developing some of the complementarity and similarity measures, we also create new measures for each category. The five different measures employed to proxy dyadic complementarities and similarities can be distinguished in regard to how fine grained they are. One group of these dyadic measures (non-overlapping niches, complementarity index, and patenting propensity) are derived from broad-based organizational capabilities held by each dyad partner, while the second group (patent cross-citation and patent common citation rates) are more fine-grained proxies of a dyad's science and technology relatedness. In evaluating the effectiveness of the different types of proxies in predicting alliance formation, two observations can be made. First, among the broad-based capabilities it is a dyad's complementarity index and patenting propensity, both developed for this study, that consistently predict alliance formation as hypothesized. Among the more fine-grained measures of similarities in technological orientation, it is a dyad's cross-citation rate that behaves in predicting alliance formation as expected, while a dyad's common citation rate behaves opposite to the hypothesized effect. The second, and perhaps even more interesting insight, emerges through the comparison across groups. When evaluating the results for the direct effects, the more broad-based capability measures appear at least as effective, if not more so, than the

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more fine-grained measures in predicting alliance formation. In addition, the more broad-based capability measures appear to be more effective than the more fine-grained proxies of technological similarities in supporting the hypothesized moderating effects (regardless of interacting them with firm age, firm size, or public status) on the relationship between complementarities, similarities, and alliance formation.

Limitations and future research

Clearly, we focus only on a subsegment of the biopharmaceutical alliances, i.e., alliances between large pharmaceutical companies and small biotechnology firms. While such a sampling could introduce a sample selection bias, it is also important to recognize that recent empirical research found that linkages between pharmaceutical and biotechnology firms account for up to 80 percent of all alliances observed in this industrial sector (Hagedoorn and Roijakkers, 2002). Moreover, we drew on the complete network comprising pharma and biotech firms as well as universities and other nonprofit research organizations when developing our indirect tie measure. We suggest that a focus on biotech–pharma dyads is useful when attempting to understand alliance formation between new technology firms (often new entrants) and old technology firms (incumbents). A focus on new and old technology firms is particularly salient since recent theoretical work has suggested that incumbents may use alliances with new entrants to adapt to radical innovations (Teece, 1992; Hill and Rothaermel, 2003).

Moreover, while focusing on a single industry may limit the generalizability of the findings to some degree, it enhances its internal validity since such an approach controls for exogenous industry factors (Stuart, 2000). Given that biotechnology and pharmaceutical firms compete in relatively risky technologies, there may be greater uncertainty concerning the future direction of these firms, which may in turn increase the risk of alliance failure relative to less technologically intense industries, and thus limit the generalizability of our findings. Furthermore, although we collected information on global players in these industries, other countries outside the United States have somewhat different institutional or market frameworks for supporting the creation of alliances, which may influence the formation of partnerships.

A better understanding of appropriate matches between complementarities and similarities among potential alliance partners can serve to more closely integrate current work in the areas of strategic management and the management of technology. Future research should investigate in more detail the interplay between the specific skills and capabilities of potential partner firms, and how these skills and capabilities complement each other and hold the possibility of creating value. A more thorough examination of the organizational and structural processes that bring firms more closely together and encourage alliance formation is also required. Further study of the question of how similarities and differences between firms impact the formation of partnerships can provide important insights into alliances as creators of economic value and relational rents (Zajac and Olsen, 1993; Dyer and Singh, 1998), and in particular how leveraging complementarities and similarities can influence alliance performance. The results of our study support the perspective that future research on alliance formation needs to take into account how *dyadic-level* constructs interact with *firm-level* variables, and thus to explicitly consider a multilevel dimension.

Managerial implications

It appears that what managers seem to consider are the broader types of capability relatedness when deciding whether or not to form an alliance. While fine-grained proxies of science and technology relatedness (like a dyad's patent cross-citation rate) appear to be a reliable predictor of alliance formation, complementarities across the value chain and similarities in overall innovation strategy seem to be foremost on the minds of managers when forming (vertical) alliances. These findings tie this research to theoretical work on dynamic capabilities, which argues that the capability to form the 'right' alliances is an important competence that allows firms not only to adapt to changing markets and technologies, but also to create market change that favors their competitive strengths (Teece, Pisano, and Shuen, 1997; Eisenhardt and Martin, 2000). We speculate that broad-based capabilities highlighted in this study can not only provide important guideposts to search for alliance partners, but may also lay the foundation of successful alliances.

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