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Partner Selection in R&D Collaborations:
Effects of Affiliations with Venture Capitalists

Jeffrey J. Reuer
Leeds School of Business
University of Colorado
Boulder, CO 80309-0419
Tel.: (303) 735-6306
E-mail: jeffrey.reuer@colorado.edu

Ramakrishna Devarakonda
CUHK Business School
The Chinese University of Hong Kong
Hong Kong
Tel: (+852) 39437780
E-mail: rama@cuhk.edu.hk

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Abstract

This paper extends information economics to the literature on alliance partner selection by demonstrating how VCs can facilitate R&D collaborations. We investigate a new role for VCs – information intermediation – that can enable R&D partnerships between entrepreneurial ventures that lack knowledge of each other's technological resources. In contrast to the more diffuse signaling benefits entrepreneurial ventures obtain by affiliating with prominent VCs, backing by a common VC can privately and directly reduce information asymmetries between entrepreneurial ventures. We demonstrate that the effects of VC information intermediation are more pronounced when prospective collaborators are at the earliest stages of product development and when they find it difficult to judge each other's technological resources, such as when they do not have previous partnerships together, do not draw upon each other's knowledge bases, and have dissimilar technology portfolios. We empirically investigate the multiple different ways in which VCs potentially facilitate R&D partner selection and identify specific conditions under which VCs' information intermediation function contributes to segmentation in markets for R&D alliances.

Keywords:

R&D partner selection; venture capitalists (VCs); entrepreneurial ventures

INTRODUCTION

Partner selection has been regarded as one of the most important choices firms make regarding their collaborative strategies (e.g., Geringer, 1991; Tallman and Shenkar, 1994; Luo, 1997; Hitt *et al.*, 2004; Ring *et al.*, 2005; Shah and Swaminathan, 2008; Beamish and Lupton, 2009; Dekker and Van den Abbeele, 2010). Specifically, these decisions can have an impact on the technological and other resources that firms access through collaborative agreements (e.g., Hagedoorn, 2002), and they are particularly important for R&D alliances involving entrepreneurial ventures in high-tech industries (e.g., Deeds and Hill, 1996; Rothaermel and Boeker, 2008). While R&D collaborations can play a significant role in enabling competitive advantage for entrepreneurial ventures (e.g., Eisenhardt and Schoonhoven, 1996; Hagedoorn, 2002; Rothaermel and Deeds, 2004), the extent to which such ventures can benefit from R&D collaborations is expected to vary depending on the partners they select (e.g., Rothaermel and Boeker, 2008; Diestre and Rajagopalan, 2012).

Although the extant literature suggests that firms should make partner selection decisions based upon the technological and other resources possessed by prospective collaborators, entrepreneurial ventures in high-tech industries can also face serious challenges understanding and evaluating the resources of others in the first place. Firms perform costly activities searching for and evaluating partners' intangible resources (e.g., Geertz, 1978; Stuart, 1998; Rangan, 2000; Vanhaverberke, Duysters, and Noorderhaven, 2002; Villalonga and McGahan, 2004). Prospective collaborators may avoid disclosure of proprietary information (e.g., Arrow, 1962, Teece, 1996; Dushnitsky and Shaver, 2009), and have incentives to overstate the quality of their R&D resources in order to obtain a partnership (e.g., Gulati, 1999; Nicholson *et al.*, 2005). As a consequence, due diligence activities for evaluating a potential partner's intangible resources can be ineffective and inefficient (e.g., Balakrishnan and Koza, 1993; Chi, 1994). Such problems magnify when prospective partners lack knowledge of each other's technological resources and their commercial prospects (Akerlof, 1970; Stuart, 1998; Dushnitsky and Lenox, 2005). Absent remedies to these problems, markets for alliance partners can fail, and partners can forego valuable collaborative partnerships (Li *et al.*, 2008). Moreover, many of the ways in which firms can overcome these hurdles, including building knowledge resources or relying on prior ties, can take time and are therefore difficult to employ for entrepreneurial ventures at early stages of development.

However, such ventures can rely upon a credible information intermediary who has detailed knowledge about both partners' resources and activities. In particular, venture capitalists (VCs) can function as credible third-parties who reduce information asymmetries between prospective partners (Lindsey, 2008). VCs specialize in appraising entrepreneurial ventures in high-tech industries before committing capital (e.g., Amit *et al.*, 1998; Gompers and Lerner, 2001), and they accumulate substantial information on ventures as they monitor their progress and offer value-added services to them (e.g., Admati and Pfleiderer, 1994; Aoki, 2000; Busenitz *et al.*, 2004; Gans and Stern, 2003). As a consequence, VCs can potentially have an impact on R&D partner selection by functioning as information intermediaries between prospective partners. In particular, VCs can provide important information about a firm's technological and other resources, ideas, plans, and market prospects to other companies in their portfolios, so they can directly reduce information asymmetries between prospective partners and facilitate alliances among their portfolio companies (Lindsey, 2008). Inasmuch as VCs can reduce information asymmetries in this manner, we suggest that the degree to which they facilitate collaborations will depend upon firms' lack of knowledge about each other's technological resources and prospects.

In this paper, we therefore aim to advance research on alliance partner selection by investigating a new role of VCs -- information intermediation -- in shaping R&D partner selection for entrepreneurial ventures. More specifically, we investigate two main research questions: First, to what extent are entrepreneurial ventures in a high-tech industry likely to select prospective partners that are backed by a common VC investor? Second, to what extent does the positive effect of having a common VC vary based upon prospective partners' lack of knowledge of each other's technological resources and prospects?

Venture capitalists might influence the R&D partnerships of startups in many other ways since VCs affect portfolio companies' strategies, offer endorsements on their quality to exchange partners, provide expertise and other value-added services to ventures, and exert influence by virtue of their ownership (e.g., Sapienza, 1992; Lerner, 1995; Hellman and Puri, 2000; Hsu, 2006). This makes it interesting to examine the ways in which such third-party intermediaries might have an influence on the R&D collaborations undertaken by high-tech startups. Rich information available on firms' technological resources and activities as well as involvement by VCs enable empirical analysis of these and other potential explanations for why firms with common VCs are more likely to partner with one another (e.g., homophily, super-additivity of technological resources, etc.). Moreover, the contingencies we investigate related to the development of new ventures and their familiarity with each other's technological resources also enable us to unpack the influences that VCs have on R&D partner selection and to help isolate the information intermediation role that VCs can fulfill.

Beyond investigating this value-added role of venture capitalists and extending information economics to the literature on partner selection, we show that investigating VCs in the alliance context can inform the partner selection literature more broadly in three ways (e.g., Tallman and Shenkar, 1994; Luo, 1997; Hitt *et al.*, 2004; Ring *et al.*, 2005; Rothaermel and Boeker, 2008; Shah and Swaminathan, 2008; Beamish and Lupton, 2009; Diestre and Rajagopalan, 2012). First, existing research highlights the signaling role of affiliations with VCs in shaping firms' opportunities for transactions (e.g., Hsu, 2006; Reuer and Ragozzino, 2012, 2014; Reuer, Tong, and Wu, 2012; Ozmel *et al.*, 2013), yet we suggest that VCs can facilitate R&D alliances between individual prospective partners that lack first-hand knowledge about each other's technological resources. Signals can be an important means of coping with information asymmetries surrounding firms, and signals are available to all prospective exchange partners. By contrast, the information intermediated by VCs between two particular companies privately and directly reduces their information asymmetries, thereby confers potential information advantages, and can help explain who partners with whom and under what conditions.

Second, research on R&D partner selection more generally emphasizes the importance of prospective partners' technological resources as a basis of fit between them (e.g., Ahuja, 2000; Gans and Stern, 2003; Rothaermel and Boeker, 2008). We would suggest, however, that partners routinely encounter difficulties judging partners' technological and other resources in the first place. Venture capitalists can help relieve such problems, enabling entrepreneurial ventures to engage in collaborations at the earliest stages of development and in less familiar technological domains.

Third, in advancing understanding of the ways in which common VCs can facilitate R&D partnerships by startups, we complement research that has focused on other ties or intermediaries (e.g., investment banks) employed by more established firms to foster economic exchanges (Gulati, 1995a; Gulati and Gargiulo, 1999; Li *et al.*, 2008; Sleptsov, Anand, and Vasudeva, 2013). We build upon and extend this research by demonstrating that the effects of information intermediation through VCs are greatest when startups are at the earliest stages of development and lack familiarity with each other's technological resources through prior ties or other means.

THEORY AND HYPOTHESES

Background Theory

R&D alliances are a prominent way in which partners exchange, share, and co-develop knowledge and contribute to the commercialization of technologies (e.g., Pisano, 1990; Mowery, Oxley, and Silverman, 1996; Tallman and Phene, 2007). Firms enter into R&D collaborations with exchange partners to utilize their technological capabilities and know-how for new product development and commercialization (e.g., Teece, 1996; Hsu, 2006). For example, entrepreneurial ventures in the biotechnology industry enter into alliances to enhance their technological capabilities and commercialization prospects (e.g., Rothaermel and Deeds, 2004). Thus, R&D alliances are important avenues for entrepreneurial ventures to obtain knowledge and access new technological resources to foster their development (e.g., Gomes-Casseres, Hagedoorn, and Jaffe, 2006).

While considerable research emphasizes that firms select partners based upon their resources and capabilities (e.g., Geringer, 1991; Mowery *et al.*, 1998; Hitt *et al.*, 2004; Li *et al.*, 2008; Dekker and Van den Abbeele, 2010; Diestre and Rajagopalan, 2012), less attention has been given to the constraints and challenges firms face during partner selection. Firms often confront considerable uncertainty concerning a prospective partner's resources and prospects, and they are subject to risks associated with asymmetric information when searching for R&D partnerships (e.g., Pisano, 1990). For example, entrepreneurial ventures exhibit short track records on their resources and projects (e.g., Shane and Stuart, 2002), just as they lack the necessary resources and capabilities to perform due-diligence activities on other partners (e.g., Stinchcombe, 1965). While complementary technological and other resources can lead to valuable exchanges between alliance partners (Rothaermel and Boeker, 2008), lack of knowledge about prospective partners' resources can exacerbate problems of appraising resources due to information asymmetries. Moreover, given that R&D resources are mostly intangible and difficult to evaluate (e.g., Arrow, 1962), R&D alliance partners would have incentives to misrepresent the technological and commercialization potential of their resources in order to obtain economic exchanges such as R&D partnerships. Under these conditions, markets for particular R&D partnerships can fail and become segmented, as we describe below (c.f., Milgrom and Stokey, 1982; Garmaise and Moskowitz, 2004).

Given that many firms in high-tech industries are VC backed (e.g., Sahlman, 1990; Gompers and Lerner, 2001), entrepreneurial ventures can obtain assistance from their VCs in their formation of R&D alliances. For example, it is well known that affiliating with prominent VCs can enable a firm to draw in many different investors as well as alliance partners based on the endorsement of these VCs (e.g., Stuart *et al.*, 1999; Gulati and Higgins, 2003; Hsu, 2006; Ragozzino and Reuer, 2007; Ozmel *et al.*, 2013). Entrepreneurial ventures can also benefit from VC backing in a second way: startups can enter into R&D alliances by searching for potential partners within the portfolios of the VCs backing them. VCs have access to idiosyncratic, project-specific information and details about the strategy and progress of each of their portfolio firms (e.g., Admati and Pfleiderer, 1994; Busenitz *et al.*, 2004). Further, they actively participate in value-creating activities of their portfolio firms and wish to maximize the accruable cash flows from their investments (e.g., Arthurs and Busenitz, 2006; Jackson *et al.*, 2012). VCs are therefore well-positioned to help their portfolio firms obtain opportunities for R&D collaborations (e.g., Gans and Stern, 2003). Thus, firms looking for R&D partners can expect their VCs to channel the information they obtain in due diligence and monitoring processes in other firms in the portfolio, thereby facilitating firms' search for potential partners (e.g., Aoki, 2000; Lindsey, 2008). In this manner, VCs act as information intermediaries for entrepreneurial ventures making partner selection decisions and can shape future R&D alliances with certain partners by directly reducing information asymmetries.

In the hypotheses developed below, we examine the information intermediary role of VCs in reducing information asymmetries for entrepreneurial ventures about prospective collaborators to hypothesize on who partners with whom and how R&D partnerships get built up within high-tech industries. A primary implication of asymmetric information between prospective alliance partners is that the likelihood of a collaboration between two firms falls with the adverse selection risk surrounding a transaction (e.g., Milgrom and Stokey, 1982). In our hypotheses we use this core idea to understand the information intermediary role of a common VC investor in reducing the information asymmetry between prospective R&D alliance partners.

