Title: Product alliances, alliance networks, and shareholder value: Evidence from the biopharmaceutical industry

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Abstract: Despite sustained interest in product alliance activity, little is known regarding the effect of product alliances on shareholder value. Whereas proponents of alliances justify their formation by emphasizing access to relevant resources and know-how, critics highlight the risks inherent in alliance partner opportunism. To reconcile these opposing viewpoints, we develop and test a conceptual framework that predicts the impact of product alliance activity and the broader network it engenders on shareholder value: stock returns, systematic risk, and idiosyncratic risk. Our examination of 359 biopharmaceutical firms and their associated networks over a 20-year observation window, shows that unanticipated product alliance activity is associated with not only lower idiosyncratic risk, but also with lower stock returns. Unanticipated network centrality of the focal firm and the unanticipated density of ties in its extended network significantly moderate the effects of product alliance activity. Our findings help to reconcile the divergent views on product alliance activity.
Product alliances, alliance networks, and shareholder value: Evidence from the biopharmaceutical industry

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ABSTRACT

Despite sustained interest in product alliance activity, little is known regarding the effect of product alliances on shareholder value. Whereas proponents of alliances justify their formation by emphasizing access to relevant resources and know-how, critics highlight the risks inherent in alliance partner opportunism. To reconcile these opposing viewpoints, we develop and test a conceptual framework that predicts the impact of product alliance activity and the broader network it engenders on shareholder value: stock returns, systematic risk, and idiosyncratic risk. Our examination of 359 biopharmaceutical firms and their associated networks over a 20-year observation window, shows that unanticipated product alliance activity is associated with not only lower idiosyncratic risk, but also with lower stock returns. Unanticipated network centrality of the focal firm and the unanticipated density of ties in its extended network significantly moderate the effects of product alliance activity. Our findings help to reconcile the divergent views on product alliance activity.

Keywords: Stock risk, Stock return, Product alliances, Networks, Marketing-finance interface
1. Introduction

Strategic alliances account for as much as one-third of firms’ revenues and value, and are increasing by approximately 25 per cent every year (Wilson & Tuttle, 2008). In particular, product alliances—defined as formalized, non-equity,\(^1\) collaborative arrangements among firms that exchange, share, or co-develop products (Rindfleisch & Moorman, 2001)—are associated with improved firm profits (Luo, Rindfleisch, & Tse, 2007) and favorable innovation outcomes (Wuyts, Stremersch, & Dutta, 2004). A dominant stream of research based on the relational view highlights the benefits of alliances through access to alliance partners’ resources, assets, capabilities, organizational processes, information, and knowledge (Dyer & Singh, 1998; Kalaignanam, Shankar, & Varadarajan, 2007).

In spite of this impressive array of benefits, failure rates for product alliances are high (Sivadas & Dwyer, 2000), as are the risks of partner opportunism and the attendant costs of coordination and monitoring (Park & Ungson, 2001). A review of prior research reveals less enthusiastic evaluations of product alliances. Specifically, agency theory-based arguments highlight information asymmetries, which arise when one firm has more or better information than the other about its motivation and ability to contribute to the alliance (Park & Ungson, 2001; Reuer & Ragozzino, 2006). Such information asymmetries increase the costs of product alliance activity and suggest a far more cautious approach to the phenomenon.

Table 1 provides an overview of empirical research that studies the effects of alliances on shareholder value. Prior research offers useful insights, but is limited by its exclusive focus on the relational viewpoint. Although the agency theory-informed downsides of product alliances

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\(^1\) Equity ownership confers greater control of one firm over another (Kale, Dyer, & Singh, 2002), which alters the relational dynamics and poses varying implications for firm outcomes. An examination of such equity relationships is beyond the scope of this study.
are widely acknowledged, there has been no formal examination of this alternate view. As a result, a definitive conclusion as to whether product alliances actually help or harm continues to elude us. This lack of conclusiveness is likely attributable to two additional limitations of prior assessments of product alliances.

--- Insert Table 1 here ---

A second limitation of prior empirical research on product alliances lies in its incomplete consideration of shareholder value. Firms create value by increasing their stock returns or decreasing their stock risk. Whereas the former refers to cash-flow levels, the latter reflects volatility and vulnerability (Hamilton, 1994). As Kale et al. (2002, p. 747) note, “while alliances can create value, they are also fraught with risk.” Furthermore, all else being equal, investors prefer less volatile stocks (Graham, Harvey, & Rajgopal, 2005). Higher stock risk indicates increased investment risk and greater cost of capital, which damages a firm’s long-term valuation (Hamilton, 1994) and survival prospects (Grinblatt & Titman, 1998). Prior research has focused primarily on the effect of product alliance activity on stock returns, largely ignoring the impact on stock risk. This unbalanced approach hinders a complete understanding of the impact product alliance activity has on shareholder value.