If having a common VC is generally valuable in reducing information asymmetries between firms (Lindsey, 2008), then we can use information economics as applied in strategy and entrepreneurship research to identify particular conditions under which this intermediary role of VCs is apt to be particularly valuable based on prospective partners' lack of first-hand knowledge about each other's technological resources and activities. To begin with, given that a firm's stage of development is indicative of the maturity of its R&D resources and their commercial potential (e.g., Aboody and Lev, 2000; Ahuja, 2000; Rothaermel and Deeds, 2004), firms that are in early stages of product development present greater information asymmetries and risk of adverse selection to potential partners. We therefore investigate whether sharing a common VC investor will have a more pronounced effect when partner firms are yet in early stages of product development. Even in such early stages of development, however, prospective partners might be more familiar with each other's technological resources and be capable of evaluating partners' capabilities through other means. This familiarity of each other's technological resources and their prospects is expected to diminish the potential impact of VC information intermediation on alliance partner selection. In particular, this familiarity and resulting ability to appreciate each other's technological capabilities can be developed by having previous alliances with each other (e.g., Vanhaverbeke *et al.*, 2002; Higgins and Rodriguez, 2006; Zaheer *et al.*, 2010), building upon each other's knowledge bases during the development of technologies (e.g., Cohen and Levinthal, 1990; Mowery *et al.*, 1998), or possessing similar technological resource endowments (e.g., Stuart, 1998; Rosenkopf and Nerkar, 2001; Gilsing *et al.*, 2008). We therefore identify particular conditions that capture a prospective alliance's information environment and hence shape the implications of common VC backing for partner selection. As we will discuss, the contingencies we investigate are useful not only in identifying the impact of VC information intermediation and relevant boundary conditions highlighted by information economics, but they also are useful in considering alternative potential ways in which VCs might affect alliance partner selection and the build-up of R&D collaborations in industries.

Research Hypotheses

Common VC Investor. Our primary interest lies in understanding the determinants of who partners with whom and under what conditions, in order to contribute to the literature on partner selection for R&D collaborations. We begin by considering how VCs can directly reduce information asymmetries between potential alliance partners, and we develop a baseline hypothesis on how VC information intermediation shapes R&D partner selection. To begin with, entrepreneurial ventures have to allocate scarce resources to search for and evaluate potential R&D alliance partners (Stuart, 1998). However, entrepreneurial ventures can rely on their VCs to overcome problems related to the selection of potential alliance partners, and this assistance allows them to efficiently enter into R&D collaborations with favorable partners (e.g., Aoki, 2000; Gans *et al.*, 2002; Lindsey, 2008).

There are several important foundations to the information intermediation function that VCs can fulfill. To begin with, VCs syndicate their investments and diversify their portfolios by investing in entrepreneurial ventures that are at different stages of development (e.g., Lerner, 1995; Sorenson and Stuart, 2001), so they have access to project-specific information and details about the strategy and progress of their portfolio of firms (e.g., Admati and Pfleiderer, 1994; Gompers, 1995; Busenitz *et al.*, 2004). VCs also obtain an equity position and cash flow rights (Kaplan and Stromberg, 2003), as well as extensive contingent control rights in ventures (e.g., Kaplan and Stromberg, 2003). VCs therefore actively participate in value-creating activities of their portfolio of firms to increase the value of their investments (e.g., Arthurs and Busenitz, 2006; Jackson *et al.*, 2012). These value-added services can include providing opportunities for the development of firms in their portfolio. To this end, VCs can use the information they obtain in their due diligence, advice, and monitoring processes in their portfolio of firms in order to match the development needs of a given firm (e.g., Aoki, 2000; Lindsey, 2008).

The foregoing arguments suggest that entrepreneurial ventures can at the margin avoid costly search and evaluation to select R&D alliance partners by relying on their VCs to draw information about favorable partners from the VC's pool of investee firms. Given that the incentives of VCs are aligned towards boosting the prospects of firms in their portfolio and enhancing their overall value, firms would positively judge the quality of the information conveyed by VCs about potential alliance partners. As a result, firms can mitigate misrepresentation risks as well as lower the costs related to due diligence activities when they select potential R&D alliance partners from their VC's portfolio. By contrast, holding everything else constant, information asymmetries are more likely to be significant when the two entrepreneurial ventures do not have a common venture capitalist backing them (Lindsey, 2008). Thus, we offer the following baseline hypothesis:

Hypothesis 1: The likelihood that an entrepreneurial venture selects a prospective R&D alliance partner is higher when they both are backed by a common VC investor.

From the foregoing discussion, it follows that the benefits of having a common VC will turn upon the ability of entrepreneurial ventures to appraise potential collaborative opportunities between them. The information intermediary role of VCs will therefore be especially useful for R&D partner selection when a firm cannot judge the value of prospective partners' R&D assets and capabilities. In particular, firms might find it difficult to assess the underlying technological resources and activities of prospective partner that are in their early stages of product development. During preliminary stages of product development, information about firm's activities is scarce, and consequently informational asymmetries during early stages of product development can jeopardize alliancing opportunities for entrepreneurial firms. However, when asymmetric information exists between firms, the intermediary role of VCs can be expected to be particularly useful.

Partner Firms' Product Development. During the early development stages of their technologies, entrepreneurial firms are usually short of track records that would provide information on their activities and technological resources (e.g, Amit et al., 1990; Shane and Stuart, 2002). In particular, when firms' technologies are in the initial stages of development, verifiable information about the underlying capabilities of firms is very limited, and information about their R&D projects and product development initiatives can be costly for outsiders to obtain (e.g., Aboody and Lev, 2000; Ahuja, 2000). By contrast, when firms achieve progress in product development activities, information is produced about their R&D activities and helps prospective partners assess firms' intangible assets and resources. In high-tech industries such as biopharmaceuticals, product development is usually subject to considerable uncertainty, is very resource intensive, and requires firms to invest their scarce resources to obtain success (e.g., Powell et al., 1996). Consequently, firms create a credible signal for outsiders about firms' R&D capabilities when they are able to progress in their product development activities (e.g., Rothaermel and Deeds, 2004). In this regard, prospective partners seeking R&D alliance partners are more likely to partner with those firms that have advanced beyond the earliest stages of product development.

Because stage of development is indicative of a firm's progress and prospects for successful commercialization of technologies, firms that are in early stages of product development present greater information asymmetries and risk of adverse selection to potential partners, and this can impede alliance formation. As a result firms in their early stages of product development may fail to establish R&D partnerships with prospective collaborators and may potentially lose out on opportunities for growth. Given this precarious situation for firms in early stages of product development they can benefit from the information intermediary role of their VCs highlighted earlier. In the absence of any credible record about a firm's product development prospects and capabilities potential alliance partners can learn about a firm's underlying activities from the common VC investor. Thus, we posit:

Hypothesis 2: The positive effect of a common VC investor on the likelihood of that an entrepreneurial venture selects a prospective R&D alliance partner will be greater when the entrepreneurial venture is in an early stage of product development.

In the foregoing hypothesis, we suggest that the significance of VC information intermediation on alliance formation will be contingent on the product development stage of prospective alliance partners. While product development stage is a useful indicator for firms to learn about activities of prospective alliance partners, firms might be able to become familiar with prospective exchange partners' technologies, irrespective of their development stages. Prior research suggests that there are least two primary ways in which potential partners can be familiar with the nature and quality of each other's resources. First, firms can accumulate partner specific knowledge and become more familiar with the quality of a partner's resources and capabilities through prior alliance relationships (e.g., Gulati, 1995a; Gulati and Gargiulo, 1999). Second, firms that have drawn knowledge from each other's technological activities are more likely to be equipped with the relevant information about their partners' capabilities (e.g., Mowery *et al.*, 1998). Because the above two dyadic features enable prospective partners to have learned about each other and directly reduce information asymmetries, we expect that they both will weaken the positive effect of VC information intermediation on R&D partner selection. By contrast, when firms lack firsthand knowledge about each other's technological and other resources because they lack prior ties or draw upon different knowledge, information asymmetries are greater, and the VC information intermediation effect is likely to be more pronounced for R&D partner selection. Below we discuss the contingent effects of technological familiarity in terms of partner-specific experience and cross citations.

Partner-Specific Experience. Previous collaborative agreements between firms are very useful in enabling firms to develop an understanding and specific knowledge about one another's technological resources. So, we expect that the significance of information intermediation by a common VC will diminish for prospective partners that already have gained partner specific experience through prior alliance relationship with each other. By contrast, and paralleling the arguments developed earlier, we expect that the effects of backing by a common VC will be more pronounced for two firms without previous alliances together.

Prior alliance agreements enable partner specific-experience and provide ways for prospective partners to gather information about each other's research and other activities (e.g., Gulati, 1995a) and reduce uncertainties related to information disclosure (Vanhaverbeke *et al.*, 2002; Zaheer *et al.*, 2010). Prior collaborations provide prospective R&D partners with rich information about each other's technological know-how and deepen partners' familiarity concerning each other's competencies (e.g., Vanhaverbeke *et al.*, 2002; Vanneste and Puranam, 2010). In particular, in the context of R&D alliances, prior alliance relationships enable firms to accumulate information about partners' intangible R&D resources and avoid misrepresentation risks (e.g., Higgins and Rodriguez, 2006). Further, prior relationships between prospective partners enable them to accumulate knowledge about each other's technological endowments and pursue new opportunities together that emerge during the course of collaboration. Given that prior relationships provide firms access to fine-grained information about partners' technological resources and activities, prospective partners can obviate the need for costly investments in due diligence activities. By contrast, when entrepreneurial ventures lack collaborative experience with each other, they will find it particularly valuable to rely upon a common VC to provide rich information about each other's technological resources and activities. Thus, we posit:

Hypothesis 3: The positive effect of a common VC investor on the likelihood that an entrepreneurial venture selects a prospective R&D alliance partner will diminish with partner-specific experience.

Cross Citations. When prospective partners draw upon each other's knowledge bases, they can become familiar with each other's technological resources, even when they have not had formal collaborative agreements together in the past. When firms have developed such a direct understanding about potential R&D partners' technological endowments, they are better equipped to evaluate the underlying quality of their resources and mitigate the risk of adverse selection in a prospective partnership (e.g., Cohen and Levinthal, 1990). One way in which firms become familiar with each other's technological resources is when they mutually draw on each other's knowledge bases in their prior technological activities such as patenting (e.g., Mowery *et al.*, 1998). For instance, in high-tech industries such as biotechnology, prospective partners that cite each other's patents would have a superior understanding about their partners' technological endowments and can avoid costly due diligence to evaluate each other's critical resources (e.g., Stuart, 1998). When prospective R&D partners extensively draw on each other's knowledge bases they accumulate knowledge about partners' difficult-to-evaluate intangible R&D resources and can utilize it to recognize and appreciate potential collaborative opportunities with each other (e.g., Cohen and Levinthal, 1990; Gilsing *et al.*, 2008). However, when firms lack such knowledge about potential partners' technological endowments they may find it difficult to accurately assess the quality of partners' technological resources (e.g., Gulati, 1999; Nicholson *et al.*, 2005), and would benefit from the information mediated by a common VC investor on a firm's research progress, plans, market prospects, and the like. Under these conditions, all else equal information asymmetry is apt to be higher, so the information mediation role of VCs is likely to take on greater importance for alliance partner selection. We therefore hypothesize:

Hypothesis 4: The positive effect of a common VC investor on the likelihood that an entrepreneurial venture selects a prospective R&D alliance partner will diminish when they mutually draw on each other's knowledge bases through patent cross citations.

Technology Relatedness. In the foregoing hypotheses we discussed how the positive effect of VC information intermediation on R&D alliance formation is contingent on the extent partner firms have firsthand knowledge about each other's technological and other resources that accrues from partner specific experience and drawing upon each other's knowledge bases. Partner firms can also be able to directly assess each other's technological resources insofar there is commonality among their activities and underlying technological resources. Because a firm's absorptive capacity will be salient in the areas in which it is active, firms will find it difficult to comprehend the nature of opportunities outside of their areas of technological operations (Rosenkopf and Nerkar, 2001; Gilsing et al., 2008). Firms would therefore face significant information asymmetries when technological activities of prospective R&D partners are unrelated, and firms would have to make costly investments to understand and judge the technologies of prospective partners (Stuart, 1998). However, the presence of a common VC investor can help firms avoid these informational problems and yet know about the difficult-to-evaluate resources of partner firms that are technologically less related to them. Given that VCs obtain information about a firm's activities through their due diligence, advice, and monitoring processes, the likelihood that prospective R&D partners that share a common VC would collaborate with each other will be more pronounced when there is less overlap in their technological activities. By contrast, the effect of having a common VC as an information intermediary would diminish for partners that are technologically more related, since commonality of technology allows partner firms to evaluate each other's technological resources. Thus, we posit:

Hypothesis 5: The positive effect of a common VC investor on the likelihood that an entrepreneurial venture selects a prospective R&D alliance partner will diminish with the technology relatedness between them.

METHODS

Data and Sample

To investigate the underexplored information intermediary role of VCs in shaping firms' R&D partner selection decisions, we focus on alliances among entrepreneurial ventures in the biotechnology industry. This industry context is interesting and appropriate for our analysis for several reasons. Biotechnology firms extensively rely upon alliances to obtain technological and other resources that are critical for their development and growth (e.g., Powell, Koput, and Doerr-Smith, 1996; Roijakkers and Hagedoorn, 2006; Anand, Oriani, and Vassolo, 2010), yet the capabilities and prospects of these entrepreneurial ventures can be difficult to evaluate due to their intangible resources and short track records (e.g., Stuart *et al.*, 1999; Gulati and Higgins, 2003; Nicholson, Danzon, and McCullough, 2005; Levitas and McFadyen, 2009). Moreover, alliances as well as venture capital are the two principal means by which biotechnology startups obtain necessary resources (e.g., Sorenson and Stuart, 2001; Hochberg *et al.*, 2007), and venture capital is also extensively used in this industry compared to other high-tech industries in which R&D alliances are also common (e.g., semiconductors). Rich information is available on characteristics of firms' relationships with venture capitalists as well as firms' technological activities, enabling an investigation of whether and when common VCs facilitation partner selection for R&D collaborations.

In order to investigate the intermediary role of VCs on who partners with whom, our research design needed to accommodate pairs of biopharmaceutical firms that collaborated together as well as those that did not engage each other in collaboration. We obtained data on alliances that occurred in the biotech setting from Thomson Reuters' Recap database. Recap has been actively tracking transactions at all levels in the biopharmaceuticals industry since the 1980s, and it is a reliable source for obtaining a representative coverage of alliance agreements in this sector (Schilling, 2009). We identified alliance dyads for which both firms are VC backed by mapping each partner to the venture capital data provided by Thomson Financial's Venture Economics database. These two data sources have been employed extensively by researchers in management, economics, and finance to investigate questions related to venture financing and cooperative strategies in the biopharmaceuticals industry (e.g., Robinson and Stuart, 2007; Adegbesan and Higgins, 2011).

In our study we explore the information intermediation effect of VCs on the likelihood of alliance formation between firms. Our analyses therefore require sampling on alliance dyads between VC backed firms that actually occurred and constructing a set of corresponding counterfactuals that are nonrealized collaborations. For a given realized alliance dyad, we built the set of nonrealized alliances by considering all firms from the universe of VC backed firms that are present in the biopharmaceutical industry at the time of the focal realized alliance dyad. This offers a comprehensive set of nonrealized deals and enables us to exploit heterogeneity in the sample for testing the hypotheses in an unbiased way when information is lacking *a priori* on those dyads for which a collaboration is feasible or likely (e.g., Gulati and Gargiulo, 1999). In supplemental analyses, we also examined more restrictive sets of nonrealized alliances based on certain matching criteria and found consistent results. Specifically, we generated counterfactuals for a focal alliance dyad by considering all possible alliance dyads that are matched on industry subgroup, therapeutic area, and state location with the focal realized alliance dyad. Our results are robust across these specifications for the set of nonrealized alliance dyads. In supplemental analyses covered below, we also discuss a range of alternative risk sets and find the same interpretations for hypothesis testing.

To construct our final samples for analysis, we employed an additional set of sampling criteria. First, we included deals that are classified by Recap as research, collaboration, development, co-development, market, co-market, promote, co-promote, manufacture, and license type agreements, and an alliance may involve more than one deal type. In this manner, we focus on alliances that have research, R&D, or R&D plus other activities (e.g., Oxley, 1997). Second, we focused on alliances that were formed between the years 1985 and 2011. Activity in alliance and private equity markets experienced significant growth in the biotechnology industry during this period (e.g., Lerner and Merges, 1998). Third, we considered only those alliance dyads where firms in a dyad had obtained at least first round VC funding, and both firms were operating as private entities at the time of the R&D collaboration. Given our focus on how having a common VC can facilitate R&D collaborations between entrepreneurial ventures, we excluded firms that had already gone public since venture capitalists might no longer be involved in such firms and more information is available to collaborators on the performance and quality of these companies (Gompers and Lerner, 2004). Further, we excluded firms that had received their last round of VC funding at least seven years before the time of a focal R&D collaboration, in order to exclude firms that are defunct, or "living dead" (e.g., Ruhnka, Feldman, and Dean, 1992).

Next, we combined these data with patent information from the US Patent and Trademarks Office (USPTO) and the National Bureau of Economic Research (NBER) after tracking company histories and name changes. Further, we also gathered data on the biotech product development activities of all firms in our sample from the Orange Book, which is a library of approved drug products of all firms in the biotechnology industry and is managed by the United States Food and Drug Administration (FDA). In order to reduce unobserved heterogeneity from cross-border transactions, we limited our analyses to VC-backed biotechnology firms based in the US. After implementing these sampling screens, we obtained an initial sample of 87562 realized and non-realized alliance deals, of which 156 were R&D partnerships that occurred. Descriptive statistics on the sample appear in the results section below.

Variables and Measurement

Dependent Variable. We examine the likelihood two entrepreneurial ventures in the biopharmaceutical industry partner with each other to form an R&D alliance. Accordingly, the dependent variable is *R&D Alliance Formation*, which takes on a value of 1 for realized alliances and zero for dyads of non-realized transactions. Considering the dichotomous nature of the dependent variable, we specified logistic regression models for our analyses. In supplemental analyses, we specified rare events logistic regression models since the likelihood of R&D collaboration in our sample of R&D collaborations (i.e., around 1 percent) may differ from the population (King and Zeng, 2001). We also randomly picked non-realized alliances (e.g., 5 or 10) for each realized R&D collaboration, and we found the same interpretations as those presented below.

Independent Variables. Our first hypothesis considered whether two firms are more likely to engage in an R&D collaboration with each other if they have a common VC, compared to firms that are backed by completely different venture capitalists. *Common VC* is therefore a dyadic measure and takes on the value of 1 if a VC firm invested in both firms within the three years prior to the date of the focal alliance, and 0 otherwise. Because firms might share more than one VC (e.g., the maximum is five in our sample), we also measured this variable using the count of the VCs the two firms share at the time of the partner selection decision, and we obtained the same interpretations as those presented below.

Our remaining hypotheses reflect contingencies that shape the information asymmetries between potential partners and hence the degree to which having a common VC investor facilitates partner selection. Our second hypothesis suggested that the VC information intermediation effect on alliance formation will be more pronounced when potential R&D collaboration partners are in early stages of product development. Given that firms' products reflects their progress in product development, we measured *Firm Product Development* and *Partner Product Development* as a dummy variable that is equal to 1 if there is at least one drug application approved by the U.S. Food and Drug Administration agency for them at the time of the R&D collaboration, and 0 otherwise.

In Hypothesis 3 and 4 we suggested that the positive effects of having a common VC investor on R&D partner selection will diminish with technological familiarity between entrepreneurial ventures in terms of partner firms' first-hand information about each other's technological resources. Specifically, our third hypothesis suggested that the positive effects of having a common VC investor on partner selection will be contingent on partnering experience between the firms. Specifically, the positive effect of having a common VC investor on alliance formation is expected to diminish with the degree of familiarity between firms through their prior alliance relationships, which provide knowledge about each other's activities and resources.

Accordingly, we measured *Partner Specific Experience* as the number of alliances between the firms during the five years prior to the focal alliance. We also measured this variable for different time windows such as three years and seven years and found interpretations similar to those presented below.

Our fourth hypothesis suggested that the positive effects of having a common VC investor on partner selection will be moderated by the extent that partner firms draw upon each other's knowledge bases. We measured this in terms of the number of patent *Cross Citations* between a firm and its potential partner during the five years prior to the date of the focal alliance (e.g., Mowery *et al.*, 1996; Rothaermel and Boeker, 2008). We also measured this variable for different time windows such as three years and seven years and found interpretations similar to those presented below.

In Hypothesis 5 we suggested that the positive effects of having a common VC investor on partner selection will be contingent on the extent of commonality of technological activities between partner firms. We measured *Technology Relatedness* as the cosine of the angular separation in firms' patents across patent classes, which is often used as a measure of the degree of similarity in two firms' patent portfolios (e.g., Gomes-Casseres, Hagedoorn, and Jaffe, 2006; Li, Eden, Hitt, and Ireland, 2008). We followed Jaffe (1986) in calculating this measure as the normalized scalar product of the patent class distribution vectors of firms in a dyad during the last five years prior to the focal alliance. We also measured this variable for different time windows such as three years and seven years and found interpretations similar to those presented below.

We also performed a number of robustness tests to explore the temporal sequence of the common VC variable and the dyadic moderating variables as well as to ensure the common VC variable is measured more recently than the others, which the common VC might itself shape. For example, we measured partner specific experience, cross citations, and technology relatedness before different time windows in which we gauged involvement by a common VC (e.g., three years and five years) and the findings are quite consistent across the different sets of analyses and support our hypothesized relationships.

Control Variables. In our models we introduced several controls that could be related to firms' technological resources and their affiliations with venture capitalists, as well as the likelihood of forging R&D collaborations. Specifically, we included control variables that account for dyad-level as well as firm-level characteristics to address the determinants of who partners with whom. To begin with, prospective R&D alliance partners may find it harder to locate as well as evaluate each other when they are farther apart, thereby reducing the likelihood of R&D collaboration between entrepreneurial ventures. We control for geographic distance between firms, measured as the natural logarithm of the great circle distance between the headquarters of the firms (i.e., *Distance*).

Given that both firms in our alliance dyads are VC backed, we also accounted for characteristics of their VCs and the firms' funding activity. Specifically, we controlled for the prominence of the VCs backing the firms in a dyad as the likelihood that they partner with other firms increases with the signals conveyed by affiliations with prominent venture capitalists. Following Hsu (2006), we calculated *Firm VC Prominence* and *Partner VC Prominence* as the natural logarithm of the Bonacich centrality of the most central VC backing them (e.g., Bonacich, 1987; Sorenson and Stuart, 2001). More specifically, we calculated the eigenvector centrality of each VC backing the firm within the VC syndication network, in order to capture both the direct and indirect ties among venture capitalists (Bonacich, 1987). We defined the centrality of a VC firm, indexed by *i*, as the Bonacich two-parameter measure in year *t* using a five-year time window between *t*-5 and *t*:

$$\text{(1) VC firm centrality}_{i,t}\ (C_{i,t}) = \sum_{j=1}^{N_t} \left(\alpha_t + \beta_t C_{j,t}\right) R_{i,j,t}$$

where $C_{j,t}$ is the centrality score of VC firm *j* in year *t*, and $R_{i,j,t}$ is an element of the relationship matrix R_t, indicating the co-investments between VC firms *i* and *j* during the five year window. α_t is a scale parameter chosen so that the sum of the squares of centralities of all firms in a network in a given year equals the number of units in the network (i.e., N_t). β_t is a weighting coefficient, indicating the effect of centralities of investment partners on the firm's centrality and is conventionally set to three-fourths of the reciprocal of the largest eigenvalue of the relationship matrix R_t.

We also accounted for the cumulative VC funding received by the firms, their number of VC rounds, and their respective stages of VC investment. Previous studies suggest that VC firms periodically evaluate the progress of ventures in their portfolio to decide whether or not to continue investing in a venture (e.g., Gompers, 1995; Lerner, 1995). In addition, these variables also reflect a venture's maturity and experience (e.g., Lerner and Merges, 1998). We calculated *Firm VC Funding* and *Partner VC Funding* as the natural logarithm of the total dollar amount of VC funding received prior to the focal alliance. *Dyad VC Investment Stage* is a dummy variable that takes on the value of one if the VC funding for at least one of the firms in an alliance dyad is reported as either seed stage or early stage at the time of R&D collaboration, and zero otherwise. In addition, we also measured *Firm VC Bio Investment Experience* and *Partner VC Bio Investment Experience* to account for the biotech investment experience of VCs backing the firms. We measure these variables as the natural log of the number of prior rounds of funding in the biotechnology industry, and we took the maximum values for the VCs backing the firms.

For firms in the biotechnology industry, firms' prior technological achievements can also convey information about their technological capabilities and prospects (e.g., Stuart, 2000; Diestre and Rajagopalan, 2012). We account for the quality of firms' patents and measured *Firm Citations* and *Partner Citations* as the natural logarithm of forward patent citations received by them during the last five years prior to the focal alliance (e.g., Jaffe *et al.*, 1993; Hall, Jaffe, and Trajtenberg, 2005).

The alliance activity of a firm may also shape the resources to which it has access and may also convey to prospective partners that its resources are in demand by other organizations (e.g., Gulati, 1995b; Stuart *et al.*, 1999; Nicholson *et al.*, 2005; Cuypers and Martin, 2010). Similar to venture capitalists, previous alliance partners have carried out evaluations of the firm's resources and capabilities (e.g., Luo, 1997; Hitt *et al.*, 2004; Ring, Doz, and Olk, 2005; Shah and Swaminathan, 2008), and alliance partners are directly involved in the operations of the firm (Balakrishnan and Koza, 1993; Almeida, Song, and Grant, 2002; Vanhaverbeke, Duysters, and Noorderhaven, 2002). In addition, prospective partners that have already engaged in collaborations may be more effective in engaging in collaborative activities (Colombo, 2003; Hoang and Rothaermel, 2005; Hagedoorn *et al.*, 2009). We controlled for the previous research collaborations of the firms in the previous five years, using a log transformation (i.e., *Firm Alliance Experience* and *Partner Alliance Experience*). We also measured *Firm Exploitative Experience* and *Partner Exploitative Experience* as the natural logarithm of the number of alliances with only a development or commercialization component, but no research component, that were formed by the prospective partners in the last five years (e.g., Rothaermel and Deeds, 2004; Lavie and Rosenkopf, 2006).