A third key limitation of prior inquiries pertains to the scope of the firms’ alliance activity. In addition to direct ties, firms are embedded within larger networks of ties, “complex, multifaceted organization structures that result from multiple strategic alliances” (Webster, 1992, p. 8). These embedded companies enjoy significant market (Achrol & Kotler, 1999) and informational (Powell, Koput, & Smith-Doerr, 1996) advantages, including improved firm innovation (Ahuja, 2000) and higher returns (Swaminathan & Moorman, 2009). Networks enable firms to learn about emerging opportunities, lower alliance partner search costs, and alleviate the
risks of partner opportunism. Yet, as displayed in Table 1, their impact on firms’ risk-return calculus remains largely unassessed.

The current research seeks to address these deficits, and provide a comprehensive assessment of the impact of product alliance activity (i.e., the degree to which firms engage in product alliances) and the networks they engender on stock returns and stock risks (systematic and idiosyncratic). We also examine the direct and moderating role of the firm’s position (network centrality) and the structure of its embedded relations (network density). Relying on a unique database that we construct from three archival sources, we undertake a rigorous examination of 359 biopharmaceutical firms, as well as the 1,381 product alliances in which they engage over a two-decade observation window and the associated networks that resulted.

We add to the growing body of knowledge about interfirm relationships and shareholder value in three key ways. First, acknowledging the conflicting perspectives of the relational view and agency theory, we develop alternate hypotheses for the effects of product alliance activity. By examining these divergent viewpoints, we acknowledge the possibility that both perspectives may be equally valid, depending on firms’ relative prioritization of increasing stock returns or decreasing stock risk. In doing so, we provide a nuanced understanding of product alliance activity.

Second, we contribute to a better understanding of the effect of product alliance activities on not only stock returns, but also systematic and idiosyncratic risk. Firms that evaluate business performance with a single-minded focus on stock returns, regardless of their volatility, are more likely to invest in risky business opportunities (Markowitz, 1952). Thus, it is important to assess the impact of product alliance activity using CEO-relevant metrics—that is, stock returns and stock risks (systematic and idiosyncratic).
Third, we extend work that focuses on dyadic relationships, recognizing that firms are embedded in a larger web of connections. We build on the information-sharing view widely acknowledged in prior work, which suggests firms benefit from the free flow of information in their network. In doing so, we acknowledge the role of indirect ties in improving shareholder value. To the best of our knowledge, this study is the first to examine the effect of product alliance activities and network characteristics on firms’ stock return and on stock risk. Our examination of the direct and indirect ties pursuant to product alliance activity and their impact on objective measures of firm performance helps to minimize survey data-related concerns (Rindfleisch, Malter, Ganesan, & Moorman, 2008). We are thus able to assess the costs and benefits attendant to interfirm relationships.

In Sections 2 and 3, we describe our conceptual background and develop our hypotheses. Section 4 provides details on the research context, data collection, and analysis approach, while Section 5 presents the results of our examination. In Section 6, we discuss the implications of this research for academics and practicing managers, acknowledge its limitations and describe future research directions.

2. Conceptual background

2.1. Shareholder value

A comprehensive assessment of shareholder value must consider stock returns and stock risks. Whereas stock returns represent the level of future cash flows of the firm, stock risks entail systematic risk and idiosyncratic risk (Markowitz, 1952; Srinivasan & Hanssens, 2009). Systematic or market risk is the “extent to which the stock’s return changes when the overall market changes” (McAlister, Srinivasan, & Kim 2007, p. 35), measured by the stock’s sensitivity to changes in the market. This market-driven risk reacts to changes in broad financial news (e.g.,
unemployment or inflation reports), so it is common to all stocks and cannot be diversified away (Lubatkin & Chatterjee, 1994). By contrast idiosyncratic risk is firm-specific and within managers’ sphere of control and also comprises a significant component of average stock variance (Goyal & Santa-Clara, 2003).

2.2. Product alliance activities and network characteristics

The complexity, cost, and expertise needed to develop innovative products may lie beyond an individual firm’s capabilities (Wind & Mahajan, 1997), and for this reason, firms engage in product alliances through direct ties in order to access external resources. Prior research offers opposing views on the impact of these direct ties. The relational view asserts that a firm’s resources extend beyond its boundaries, and that interfirm relationships provide a source of competitive advantage (Dyer & Singh, 1998). An alternate viewpoint deriving from agency theory contends that tension between alliance partners is inherent because one firm has more or better information than the other (Bergen, Dutta, & Walker, 1992; Jensen & Meckling, 1976).

In forging direct ties with a partner, a firm becomes part of a larger network of indirect ties that consists of its partner’s partners (Swaminathan & Moorman, 2009). Networks constitute complex social relational forms that arise and evolve over time as a result of alliances undertaken by the focal firm and its partners (Achrol & Kotler, 1999; Swaminathan & Moorman, 2009). Fig. 1 contains a stylized example of these indirect connections. Firm B’s alliance with Firm C creates indirect ties with other firms in the network (A, D, E, F, G, and H) that B has not undertaken on its own. In contrast to the explicit resource-sharing mandate of product alliance activity, firms in a network do not formally share resources, such as physical assets or proprietary know-how. Yet, in providing potential routes by which important information may be transmitted, networks constitute a key strategic resource (Gulati, 1999).
Two views describe the role of information in a network. According to the *information-sharing* view, firms in a network benefit from free flows of information (Coleman, 1988). This view emphasizes how firms can access information from network resources and leverage it to their advantage. Accordingly, network characteristics consist of closeness centrality and density, which emphasize resource-sharing. The *information control* view instead emphasizes brokerage opportunities for firms in bridging roles that can serve as gatekeepers of information, such that they benefit from controlling information flows (McEvily & Zaheer, 1999; Provan, Fish, & Sydow, 2007). This perspective is consistent with Burt’s (1992, 1997) work on social capital describing how firms use power and control to manage network resources (Provan et al., 2007). The network characteristics examined in this stream of research include betweenness centrality (i.e., how firms positioned between pairs of otherwise disconnected firms serve as bridging ties in a network) and structural holes (i.e., brokerage opportunities between otherwise independent networks). Whereas the former view prioritizes the free flow of information through networks of ties, the latter emphasizes firms’ efforts to seek control of information in a network. We adopt the former conceptualization of networks, as it is consistent with our emphasis on the flow of information between alliance partners; thus, we focus on *network closeness centrality* and *network density*. This approach is consistent with prior research on alliance performance examining the access to information and resources provided by networks (Swaminathan & Moorman, 2009).

*Network closeness centrality* refers to the distance from the focal firm to all other firms in the network (Gulati, 1999), with more central position increasing the proximity between the focal firm and other members of the network. *Network density* refers to the degree of ties among firms
in the firm’s ego network\(^2\) (Coleman, 1988), with more dense networks facilitating the diffusion of fine-grained information (Uzzi & Lancaster, 2003). It is therefore critical to consider how “commingling of the firm with entities (other firms) in the external environment” might affect stock returns and systematic and idiosyncratic risks (Srivastava, Shervani, & Fahey, 1998, p. 2). In addition to examining the direct effects of network characteristics, we examine how they moderate the relationship between product alliance activity and stock returns and systematic and idiosyncratic risks.

3. **Hypotheses**

3.1. **Product alliance activity and shareholder value**

The relational view of the firm posits that access to resources and know-how from product alliance partners improves product development efforts (Dyer & Singh, 1998). Such benefits may also translate into increased future cash flows or provide stability in cash flows by insulating the firm’s stock from market downturns and reducing firm-specific risk. We believe product alliances increase stock returns and reduce systematic and idiosyncratic risks in three main ways. First, from their alliance partners, firms gain access to complementary resources that were not internally available (Sivadas & Dwyer, 2000). Second, firms gain access to the tacit knowledge and information their alliance partners possess (Rindfleisch & Moorman, 2001). For example, technical expertise gathered from alliance partners reduces the need to abandon efforts that cannot be completed internally. Third, along with product development know-how—which is specific to the alliance—firms internalize certain capabilities and skills of alliance partners that can be used beyond the alliance boundaries (Lee, Johnson, & Grewal, 2008).

\(^2\) The firm’s ego network consists of ties between the focal firm and its alliance partners, as well as any ties among the focal firm’s alliance partners (Soh, 2010).
Resources and know-how acquired through product alliances also can increase the speed of internal capability development, minimize exposure to technological uncertainties, and reduce new-product failure (Lane & Lubatkin, 1998). Srivastava, Shervani, and Fahey (1999) similarly suggest that, all else being equal, increased product alliance activity (1) accelerates cash flows by speeding up product development and reducing time-to-market, (2) enhances cash flows by granting access to technology and decreasing costs associated with product development, and (3) reduces the risk and volatility of cash flows by improving the rate of innovation. Importantly, all of these benefits insulate the firm from negative consequences associated with market competition and economic turmoil. More product alliance activity—and thus, greater access to alliance partners’ resources—improves a firm’s chances of success and reduces uncertainty associated with new product development, which then improves the level and stability of future cash flows. Based on this rationale, we hypothesize:

**H1.** The greater a firm’s product alliance activity, the (a) higher its stock return, (b) lower its systematic risk, and (c) lower its idiosyncratic risk.