We also controlled for the age of entrepreneurial firms since startups may be technologically attractive to prospective partners but also can present greater uncertainty given their shorter track records (e.g., Stuart *et al.*, 1999; Nicholson *et al.*, 2005; Hsu, 2006). We measured *Firm Age* and *Partner Age* as the logged value of the age of both firms at the time of focal R&D collaboration. In addition, we also controlled for several other sources of unobserved effects. We defined *Firm Patent Class Effects* and *Partner Patent Class Effects* to control for whether firms in a dyad patented in particular 3-digit technology classes that might affect R&D collaboration (e.g., Jaffe, 1989; Jaffe, Trajtenberg, and Henderson, 1993). We also controlled for heterogeneity among industry subgroups of firms in our sample and included *Firm Industry Subgroup Effects* and *Partner Subgroup Effects*. Finally, we also included *Therapeutic Area Effects* and *Year Effects* to control for effects related to the therapeutic area of the focal alliance and the year during which an alliance was formed or not between the firms.

RESULTS

Table 1 reports descriptive statistics and correlations of variables used in our analyses. About three quarters of the realized alliances in our sample involve R&D or R&D plus other activities, and the remaining alliances are pure research agreements. Roughly 54 percent of the alliances in our sample include "collaboration" or "co-development" agreements in which both partners actively conduct R&D activities. Summary statistics indicate differences across the realized and non-realized collaborations for the key theoretical variables. For example, the proportion of firms having a common VC is 0.13 in the group of realized alliances, while it is only 0.05 for the non-realized collaborations ($p<0.01$). The average likelihood that any two firms form an alliance is 0.005 when they share a common VC, while it is 0.001 for firms that do not have a common VC ($p<0.01$). The average number of cross citations is greater for firms that engage in future partnerships (i.e., 0.08) versus those that do not collaborate (i.e., 0.004) (p<0.05). The average number of prior ties is 0.08 for partners engaging in an alliance together, and 0.002 for the group of non-realized alliances (p<0.01). Similarly, the average technological relatedness is greater for firms that engage in partnerships (i.e., 0.18) versus those that do not collaborate (i.e., 0.07) (p<0.001). Correlations also indicate that firms are also more likely to partner with each other when they are closer to each other (p<0.001).

Firms with a more prominent VC backing them are also more likely to share a common VC with prospective collaborators (p<0.001), just as common VCs are more likely to involve venture capitalists experienced in biotechnology (p<0.001). Firms that share a common VC and partner with each other are more likely to be in their early stages of product development (p<0.001). Potential collaborators that have fewer cross citations and partner specific experience and yet partner with each other are more likely to share a common VC (p<0.01). Correlations among the variables are generally modest and the maximum variance inflation factor (VIF) for the variables is 2.45, providing no evidence of multicollinearity in the estimated models.

****Insert Table 1 here****

Table 2 reports the estimates of logistic regression models for the partner selection analyses. Model 1 is a baseline specification consisting of control variables, and Model 2 augments this model with the direct effect of the common VC variable. Hypothesis 1 suggests that firms are more likely to partner with each other when they share a VC investor. The multivariate estimation results confirm that the incidence of R&D collaboration between any two firms is greater when they have a common VC investing in them (p<0.001). Thus, H1 is supported. We also investigated the economic significance of this effect on the likelihood of

R&D alliance formation between two firms. With all variables at their means, the likelihood of R&D collaboration increases approximately twofold when they have a common VC.

****Insert Tables 2 and 3 here****

Models 1-5 in Table 3 report the estimates for our hypothesized interactions, and Model 6 is the full model that contains all interactions estimated at once. Hypotheses 2 suggests that the positive effect of having a common VC investor on R&D alliance formation will be contingent on a partnering firm's progress in product development. Hypotheses 3, 4, and 5 suggest the moderating effects of the degree of technological familiarity between firms in terms in terms of partner firms' direct knowledge about each other's technological resources that could be a result of their cross-citations, partner specific experience, and relatedness of their technology portfolios, respectively. Consistent with H2, the coefficient estimate of the interaction between common VC and product development stage is negative and significant ($p<0.001$). In accord with H3, the coefficient estimate of the interaction between partner specific experience and common VC is negative and significant ($p<0.001$). Consistent with H4, the coefficient estimate of the interaction between common VC and cross citations variable is negative and significant ($p<0.001$). Finally, hypothesis 5 suggested that the positive effect of having a common VC on R&D alliance formation will be greater between partner firms that do not share similar technological activities. The coefficient estimate of the interaction between common VC and technology relatedness is negative and significant ($p<0.001$), as expected.

It is well recognized that interpreting interaction effects is difficult in nonlinear models such as logistic regression (e.g., Hoetker, 2007). So, we also examined the marginal effects for individual observations of the interaction effects, and found them to be consistent with our interpretations. Further, we also examined the interaction effects graphically (please see Figures

1-5). For instance, Figures 1 and 2 illustrate the interaction effect between common VC variable and partner firms' product development. It indicates that the positive effect of a common VC will be greater for partner firms that are in their early stages of product development. Figures 3 and 4 illustrate the interaction effect between common VC variable and familiarity about prospective alliance partners in terms of cross citations and partner specific experience, respectively. The figures illustrate that the positive effect of having a common VC on the likelihood of R&D collaboration is evident only when firms lack direct experience with each other through cross citations and prior collaborations. Similarly, Figure 5 illustrates that a one standard deviation decrease from the mean in technology relatedness increases the positive effect of having a common VC on likelihood of alliance formation greater by almost 15 percent. Together, these figures provide evidence that backing by a common VC can privately and directly reduce information asymmetries between two firms and can be especially valuable for two firms that lack first-hand knowledge of each other's technological resources (i.e., due to stage of product development, lack of cross-citations or previous collaborations, and dissimilar technology portfolios) is an important boundary condition shaping the impact of the information intermediary role of VCs in markets for alliance partners.

****Insert Figures 1-5 here****

Finally, the results for some of the control variables are also noteworthy. While our theory and evidence indicates how VCs can provide an information intermediary role in facilitating R&D partnerships, particularly when partners face significant information asymmetries, our findings suggest other roles that VCs can play in enabling these alliances. There is some evidence that firms are able to attract partnerships when their VCs are prominent, as this signal on firms' technological resources and prospects extends broadly to would-be collaborators (Hsu, 2006). The level of funding by venture capitalists does not appear to enable collaborations overall, however. We also see that firms' previous alliance ties as well as downstream or upstream alliance experiences with other organizations can have a bearing on alliance formation. As a final example, we see that geographic distance appears to be a friction for alliance formation as firms tend to prefer to partner with geographically nearby collaborators.

Robustness Analyses

In supplemental analyses we have examined several possible alternative explanations for the VC intermediation effect on alliance formation between firms (results available upon request). For instance, it is possible to argue that a focal VC could see value in two ventures in his portfolio collaborating with each other as a consequence of either homophily or portfolio super-additivity considerations. For instance, homophily would suggest that venture capitalists might invest in firms with similar technological resources, and they might then collaborate due to the firms sharing such underlying similarities (e.g., Kossinets and Watts, 2009). Their similar technological resources might also present super-additive value that VCs recognize for a potential collaboration (e.g., Vassolo *et al.*, 2004). Whereas these explanations would suggest a positive interaction between the common VC and technology relatedness variables, the information intermediation effect would suggest the opposite, which we observe in support of Hypothesis 5: information asymmetries are greater when the ventures' technological resources are more dissimilar, so the positive common VC effect will be greater in this situation inasmuch as this effect is due to the information intermediation mechanism. We obtained similar interpretations when we employed common patent citations as an indicator of the similarity between partners' technological activities (e.g., Mowery, Oxley, and Silverman, 1998; Rothaermel and Boeker, 2008). We have also investigated the possibility that a common VC might exert its (e.g., ownership) in bringing portfolio companies together in partnerships by considering the amount of cumulative investment by the common VCs in both partner firms (e.g., Sahlman, 1990; Lerner, 1995), yet we did not find any evidence for this effect on alliance formation.

Furthermore, we also considered a number of situations where firms face an express need to partner or look for opportunities for alliance formation. For example, we examined whether the intermediary role of VCs is more useful when prospective partner firms need partners and yet face difficulties in attracting partners. In particular, we examined whether having a common VC is more beneficial for bridging alliances between partner firms that are in their nascent stage of venture activity. Firms that are in their nascent stage of venture activity look for alliance opportunities with potential partners to overcome resource constraints. However, they often fail to attract partners because of their poor information conditions. In our analysis, we found that the intermediary role of a common VC is more significant for potential partner firms when at least one of them is in its nascent stage of venture activity. This is in accord with our theory and evidence on the effects of having a common VC when firms are at an early stage of product development. We did not observe similar effects when we examined age as a contingency, presumably because firm age reflects many theoretical considerations, so overall we see that contingencies more directly tied to information asymmetries surrounding firms' technological resources and their prospects matter to partner selection and the build-up of R&D partnerships in the biotechnology industry.

We performed a number of additional analyses in order to examine the sensitivity of our particular findings and interpretations. Specifically, we examined whether our results are robust to alternative sampling approaches since different ones have merits and practices vary in the literature on the selection of exchange partners (e.g., Gulati and Gargiulo, 1999; Sorenson and

Stuart, 2001; Rothaermel and Boeker, 2008). While we constructed our main sample for analyses in a comprehensive way by generating all the possible dyads for a given realized alliance dyad in order to exploit heterogeneity in the sample for testing the hypotheses (e.g., Gulati and Gargiulo, 1999), we also constructed several additional sets of counterfactuals based on certain matching criteria. To begin with, we obtained non-realized dyads that are matched on industry subgroup for the partnering firms, therapeutic area, and state location (estimation results appear in Table 4). The VentureExpert database provides industry subgroup classifications (such as biotech-human, biotech-research, and pharmaceutical) of the entire sample of biopharmaceutical firms. For instance, suppose there is a realized alliance dyad where the firms belong to biotech-research and biotech-human subgroups, respectively, while the therapeutic focus of the alliance is cardiovascular. To construct the counterfactuals, we considered all potential dyads that belong to biotech-research and biotech-human subgroups, with firms that have cardiovascular as one of their active therapeutic areas. We also developed samples of non-realized alliances from matches on industry subgroup alone or industry subgroup and therapeutic area, and we obtained the same interpretations.

****Insert Table 4 here****

Given that we focus on the common VC variable and its interactions, we also considered the potential endogeneity of this core variable. While a particular VC is probably not likely to invest in two firms given their prospects for future collaboration, and this mitigates potential feedback relationships in our dyadic analyses (e.g., Hayashi, 2000), we wanted to empirically examine the potential endogeneity of the common VC variable using Heckman's approach. We relied on the fact that VCs cluster in California and prefer to invest in nearby firms, so we used a dummy variable to indicate whether or not both potential partners are based in California (e.g., Baker and Gompers, 2003). This variable is positively correlated with backing by a common VC ($p<0.001$) but is not related to alliance formation. We estimated a first stage probit model examining the determinants of having a common VC, and in a second stage model of alliance partner selection examined whether the common VC variable is endogenous. The insignificance of the inverse mills ratio in this model indicated that we could not reject the null of exogeneity (Wooldridge, 2002).

DISCUSSION

Contribution and Implications

In this study, we extend information economics to the literature on partner selection for R&D collaborations and advance research by investigating a new role of VCs -- information intermediation -- in shaping partner selection for entrepreneurial ventures (e.g., Lindsey, 2008). Specifically, we examine the information intermediary role of VCs in reducing information asymmetries between entrepreneurial ventures and hypothesize on who partners with whom and how R&D partnerships get built up within high-tech industries. Given the difficulties firms might have in understanding and evaluating the resources and prospects of potential R&D partners, VC affiliations can provide remedies to the risk of adverse selection and have important implications for who partners with whom and how markets for alliance partners become segmented in high-tech industries. Prior research that investigated the role of VCs in R&D partner selection has focused on the signaling role of prominent VC affiliations in shaping firms' R&D alliance decisions (e.g., Hsu, 2006; Ozmel *et al.*, 2013). Signals of prominent VC affiliations are widely available to exchange partners and a significant means for overcoming the hazards of information asymmetries. By contrast, the information intermediary role of a VC that we investigate in this paper privately and directly reduces information asymmetries between prospective partners, and it is a novel way in which VCs can remedy the risk of adverse selection and influence who partners with whom in the market for R&D alliances.

At a broad level, we therefore complement previous research on partner selection that examined the signaling role of VCs (e.g., Hsu, 2006; Ozmel *et al.*, 2013) by investigating the information intermediary role of the VCs. In particular, we argue and show that information intermediation of VCs helps prospective partners learn about the underlying quality of each other's technological resources and activities, and it is particularly valuable for entrepreneurial ventures that find it difficult to overcome information asymmetries on their own when seeking potential R&D alliance partners. Our findings suggest that the information intermediary role of a VC has a more impactful role in partner selection for entrepreneurial ventures that face adverse selection risks on account of their inability to determine the quality of potential R&D partners' intangible assets and capabilities.

Specifically, as a potential R&D partner's progress in product development corresponds with the information about its underlying technological resources and activities, we find that the VC information intermediation will be more useful to mitigate informational risks when firms find it challenging to evaluate the resources of potential R&D partners that are yet in early stages of product development. The information intermediary role of VCs on R&D partner selection can also matter more or less for firms on the basis of their knowledge about prospective R&D alliance partners. Firms can also be better able to judge the quality of prospective partners' technological resources when they are familiar with potential partners' activities. In particular, partner specific experience that comes from prior alliance relations between potential R&D collaborators provides information about each other's technological resources and R&D activities, and our findings indicate that VC information intermediation is particularly useful when prospective exchange partners lack such partner specific experience. We also considered how firms that extensively draw on each other's knowledge bases become familiar about each other's technological resources, and we find that the VC information intermediation is particularly useful when prospective exchange partners lack such familiarity with potential partners' knowledge bases. Further, prospective R&D alliance partners can also be able to directly assess each other's technological resources insofar there is commonality among their activities and underlying technological resources, and we find that the VC information intermediation effect would be more valuable for partners that are technologically dissimilar from each other. In this manner, we identify specific contingencies when information asymmetries about partner firms' technological resources and activities tend to be greatest between firms, and in so doing we identify some critical boundary conditions related to the value of the information intermediary function that VCs can fulfill for R&D collaborations. These contingencies help to understand the mechanism underlying the common VC effect we observe and enable us to rule out alternative explanations why companies in a VC's portfolio have a more pronounced tendency to collaborate with one another.

This paper contributes in several specific ways to the literature on strategic alliances, and especially to research on partner selection for R&D collaborations. First, our extension of information economics to the literature on partner selection adds to other theories used to understand which partners a firm selects or should select. For instance, much of the research on partner selection emphasizes how firms should prioritize exchange partners that present strategic, organizational, and cultural fit, as well as those having complementary resources, for effective alliance implementation (e.g., Tallman and Shenkar, 1994; Luo, 1997; Hitt et al., 2004; Ring et al., 2005; Rothaermel and Boeker, 2008; Shah and Swaminathan, 2008; Beamish and Lupton, 2009; Mitsuhashi and Greve, 2009; Diestre and Rajagopalan, 2012). Our theory suggests that in spite of such resource considerations for selecting exchange partners, firms often confront inefficiencies and difficulties in judging each other's technological and other resources in the first place. We argued and showed how the information intermediation function of VCs can privately and directly address informational frictions that crop up in the partner search processes. Specifically, our study advances prior research that has investigated the importance of firms' resources in R&D partner selection (e.g., Rothaermel and Boeker, 2008; Diestre and Rajagopalan, 2012) and suggests that the VC information intermediation is particularly valuable for firms when they lack first-hand knowledge about each other's technological resources.

By investigating the underexplored information intermediary role of VCs in R&D partner selection and how it matters when firms face information asymmetries surrounding their technological resources and activities, we make an important contribution to research on the role of VCs in new ventures' growth prospects and on the informational spillovers VCs have on other markets. This body of research has emphasized the signaling role of VCs and has shown that backing by prominent VCs can provide signals on high-tech new ventures that facilitate IPOs, acquisitions, and partnerships (e.g., Stuart *et al.*, 1999; Gulati and Higgins, 2003; Chang, 2004; Hsu, 2006; Ozmel *et al.*, 2013). We build upon and advance this research by demonstrating the influence of VCs in intermediating relationships with exchange partners by functioning as credible third-parties who privately and directly reduce information asymmetries between prospective partners and influence partner selection for R&D alliances. In this way, we also contribute to research about the value-added role of VCs in the development of firms (e.g., Hellman and Puri, 2002; Arthurs and Busenitz, 2006; Lindsey, 2008; Jackson *et al.*, 2012). Our findings suggest that future research might consider the multiple ways that VCs can affect the development of firms as well as the returns they obtain in market contexts such as strategic alliances, mergers and acquisitions, and so forth.

Beyond exploring the information intermediary role of VCs in R&D partner selection when firms face information asymmetries surrounding their technological resources, our study also contributes more broadly to research on interorganizational relationships and the role of information intermediaries. For research that has examined the value of prior relationships in reducing uncertainty between firms (e.g., Gulati, 1995a, 1999; Chung *et al.*, 2000), our study suggests that prospective exchange partners can also obtain informational benefits from VCs as third-party intermediaries providing indirect ties between organizations. We also extend prior research suggesting that firms can exploit alliance opportunities through the social networks of their top management team (e.g., Gulati and Westphal, 1999) by showing that VCs can function as credible intermediaries who reduce information asymmetries between prospective partners. Since VCs invest in new ventures and intensively monitor them and have access to private information about new ventures' resources that is difficult to observe for outsiders (e.g., Gompers and Lerner, 2001), our theory about the information intermediary role of VCs suggests that this role is particularly valuable for new ventures that face severe information asymmetry about alliance partners' technological resources. By emphasizing that VC intermediation can reduce adverse selection risks in R&D partner selection, our study therefore complements previous research by suggesting that the role of information intermediaries in interorganizational relationships can be approached from multiple theoretical perspectives. For example, Sleptsov, Anand, and Vasudeva (2013) examine relationships between acquiring firms and investment banks to understand how relational configurations can enhance intermediaries' willingness and ability to provide information. Given our focus on high-tech, privately-held startups and the information asymmetries that surround such firms' technological resources in particular, we emphasize the value of common VCs in mitigating hazards due to information asymmetries in prospective R&D collaborations. These intermediaries appear to matter most at the earliest stages of technology development and in cases where a potential exchange partner lacks familiarity with the firm's technological resources and their commercial prospects. Since informational considerations broadly have a bearing on firms' partner selection decisions, future research could also examine other types of interorganizational ties (e.g., corporate venture capital vs. independent VCs) and relationships (e.g., employee mobility) through which prospective partners can learn about each other's resources and reduce adverse selection risks in alliance partner selection (e.g., Rosenkopf and Almeida, 2003; Alvarez-Garrido and Dushnitsky, 2016). The degree to which these alternative channels substitute or complement each other in facilitating economic exchanges such as R&D alliances would also be valuable to investigate. We would encourage research that adopts other theoretical perspectives (e.g., the relational view, resource-based view, etc.) that would facilitate research on the ways in which third-parties such as VCs can help firms build valuable relationships and access resources lying outside firms' boundaries.

Finally, by showing how information economics contributes to understanding of partner selection for R&D alliances, we also complement other streams of alliance research that have used this perspective to investigate structural aspects of interfirm collaboration. Specifically, previous empirical research has focused upon the deals that have been formed and emphasizes how firms make entry mode, governance, or alliance design decisions for these transactions based on the adverse selection risks or other exchange hazards that firms confront (e.g., Balakrishnan and Koza, 1993; Chi, 1994; Vanhaverberke, Duysters, and Noorderhaven, 2002;

Villalonga and McGahan, 2004; Cuypers and Martin, 2010). By employing a dyadic perspective to investigate which firms engage in partnerships with whom and by accommodating non-realized alliances in our research design, we allow for the possibility that firms contend with adverse selection prior to alliance contracting and implementing any *ex post* governance mechanisms. As a consequence, we would suggest that information economics holds the potential to begin to integrate research on partner selection and alliance governance, and we would encourage future studies along these lines. As a specific example, it would be value for future research to examine how partner selection and VC information intermediation also have a bearing upon the design of collaborations and the monitoring mechanisms firms employ during alliance execution.

Limitations and Future Research Directions

In addition to the research opportunities already noted, extensions might also pursue additional research opportunities presented by some of the specific limitations of this study. Given our interest in partner selection for R&D collaborations and the information intermediary role of VCs, we focused our analysis on R&D collaborations between VC-backed biotechnology firms. It would therefore be valuable in future research to examine other types of exchanges that occur between firms within VCs' portfolios (e.g., buyer-supplier relationships, partnerships for other value chain activities, acquisitions, etc.) to investigate other potential ways that VCs can add value to their portfolio companies. Such research would also be valuable in order to explore the generalizability of our findings to other industrial settings. Similarly, since we have focused on firms situated in the US, it would be worthwhile to examine partner selection in international contexts in which information asymmetries might be higher between firms.

In order to examine how R&D markets for alliance partners become segmented based on informational considerations, we have used a set of realized partnerships and synthetic non-deals based several characteristics of firms and partnerships (e.g., therapeutic areas, geographic location, etc.). This research design accommodates non-realized alliances as counterfactuals rather than sampling only upon completed transactions, and similar matching techniques are often used in prior research on alliances and other market transactions (e.g., Stuart, 1998; Garmaise and Moskowitz, 2004; Rothaermel and Boeker, 2008). However, a limitation of this empirical design lies in not knowing the actual search processes of firms regarding the R&D partners considered, the information sources employed, and the selection among partners as negotiations commence. For instance, primary data acquired through field surveys or longitudinal case studies can be used to verify the extent to which entrepreneurial firms rely on their VCs to overcome challenges related to the selection of potential alliance partners. More broadly, such research could also enrich our understanding of how firms locate potential partners, the criteria they employ (including those from different theoretical perspectives besides the one we have emphasized), and how they use various advisers (e.g., consultants, attorneys, financial advisers, brokers, etc.) during these processes. This research could examine the role of third-party intermediaries other than the venture capitalists that have been the focus of our study. This research could investigate whether information asymmetries or other theoretical considerations potentially explain the value that such third-parties bring to organizations carrying out alliances or other economic exchanges.

While our study has focused upon how VC information intermediation might address adverse selection for entrepreneurial firms in the formation of R&D collaborations, our study is silent upon the performance implications for collaborators. While our analysis adopts an efficiency perspective in deriving hypotheses upon who partners with whom, in future research it would be valuable to investigate whether the information intermediary role of VC affiliations actually relieves inefficiencies that firms encounter during partner selection and in fact enhances the performance of R&D partnerships. Such research could investigate the degree to which partners experience performance penalties (e.g., lack of survival, execution problems, etc.) when they do not have a common VC or how they stand to benefit from the information intermediation function of common VCs. Research along these lines on the information advantages of VCs might investigate the new technologies, products, or commercialization successes that result from collaborations fostered by venture capitalists.

REFERENCES

Aboody, D., & Lev, B. 2000. Information asymmetry, R&D, and insider gains. ***Journal of Finance***, 55(6): 2747–2766.

Adegbesan, J. A., & Higgins, M. J. 2010. The intra-alliance division of value created through collaboration. ***Strategic Management Journal,*** 32(2): 187-211.

Admati, A. R., & Pfleiderer, P. 1994. Robust financial contracting and the role of venture capitalists. ***The Journal of Finance***, 49(2): 371–402.

Ahuja, G. 2000. The duality of collaboration: inducements and opportunities in the formation of interfirm linkages. ***Strategic Management Journal***, 21(3): 317–343.

Akerlof, G. A. 1970. The market for lemons: Quality uncertainty and the market mechanism. ***Quarterly Journal of Economics,*** 84(3): 488-500.

Almeida, P., Song, J., & Grant, R. M. 2002. Are firms superior to alliances and markets? An empirical test of cross-border knowledge building. ***Organization Science***, 13(2): 147-161.

Alvarez-Garrido, E., & Dushnitsky, G. 2016. Are entrepreneurial venture's innovation rates sensitive to investor complementary assets? Comparing biotech ventures backed by corporate and independent VCs. ***Strategic Management Journal***, 37(5): 819-834.

Amit, R., Brander, J., & Zott, C. 1998. Why do venture capital firms exist? Theory and Canadian evidence. ***Journal of Business Venturing,*** 13(6): 441-466.

Anand, J., Oriani, R., & Vassolo, R. S. 2010. Alliance activity as a dynamic capability in the face of a discontinuous technological change. ***Organization Science,*** 21(6): 1213-1232.

Aoki, M. 2000. ***Information, corporate governance, and institutional diversity: Competitiveness in Japan, the USA, and the transitional economies***. Oxford, UK: Oxford University Press.

Arrow, K. J. 1962. Economic welfare and the allocation of resources for invention. ***The rate and direction of inventive activity: Economic and social factors***: pp. 609 – 626. New Jersey: Princeton University Press.

Arthurs, J. D., & Busenitz, L. W. 2006. Dynamic capabilities and venture performance: The effects of venture capitalists. ***Journal of Business Venturing,*** 21(2): 195-215.

Baker, M., & Gompers, P. A. 2003. The determinants of board structure at the initial public offering. ***Journal of Law and Economics***, 46(2): 569–598.

Balakrishnan, S., & Koza, M. P. 1993. Information asymmetry, adverse selection and joint-ventures: Theory and evidence. ***Journal of Economic Behavior and Organization,*** 20(1): 99-117.

Beamish, P. W., & Lupton, N. C. 2009. Managing joint ventures. ***Academy of Management Perspectives***, 23(2): 75-94.

Bonacich, P. 1987. Power and centrality: A family of measures. ***American Journal of Sociology,*** 92(5): 1170-1182.

Busenitz, L. W., Fiet, J. O., & Moesel, D. D. 2004. Reconsidering the venture capitalists' “value added” proposition: An interorganizational learning perspective. ***Journal of Business Venturing,*** 19(6): 787-807.

Chang, S. J. 2004.Venture capital financing, strategic alliances, and the initial public offerings of internet startups. ***Journal of Business Venturing,*** 19(5): 721-741.

Chi, T. 1994. Trading in strategic resources: Necessary conditions, transaction cost problems, and choice of exchange structure. ***Strategic Management Journal,*** 15(4): 271-290.

Chung, S., Singh, H., & Lee, K. 2000. Complementarity, status similarity and social capital as drivers of alliance formation. ***Strategic Management Journal***, 21(1): 1–22.

Cohen, W. M., & Levinthal, D. A. 1990. Absorptive capacity: A new perspective on learning and innovation. ***Administrative Science Quarterly,*** 35(1): 128-152.

Colombo, M. G. 2003. Alliance form: A test of the contractual and competence perspectives. ***Strategic Management Journal,*** 24(12): 1209-1229.

Cuypers, I. R., & Martin, X. 2009. What makes and what does not make a real option? A study of equity shares in international joint ventures. ***Journal of International Business Studies,*** 41(1): 47-69.

Deeds, D. L., & Hill, C. W. L. 1996. Strategic alliances and the rate of new product development: An empirical study of entrepreneurial biotechnology firms. ***Journal of Business Venturing,*** 11(1): 41-55.

Dekker, H. C., & Abbeele, A. V. den. 2010. Organizational learning and interfirm control: The effects of partner search and prior exchange experiences. ***Organization Science***, 21(6): 1233–1250.

Diestre, L., & Rajagopalan, N. 2012. Are all ‘sharks’ dangerous? New biotechnology ventures and partner selection in R&D alliances. ***Strategic Management Journal,*** 33(10): 1115-1134.

Dushnitsky, G., & Lenox, M. J. 2005. When do incumbents learn from entrepreneurial ventures? Corporate venture capital and investing firm innovation rates. ***Research Policy,*** 34(5): 615-639.

Dushnitsky, G., & Shaver, J. M. 2009. Limitations to interorganizational knowledge acquisition: The paradox of corporate venture capital. ***Strategic Management Journal***, 30(10): 1045–1064.

Eisenhardt, K. M., & Schoonhoven, C. B. 1996. Resource-based view of strategic alliance formation: Strategic and social effects in entrepreneurial ventures. ***Organization Science,*** 7(2): 136-150.

Gans, J. S., Hsu, D. H., & Stern, S. 2002. When does start-up innovation spur the gale of creative destruction? ***The RAND Journal of Economics***, 33(4): 571–586.

Gans, J. S., & Stern, S. 2003. The product market and the market for “ideas”: commercialization strategies for technology entrepreneurs. ***Research Policy***, 32(2): 333–350.

Garmaise, M. J., & Moskowitz, T. J. 2004. Confronting information asymmetries: Evidence from real estate markets. ***Review of Financial Studies***, 17(2): 405-437.

Geertz, C. 1978. The bazaar economy: Information and search in peasant marketing. ***American Economic Review***, 68(2): 28–32.

Geringer, J. M. 1991. Strategic determinants of partner selection criteria in international joint ventures. ***Journal of International Business Studies***, 22(1): 41–62.

Gilsing, V., Nooteboom, B., Vanhaverbeke, W., & van den Oord, A. 2008. Network embeddedness and the exploration of novel technologies: Technological distance, betweenness centrality and density. ***Research Policy,*** 37(10): 1717-1731.

Gomes-Casseres, B., Hagedoorn, J., & Jaffe, A. B. 2006. Do alliances promote knowledge flows? ***Journal of Financial Economics,*** 80(1): 5-33.

Gompers, P. 1995. Optimal investment, monitoring, and the staging of venture capital. ***Journal of Finance,*** 50(5): 1461-1489.

Gompers, P., & Lerner, J. 2001. The venture capital revolution. ***Journal of Economic Perspectives,*** 15(2): 145-168.

Gompers, P., & Lerner, J. 2004. ***The venture capital cycle.*** Cambridge, MA: MIT Press.

Gulati, R. 1995a. Does familiarity breed trust? The implications of repeated ties for contractual choice in alliances. ***Academy of Management Journal,*** 38(1): 85-112.

Gulati, R. 1995b. Social structure and alliance formation patterns: A longitudinal analysis. ***Administrative Science Quarterly***, 40(4): 619–652.

Gulati, R. 1999. Network location and learning: The influence of network resources and firm capabilities on alliance formation. ***Strategic Management Journal***, 20(5): 397–420.

Gulati, R., & Garguilo, M. 1999. Where do interorganizational networks come from? ***American Journal of Sociology,*** 104(5): 1439-1493.

Gulati, R., & Higgins, M. C. 2003. Which ties matter when? The contingent effects of interorganizational partnerships on IPO success. ***Strategic Management Journal,*** 24(2): 127-144.

Gulati, R., & Westphal, J. D. 1999. Cooperative or controlling? The effects of CEO-board relations and the content of interlocks on the formation of joint ventures. ***Administrative Science Quarterly***, 44(3): 473–506.

Hagedoorn, J. 2002. Inter-firm R&D partnerships: An overview of major trends and patterns since 1960. ***Research Policy,*** 31(4): 477-492.

Hagedoorn, J., Lorenz-Orlean, S., & van Kranenburg, H. 2009. Inter-firm technology transfer: Partnership-embedded licensing or standard licensing agreements? ***Industrial and Corporate Change***, 18(3), 529–550.

Hall, B. H., Jaffe, A., & Trajtenberg, M. 2005. Market value and patent citations. ***RAND Journal of Economics***, 36(1): 16–38.

Hayashi, F. 2000. ***Econometrics***. New Jersey: Princeton University Press.

Hellmann, T., & Puri, M. 2002. Venture capital and the professionalization of start-up firms: Empirical evidence. ***Journal of Finance***, 57(1): 169–197.

Higgins, M. J., & Rodriguez, D. 2006. The outsourcing of R&D through acquisitions in the pharmaceutical industry. ***Journal of Financial Economics***, 80(2): 351–383.

Hitt, M. A., Ahlstrom, D., Dacin, M. T., Levitas, E., & Svobodina, L. 2004. The institutional effects on strategic alliance partner selection in transition economies: China vs. Russia. ***Organization Science,*** 15(2): 173-185.

Hoang, H., & Rothaermel, F. T. 2005. The effect of general and partner-specific alliance experience on joint R&D project performance. ***Academy of Management Journal,*** 48(2): 332-345.

Hochberg, Y. V., Ljungqvist, A., & Lu, Y. 2007. Whom you know matters: Venture capital networks and investment performance. ***Journal of Finance,*** 62(1): 251-301.

Hoetker, G. 2007. The use of logit and probit models in strategic management research: Critical issues. ***Strategic Management Journal***, 28(4): 331-343.

Hsu, D. H. 2006. Venture capitalists and cooperative start-up commercialization strategy. ***Management Science,*** 52(2): 204-219.

Jackson III, W. E., Bates, T., & Bradford, W. D. 2012. Does venture capitalist activism improve investment performance? ***Journal of Business Venturing,*** 27(3): 343-354.

Jaffe, A. B. 1986. Technological opportunity and spillovers of R&D: Evidence from firms' patents, profits, and market value. ***American Economic Review***, *76*(5), 984–1001.

Jaffe, A. B. 1989. Real effects of academic research. ***American Economic Review***, 79(5): 957–970.

Jaffe, A. B., Trachtenberg, M., & Henderson, R. 1993. Geographic localization of knowledge spillovers as evidenced by patent citations. ***Quarterly Journal of Economics,*** 108(3): 577-598.

Kaplan, S. N., & Stromberg, P. 2003. Financial contracting theory meets the real world: An empirical analysis of venture capital contracts. ***Review of Economic Studies,*** 70(2): 281-315.

King, G., & Zheng, L. 2001. Logistic regression in rare events data. ***Society for Political Methodology,*** 12(54): 137-163.

Kossinets, G., & Watts, D. 2009. Origins of homophily in an evolving social network. ***American Journal of Sociology***, 115(2): 405-450.

Lavie, D., & Rosenkopf, L. 2006. Balancing exploration and exploitation in alliance formation. ***The Academy of Management Journal***, 49(4): 797–818.

Lerner, J. 1995. Venture capitalists and the oversight of private firms. ***Journal of Finance,*** 50(1): 301-318.

Lerner, J., & Merges, R. P. 1998. The control of technology alliances: An empirical analysis of the biotechnology industry. ***Journal of Industrial Economics,*** 46(2): 125-156.

Levitas, E., & McFayden, M. A. 2009. Managing liquidity in research-intensive firms: signaling and cash flow effects of patents and alliance activities. ***Strategic Management Journal,*** 30(6): 659-678.

Li, D., Eden, L., Hitt, M. A., & Ireland, R. D. 2008. Friends, acquaintances, or strangers? Partner selection in R&D alliances. ***Academy of Management Journal,*** 51(2): 315-334.

Lindsey, L. 2008. Blurring firm boundaries: The role of venture capital in strategic alliances. ***Journal of Finance,*** 63(3): 1137-1168.

Luo, Y. 1997. Partner selection and venturing success: The case of joint ventures with firms in the People's Republic of China. ***Organization Science,*** 8(6): 648-662.

Milgrom, P., & Stokey, N. 1982. Information, trade and common knowledge. ***Journal of Economic Theory***, 26(1): 17-27.

Mitsuhashi, H., & Greve, H. R. 2009. A matching theory of alliance formation and organizational success: Complementarity and compatibility. ***Academy of Management Journal***, 52(5): 975–995.

Mowery, D. C., Oxley, J. E., & Silverman, B. S. 1996. Strategic alliances and interfirm knowledge transfer. ***Strategic Management Journal,*** 17: 77-91.

Mowery, D. C., Oxley, J. E., & Silverman, B. S. 1998. Technological overlap and interfirm cooperation: implications for the resource-based view of the firm. ***Research Policy***, 27(5): 507–523.

Nicholson, S., Danzon, P. M., & McCullough, J. 2005. Biotech-pharma alliances as a signal of asset and firm quality. ***Journal of Business***, 78(4): 1433–1464.

Oxley, J. E. 1997. Appropriability hazards and governance in strategic alliances: A transaction cost approach. ***Journal of Law, Economics, & Organization,*** 13(2): 387-409.

Ozmel, U., Reuer, J. J., & Gulati, R. 2013. Signals across multiple networks: How venture capital and alliance networks affect interorganizational collaboration. ***Academy of Management Journal,*** 56(3): 852-866.

Pisano, G. P. 1990. The R&D boundaries of the firm: An empirical analysis. ***Administrative Science Quarterly,*** 35(1): 153-176.

Powell, W. W., Koput, K. W., & Smith-Doerr, L. 1996. Interorganizational collaboration and the locus of innovation: Networks of learning in biotechnology. ***Administrative Science Quarterly***, 41(1): 116–145.

Ragozzino, R., & Reuer, J. J. 2007. Initial public offerings and the acquisition of entrepreneurial firms. ***Strategic Organization***, 5: 155-176.

Rangan, S. 2000. The problem of search and deliberation in economic action: When social networks really matter. ***Academy of Management Review***, 25(4): 813–828.

Reuer, J. J., & Ragozzino, R. 2012. The choice between joint ventures and acquisitions: Insights from signaling theory. ***Organization Science***, 23: 1175-1190.

Reuer, J. J., & Ragozzino, R. 2014. Signals and international alliance formation: The roles of affiliations and international activities. ***Journal of International Business Studies***, 45: 321-337.

Reuer, J. J., Tong, W., & Wu, C.-W. 2012. A signaling theory of acquisition premiums: Evidence from IPO targets. ***Academy of Management Journal***, 55: 667-683.

Ring, P. S., Doz, Y. L., & Olk, P. M. 2005. Managing formation processes in R&D consortia. ***California Management Review,*** 47(4): 137-156.

Robinson, D. T., & Stuart, T. E. 2007. Financial contracting in biotech strategic alliances. ***Journal of Law and Economics***, 50(3): 559–596.

Roijakkers, N., & Hagedoorn, J. 2006. Inter-firm R&D partnering in pharmaceutical biotechnology since 1975: Trends, patterns, and networks. ***Research Policy,*** 35(3): 431-446.

Rosenkopf, L., & Almeida, P. 2003. Overcoming local search through alliances and mobility. ***Management Science***, 49(6): 751–766.

Rosenkopf, L. & Nerkar, A. 2001. Beyond local search: Boundary-spanning, exploration, and impact in the optical disk industry. ***Strategic Management Journal***, 22(4): 287-306.

Rothaermel, F. T., & Deeds, D. L. 2004. Exploration and exploitation alliances in biotechnology: A system of new product development. ***Strategic Management Journal,*** 25(3): 201-221.

Rothaermel, F. T., & Boeker, W. 2008. Old technology meets new technology: Complementarities, similarities, and alliance formation. ***Strategic Management Journal,*** 29(1): 47-77.

Ruhnka, J. C., Feldman, H. D., & Dean, T. J. 1992. The “living dead” phenomenon in venture capital investments. ***Journal of Business Venturing,*** 7(2): 137-155.

Sahlman, W. A. 1990. The structure and governance of venture-capital organizations. ***Journal of Financial Economics***, 27(2): 473–521.

Sampson, R. C. 2007. R&D alliances and firm performance: The impact of technological diversity and alliance organization on innovation. ***Academy of Management Journal***, 50(2): 364–386.

Sapienza, H. 1992. When do venture capitalists add value? ***Journal of Business Venturing***, 7(1): 9-27.

Schilling, M. A. 2009. Understanding the alliance data. ***Strategic Management Journal,*** 30(3): 233-260.

Shah, R. H., & Swaminathan, V. 2008. Factors influencing partner selection in strategic alliances: The moderating role of alliance context. ***Strategic Management Journal,*** 29(5): 471-494.

Shan, W. 1990. An empirical analysis of organizational strategies by entrepreneurial high-technology firms. ***Strategic Management Journal***, 11(2): 129–139.

Shane, S., & Stuart, T. 2002. Organizational endowments and the performance of university start-ups. ***Management Science***, 48(1): 154–170.

Sleptsov, A., Anand, J., & Vasudeva, G. 2013. Relational configurations with information intermediaries: The effect of firm-investment bank ties on expected acquisition performance. ***Strategic Management Journal***, 34(8): 957-977.

Sorenson, O., & Stuart, T. E. 2001. Syndication networks and the spatial distribution of venture capital investments. ***American Journal of Sociology,*** 106(6): 1546-1588.

Stinchcombe, A. L. 1965. Social structure of organizations. In J.G. March (Ed.), ***Handbook of Organizations***: 142–93. Chicago: Rand McNally.

Stuart, T. E. 1998. Network positions and propensities to collaborate: An investigation of strategic alliance formation in a high-technology industry. ***Administrative Science Quarterly,*** 43(3): 668-698

Stuart, T. E., Hoang, H., & Hybels, R. C. 1999. Interorganizational Endorsements and the Performance of Entrepreneurial Ventures. ***Administrative Science Quarterly***, 44(2): 315–349.

Stuart, T. E. 2000. Interorganizational alliances and the performance of firms: A study of growth and innovation rates in a high-technology industry. ***Strategic Management Journal***, 21(8): 791–811.

Tallman, S. B., & Phene, A. 2007. Leveraging knowledge across geographic boundaries. ***Organization Science,*** 18(2): 252-260.

Tallman, S. B., & Shenkar, O. 1994. A managerial decision model of international cooperative venture formation. ***Journal of International Business Studies***, 25(1): 91–113.

Teece, D. J. 1986. Profiting from technological innovation: Implications for integration, collaboration, licensing and public policy. ***Research Policy***, 15(6): 285–305.

Teece, D. J. 1996. Firm organization, industrial structure, and technological innovation. ***Journal of Economic Behavior & Organization***, 31(2): 193–224.

Vanhaverbeke, W., Duysters, G., & Noorderhaven, N. 2002. External technology sourcing through alliances or acquisitions: An analysis of the application-specific integrated circuits industry. ***Organization Science,*** 13(6): 714-733.

Vanneste, B. S., & Puranam, P. 2010. Repeated interactions and contractual detail: Identifying the learning effect. ***Organization Science***, 21(1): 186–201.

Vassolo, R., Anand, J., & Folta, T. 2004. Non-additivity in portfolios of exploration activities: A real options-based analysis of equity alliances in biotechnology. ***Strategic Management Journal***, 25(11): 1045-1061.

Villalonga, B., & McGahan, A. M. 2004. The choice among acquisitions, alliances, and divestitures. ***Strategic Management Journal,*** 26(13): 1183-1208.

Wooldridge, J. M. 2002. ***Econometric analysis of cross section and panel data***. Boston, MA: The MIT Press.

Zaheer, A., Hernandez, E., & Banerjee, S. 2010. Prior alliances with targets and acquisition performance in knowledge-intensive industries. ***Organization Science***, 21(5): 1072–1091.

Table 1: Descriptive Statistics[a]

	Variables	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**
1	R&D Alliance Formation	1.00																						
2	Common VC	**0.01**	1.00																					
3	Technology Relatedness	**0.02**	**0.04**	1.00																				
4	Cross Citations	**0.02**	0.00	**0.07**	1.00																			
5	Partner Specific Experience	**0.05**	0.00	**0.03**	**0.02**	1.00																		
6	Firm Product Development	0.00	**-0.03**	**0.06**	**0.02**	**0.03**	1.00																	
7	Partner Product Development	**0.01**	0.00	**0.03**	0.00	**0.01**	**-0.01**	1.00																
8	Distance	**-0.01**	**-0.05**	**-0.02**	0.00	0.00	**-0.02**	**-0.01**	1.00															
9	Firm VC Prominence	0.00	**0.01**	**0.01**	0.00	0.00	**0.24**	0.00	**0.01**	1.00														
10	Partner VC Prominence	0.00	**0.01**	**0.01**	0.00	**0.01**	0.00	**0.01**	**0.02**	**0.01**	1.00													
11	Firm VC Funding	0.00	**0.07**	**0.07**	**0.01**	**-0.01**	**0.08**	0.00	**0.02**	**0.11**	0.00	1.00												
12	Partner VC Funding	0.00	**0.10**	**0.09**	**0.02**	**0.02**	**0.02**	**0.05**	0.00	**0.02**	**0.05**	0.00	1.00											
13	Dyad VC Investment Stage	0.00	**0.03**	**-0.06**	**-0.02**	**-0.01**	**-0.03**	**-0.01**	**-0.01**	**-0.01**	0.00	**-0.05**	**-0.19**	1.00										
14	Firm VC Bioinvestment Experience	0.00	**0.14**	**0.05**	0.00	**-0.01**	**0.12**	0.00	**-0.01**	**0.11**	**0.01**	**0.54**	**0.01**	**-0.02**	1.00									
15	Partner VC Bioinvestment Experience	0.01	**0.16**	**0.06**	0.00	-0.01	**0.01**	**0.06**	**-0.04**	**0.01**	**0.02**	0.00	**0.59**	**-0.09**	0.00	1.00								
16	Firm Citations	0.00	**-0.05**	**-0.03**	**0.03**	**0.01**	**0.25**	0.00	0.00	**0.16**	0.00	**0.05**	0.00	**-0.07**	**-0.08**	0.00	1.00							
17	Partner Citations	0.00	**-0.04**	**-0.14**	**0.02**	**-0.01**	0.00	**0.03**	**0.01**	0.00	**0.02**	0.00	**0.02**	**-0.07**	0.00	**-0.01**	0.00	1.00						
18	Firm Alliance Experience	0.00	**-0.02**	**0.13**	**0.03**	**0.05**	**0.25**	**0.01**	**-0.01**	**-0.08**	**-0.02**	**0.09**	**-0.04**	**-0.12**	**-0.06**	**-0.02**	**0.26**	**-0.01**	1.00					
19	Partner Alliance Experience	**0.03**	**0.03**	**0.13**	**0.05**	**0.05**	0.00	**0.11**	**-0.01**	**0.01**	**0.03**	0.00	**0.27**	**-0.10**	**0.01**	**0.13**	0.00	0.00	**-0.02**	1.00				
20	Firm Exploitative Experience	0.00	**-0.02**	**0.01**	0.00	0.00	**-0.03**	0.00	**-0.01**	**0.10**	0.00	**-0.06**	0.00	**-0.01**	**-0.13**	0.00	**0.12**	0.00	**0.06**	0.00	1.00			
21	Partner Exploitative Experience	**-0.01**	**-0.01**	**0.04**	**0.03**	**0.01**	0.00	**0.16**	**-0.01**	0.00	**0.04**	0.00	**0.11**	**-0.07**	0.00	**0.05**	0.00	**0.15**	0.00	**0.46**	0.00	1.00		
22	Firm Age	0.00	**-0.04**	**0.11**	**0.03**	**0.03**	**0.22**	0.00	0.00	0.00	0.00	0.00	0.00	**-0.14**	**-0.12**	0.00	**0.34**	0.00	**0.59**	0.00	**0.16**	0.00	1.00	
23	Partner Age	0.00	**-0.03**	**0.05**	**0.02**	0.00	**0.02**	**0.04**	**0.02**	**0.02**	0.00	**0.01**	**0.21**	**-0.19**	**0.03**	**-0.04**	**-0.01**	**0.31**	**-0.06**	**0.26**	0.00	**0.22**	0.00	1.00
	Mean	0.00	0.04	0.07	0.00	0.00	0.19	0.04	6.48	0.21	0.21	0.29	0.11	0.44	3.21	2.93	0.15	0.11	1.58	0.72	0.03	0.11	7.82	7.71
	S.D.	0.03	0.19	0.22	0.05	0.05	1.12	0.46	1.72	0.40	0.46	0.75	0.97	0.50	1.20	1.18	1.08	1.10	1.12	0.76	0.16	0.32	0.85	0.82

[a]N=87562, $p<0.05$ in bold

Table 2: Logistic Regression Estimates for the Likelihood of R&D Alliance Formation[a]

Variables	**1**	**2**
Constant	-5.899*	-6.125*
	(2.538)	(2.562)
Year, Therapeutic, Firm and Partner Industry Subgroup, and Firm and Partner Patent Class Fixed Effects	Incl.	Incl.
Partner Age	-0.487*	-0.460†
	(0.240)	(0.242)
Firm Age	0.089	0.115
	(0.180)	(0.182)
Partner Exploitative Experience	-4.061***	-4.059***
	(1.189)	(1.202)
Firm Exploitative Experience	-1.405*	-1.493*
	(0.677)	(0.686)
Partner Alliance Experience	1.258***	1.256***
	(0.184)	(0.185)
Firm Alliance Experience	0.013	0.003
	(0.115)	(0.116)
Partner Citations	0.245†	0.260†
	(0.134)	(0.135)
Firm Citations	0.009	0.021
	(0.108)	(0.109)
Partner VC Bioinvestment Experience	0.093	0.043
	(0.134)	(0.132)
Firm VC Bioinvestment Experience	0.051	0.007
	(0.125)	(0.128)
Dyad VC Investment Stage	-0.400	-0.390
	(0.258)	(0.258)
Partner VC Funding	-0.385*	-0.399**
	(0.152)	(0.153)
Firm VC Funding	-0.157	-0.187
	(0.147)	(0.150)
Partner VC Prominence	0.308	0.302
	(0.237)	(0.238)
Firm VC Prominence	0.401*	0.381*
	(0.182)	(0.186)
Distance	-0.123*	-0.116*
	(0.052)	(0.051)
Partner Product Development	0.336***	0.340***
	(0.078)	(0.079)
Firm Product Development	0.039	0.053
	(0.068)	(0.068)
Partner Specific Experience	1.575***	1.630***
	(0.395)	(0.413)
Cross Citations	1.667***	1.698***
	(0.347)	(0.348)
Technology Relatedness	0.860*	0.844*
	(0.417)	(0.420)
Common VC		1.145***
		(0.342)
Log likelihood	-505.78	-502.03
χ^2	707.32***	746.65***

[a]N=87562. Clustered robust standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05, † p<0.10.

Table 3: Estimates for Interaction Effects[a]

Variables	1	2	3	4	5	6
Constant	-6.200*	-6.126*	-6.186*	-6.128*	-6.068*	-6.161*
	(2.567)	(2.560)	(2.565)	(2.561)	(2.577)	(2.580)
Year, Therapeutic, Firm and Partner Industry Subgroup, and Firm and Partner Patent Class Fixed Effects	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.
Partner Age	-0.451†	-0.462†	-0.459†	-0.459†	-0.455†	-0.450†
	(0.243)	(0.242)	(0.243)	(0.242)	(0.242)	(0.245)
Firm Age	0.114	0.117	0.120	0.115	0.110	0.116
	(0.182)	(0.182)	(0.182)	(0.182)	(0.182)	(0.182)
Partner Exploitative Experience	-4.076***	-4.060***	-4.060***	-4.054***	-4.063***	-4.075***
	(1.193)	(1.203)	(1.204)	(1.202)	(1.206)	(1.199)
Firm Exploitative Experience	-1.487*	-1.495*	-1.489*	-1.489*	-1.484*	-1.470*
	(0.684)	(0.685)	(0.687)	(0.685)	(0.680)	(0.679)
Partner Alliance Experience	1.260***	1.258***	1.258***	1.256***	1.253***	1.255***
	(0.185)	(0.185)	(0.185)	(0.185)	(0.184)	(0.184)
Firm Alliance Experience	0.012	-0.001	0.006	0.003	-0.004	0.003
	(0.117)	(0.116)	(0.116)	(0.116)	(0.114)	(0.116)
Partner Citations	0.257†	0.261†	0.258†	0.259†	0.262†	0.259†
	(0.135)	(0.135)	(0.135)	(0.135)	(0.136)	(0.137)
Firm Citations	0.023	0.020	0.021	0.021	0.026	0.027
	(0.110)	(0.109)	(0.110)	(0.109)	(0.109)	(0.109)
Partner VC Bioinvestment Experience	0.046	0.044	0.044	0.043	0.036	0.037
	(0.132)	(0.132)	(0.132)	(0.132)	(0.132)	(0.133)
Firm VC Bioinvestment Experience	0.007	0.007	0.008	0.007	-0.009	-0.010
	(0.127)	(0.128)	(0.128)	(0.128)	(0.128)	(0.128)
Dyad VC Investment Stage	-0.393	-0.389	-0.389	-0.391	-0.394	-0.392
	(0.257)	(0.258)	(0.259)	(0.258)	(0.257)	(0.258)
Partner VC Funding	-0.401**	-0.399**	-0.401**	-0.398**	-0.401**	-0.404**
	(0.153)	(0.153)	(0.153)	(0.153)	(0.154)	(0.155)
Firm VC Funding	-0.186	-0.187	-0.186	-0.186	-0.174	-0.169
	(0.150)	(0.150)	(0.150)	(0.150)	(0.150)	(0.150)
Partner VC Prominence	0.300	0.301	0.304	0.301	0.288	0.286
	(0.239)	(0.238)	(0.237)	(0.238)	(0.239)	(0.239)
Firm VC Prominence	0.379*	0.374*	0.386*	0.381*	0.372*	0.371*
	(0.184)	(0.185)	(0.186)	(0.186)	(0.187)	(0.185)
Distance	-0.117*	-0.116*	-0.116*	-0.116*	-0.120*	-0.121*
	(0.052)	(0.051)	(0.051)	(0.051)	(0.051)	(0.051)
Partner Product Development	0.361***	0.340***	0.343***	0.340***	0.336***	0.361***
	(0.076)	(0.079)	(0.078)	(0.079)	(0.079)	(0.076)
Firm Product Development	0.057	0.060	0.052	0.053	0.053	0.059
	(0.068)	(0.067)	(0.069)	(0.068)	(0.066)	(0.066)
Partner Specific Experience	1.644***	1.631***	1.669***	1.631***	1.606***	1.656***
	(0.415)	(0.414)	(0.424)	(0.413)	(0.405)	(0.417)
Cross Citations	1.695***	1.698***	1.700***	1.709***	1.667***	1.672***
	(0.348)	(0.348)	(0.348)	(0.351)	(0.348)	(0.348)
Technology Relatedness	0.843*	0.850*	0.835*	0.847*	1.101**	1.099**
	(0.421)	(0.419)	(0.423)	(0.419)	(0.409)	(0.410)
Common VC	1.012**	0.807*	1.130***	0.931**	1.321***	0.558†
	(0.335)	(0.338)	(0.341)	(0.340)	(0.348)	(0.333)
Common VC*Partner Product Development	-2.380***					-2.624***
	(0.182)					(0.185)
Common VC*Firm Product Development		-2.593***				-2.728***
		(0.220)				(0.272)
Common VC*Partner Specific Experience			-0.884***			-1.090***
			(0.078)			(0.097)
Common VC*Cross Citations				-2.232***		-2.165***
				(0.234)		(0.225)
Common VC*Technology Relatedness					-1.554***	-1.512***
					(0.465)	(0.460)
Log likelihood	-501.46	-501.86	-501.68	-501.97	-500.26	-499.33
χ^2	1683.11***	1317.18***	1451.02***	804.53***	783.93***	3612.95***

[a]N=87562. Clustered robust standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05, † p<0.10.

Table 4: Logistic Regression Estimation Results for Matched Sample[a]

Variables	1	2	3	4	5	6	7
Constant	-6.263*	-6.266*	-6.405*	-6.419*	-6.247*	-6.247*	-6.374*
	(2.484)	(2.479)	(2.788)	(2.788)	(2.474)	(2.474)	(2.481)
Year, Therapeutic, Firm and Partner Industry Subgroup, and Firm and Partner Patent Class Fixed Effects	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.
Partner Age	-0.100	-0.097	-0.100	-0.100	-0.099	-0.099	-0.073
	(0.247)	(0.245)	(0.247)	(0.246)	(0.247)	(0.247)	(0.244)
Firm Age	0.378	0.375	0.378	0.379	0.373	0.373	0.369
	(0.262)	(0.262)	(0.262)	(0.262)	(0.261)	(0.261)	(0.261)
Partner Exploitative Experience	-2.714***	-2.737***	-2.714***	-2.668***	-2.673***	-2.673***	-2.617***
	(0.779)	(0.795)	(0.779)	(0.778)	(0.763)	(0.763)	(0.760)
Firm Exploitative Experience	1.638	1.644	1.638	1.633	1.643	1.643	1.678†
	(1.017)	(1.019)	(.017)	(1.012)	(1.013)	(1.013)	(1.007)
Partner Alliance Experience	0.829***	0.819***	0.829***	0.830***	0.830***	0.830***	0.823***
	(0.194)	(0.195)	(0.194)	(0.194)	(0.194)	(0.194)	(0.195)
Firm Alliance Experience	-0.231	-0.224	-0.231	-0.232	-0.231	-0.231	-0.250
	(0.197)	(0.198)	(0.197)	(0.197)	(0.197)	(0.197)	(0.198)
Partner Citations	0.346†	0.345†	0.346†	0.347†	0.346†	0.346†	0.346†
	(0.178)	(0.178)	(0.178)	(0.178)	(0.178)	(0.178)	(0.178)
Firm Citations	-0.021	-0.026	-0.021	-0.021	-0.019	-0.019	-0.016
	(0.178)	(0.179)	(0.178)	(0.178)	(0.177)	(0.177)	(0.177)
Partner VC Bioinvestment Experience	0.009	0.009	0.009	0.010	0.010	0.010	0.016
	(0.143)	(0.143)	(0.143)	(0.143)	(0.143)	(0.143)	(0.143)
Firm VC Bioinvestment Experience	-0.140	-0.138	-0.140	-0.140	-0.140	-0.140	-0.164
	(0.159)	(0.159)	(0.159)	(0.159)	(0.159)	(0.159)	(0.159)
Partner VC Funding	-0.659***	-0.657***	-0.658***	-0.659***	-0.660***	-0.660***	-0.672***
	(0.168)	(0.168)	(0.168)	(0.168)	(0.168)	(0.168)	(0.165)
Firm VC Funding	-0.192	-0.194	-0.191	-0.191	-0.191	-0.191	-0.165
	(0.179)	(0.179)	(0.179)	(0.179)	(0.178)	(0.178)	(0.181)
Dyad VC Investment Stage	-0.543†	-0.536†	-0.543†	-0.544†	-0.543†	-0.543†	-0.541†
	(0.298)	(0.296)	(0.298)	(0.297)	(0.298)	(0.298)	(0.296)
Distance	0.008	0.008	0.008	0.007	0.009	0.009	0.008
	(0.057)	(0.057)	(0.057)	(0.057)	(0.057)	(0.057)	(0.057)
Partner VC Prominence	0.699	0.689	0.699	0.696	0.702	0.702	0.658
	(0.492)	(0.498)	(0.492)	(0.491)	(0.490)	(0.490)	(0.502)
Firm VC Prominence	0.480*	0.483*	0.480*	0.479*	0.480*	0.480*	0.449†
	(0.242)	(0.243)	(0.242)	(0.241)	(0.241)	(0.241)	(0.241)
Partner Product Development	0.700***	0.743***	0.700***	0.698***	0.696***	0.696***	0.717***
	(0.150)	(0.169)	(0.150)	(0.151)	(0.150)	(0.150)	(0.169)
Firm Product Development	0.354***	0.356***	0.354***	0.355***	0.351***	0.351***	0.355***
	(0.091)	(0.092)	(0.091)	(0.092)	(0.091)	(0.091)	(0.092)
Partner Specific Experience	2.625***	2.620***	2.625***	2.639***	2.623***	2.623***	2.611***
	(0.752)	(0.753)	(0.752)	(0.760)	(0.750)	(0.750)	(0.760)
Technology Relatedness	1.009*	1.014*	1.009*	1.008*	1.019*	1.019*	1.283**
	(0.499)	(0.500)	(0.499)	(0.499)	(0.498)	(0.498)	(0.492)
Cross Citations	1.867***	1.870***	1.867***	1.866***	1.886***	1.886***	1.826***
	(0.543)	(0.544)	(0.543)	(0.543)	(0.546)	(0.546)	(0.528)
Common VC	1.113**	0.996*	1.113**	1.071**	0.927*	0.927*	0.873*
	(0.411)	(0.408)	(0.411)	(0.410)	(0.407)	(0.407)	(0.432)
Common VC*Partner Product Development		-1.720***					-1.669***
		(0.193)					(0.224)
Common VC*Firm Product Development			-2.049***				-2.006***
			(0.197)				(0.198)
Common VC*Partner Specific Experience				-0.838***			-0.787***
				(0.122)			(0.126)
Common VC*Cross Citations					-2.002***		-2.085***
					(0.266)		(0.308)
Common VC*Technology Relatedness						-0.986*	-0.944†
						(0.446)	(0.489)
Log likelihood	-279.87	-279.69	-279.75	-279.71	-279.81	-279.77	-278.27
χ^2	724.71***	835.95***	816.36***	901.98***	773.36***	80.5.50***	2777.70***

[a]N=2920. Clustered robust standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05, † p<0.10.

Figure 1: Interaction Effect between Partner Product Development and Common VC

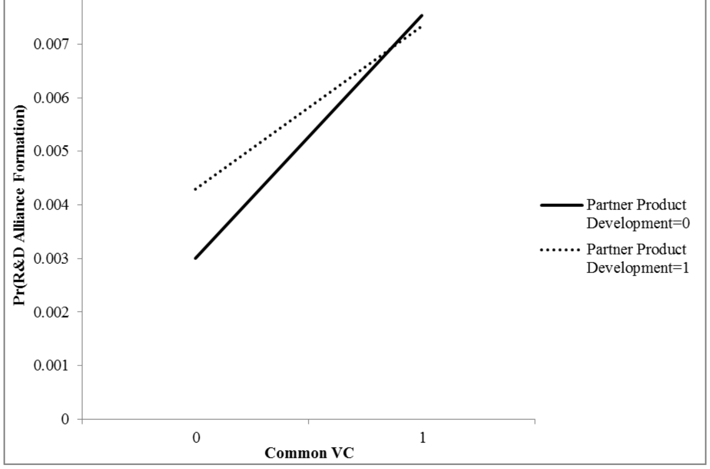

Figure 2: Interaction Effect between Firm Product Development and Common VC

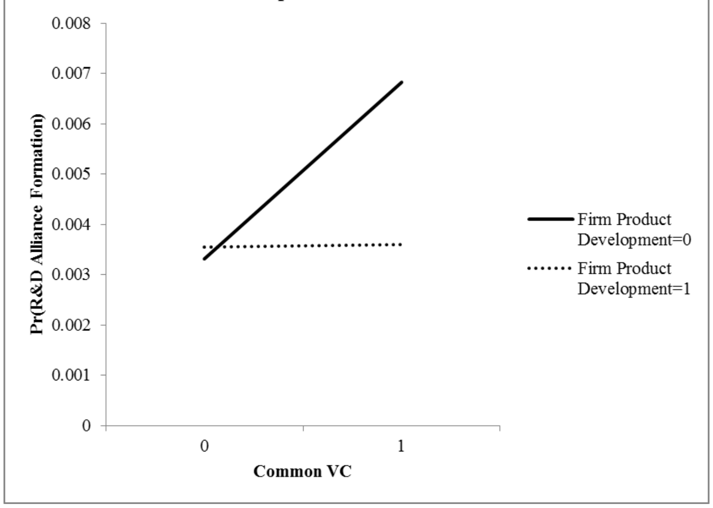

Figure 3: Interaction Effect between Partner Specific Experience and Common VC

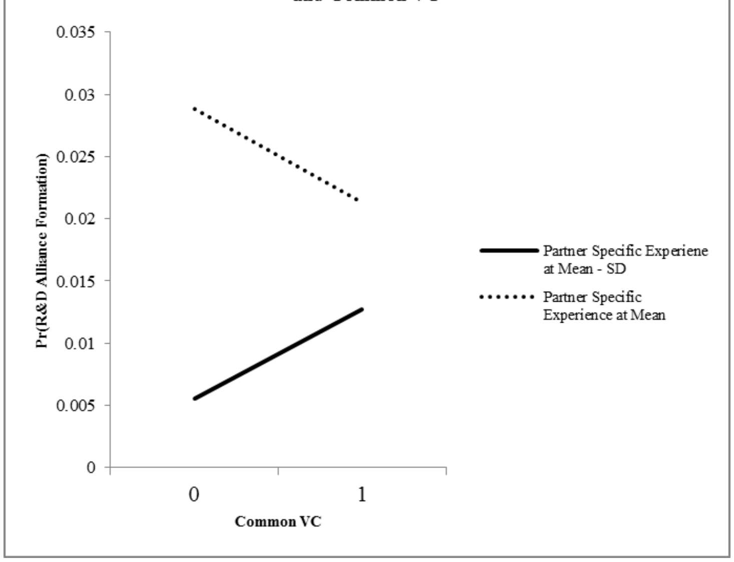

Figure 4: Interaction Effect between Cross Citations and Common VC

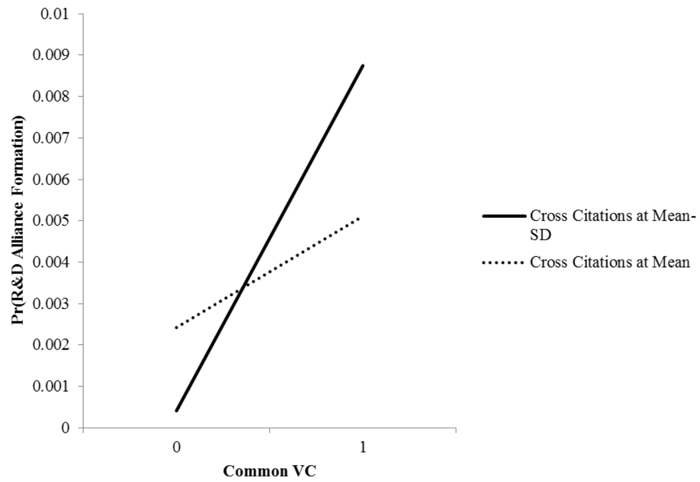

Figure 5: Interaction Effect betweeen Technology Relatedness and Common VC