According to agency theory, increased risk due to adverse selection and moral hazard negatively affects product development outcomes, which in turn decreases (increases) the level (volatility) of future cash flows. Considering the information asymmetries that exist during the formation of a product alliance, it may be difficult to assess alliance partner competence *ex ante* (Bergen et al., 1992). Prospective alliance partners can misrepresent themselves or fail to possess the promised resources, capabilities, and know-how that are necessary to complete joint product development efforts (Mohr & Spekman, 1994). A firm’s increased dependence on its alliance partners’ competence may lead to product development delays or failures.

Information asymmetries between alliance partners could also persist after the alliance formation. The associated risk of partner free-riding constitutes a “hidden action” problem.
After product alliances form, an opportunistic alliance partner skimps on its resource and capability investments or knowledge-sharing (Mishra, Heide, & Cort, 1998). If alliance partners fail to perform to the best of their ability, they jeopardize alliance success. Because of information asymmetry, such shirking by the partner may be difficult to detect (Singh & Sirdeshmukh, 2000), requiring the allocation of resources to monitoring and coordinating product alliance activities instead of supporting product development efforts (White & Lui, 2005). Thus, greater reliance on product alliance partners may slow product development efforts and increase the risk of product development failures, which in turn diminishes future cash flows. The heightened risk of product development failure makes the firm more vulnerable to market downturns and decreases the predictability of its future income streams. Therefore, we predict:

\[ H_{1alt} \] The greater a firm’s product alliance activity, the (a) lower its stock return, (b) higher its systematic risk, and (c) higher its idiosyncratic risk.

3.2. Network characteristics and shareholder value

3.2.1. Network closeness centrality. Firms central to an alliance network have access to information resources through both their alliance partners and their partners’ partners, due to their position in the network (Gulati, 1999). Firms central in a network create a web of intelligence through their indirect ties (Gulati & Gargiulo, 1999). Network closeness centrality affects stock returns, systematic risk, and idiosyncratic risk in two ways. First, more centrally positioned firms can create communication channels with distant members of the network to facilitate access to information and know-how (Soh, 2010). Centrally positioned firms thus innovate better because of their access to information about product development activities in various network locations (Chen, Zou, & Wang, 2009; Salman & Saives, 2005). More central firms are better at exploiting emerging opportunities by focusing on promising product development efforts and abandoning
efforts that have not yielded favorable results for other firms (Ferriani, Cattani, & Baden-Fuller, 2009). Second, central firms typically enjoy greater visibility and more favorable reputations, enabling them to attract talented employees who can contribute effectively to product development efforts (Powell et al., 1996). These improved product development efforts serve to enhance future cash flows, cushion the impact of market downturns on firm cash flows, and reduce unpredictability. That is, greater network closeness centrality improves information access, which facilitates firms’ internal product development efforts and improves the level and stability of firms’ future cash flows. Thus, we hypothesize:

**H2.** The higher a firm’s network closeness centrality, the (a) higher its stock returns, (b) lower its systematic risk, and (c) lower its idiosyncratic risk.

In addition to its direct benefits, network closeness centrality can improve the selection, management, and coordination of product alliance activities, thereby improving the level of cash flows and also reducing volatility. Firms central in an alliance network create webs of intelligence, such that they can access information and temper associated agency problems. Further, firms in more central positions have access to information, which facilitates their identification of alliance partners with necessary capabilities, reputation, and reliability (Swaminathan & Moorman, 2009). Such information about alliance partners also strengthens their ability to access external resources, reduces information asymmetries, and mitigates hidden information problems. Centrally positioned firms can share information about opportunistic behaviors, which further mitigates the hidden action problem and improves partner firm compliance (Swaminathan & Moorman, 2009). Partnering with a central firm also should encourage norms of cooperation and discourage alliance termination over concerns about backlash (Gulati, 1999). Furthermore, central firms with more social capital, power, and status
can negotiate agreements designed to improve alliance success (Burt, 2000; Podolny, 1993).

Increased network closeness centrality improves resource access and reduces the information asymmetries associated with product alliance activity, in turn improving the level of cash flows, diminishing the impact of market downturns, and reducing the volatility of cash flows.

Extending this reasoning, we expect to find:

**H3.** Greater network closeness centrality strengthens (weakens) (a) the positive (negative) relationship between product alliance activity and stock returns, (b) the negative (positive) relationship between product alliance activity and systematic risk, and (c) the negative (positive) relationship between product alliance activity and idiosyncratic risk.

3.2.2. **Network density.** More ties among firms in a network should improve transfers of fine-grained information and tacit knowledge while also enforcing behavioral norms. We take Coleman’s (1988) perspective on network cohesion and posit that firms benefit from participating in dense networks. Interconnections in a dense network create knowledge-sharing routines and encourage reciprocity and sharing (Walker, Kogut, & Shan, 1997). Cohesive ties promote exploratory learning about customer preferences and technology developments, and dense networks create system-level information or common, shared understanding that easily diffuses throughout the network (Soh, 2010). This rapid pace of information diffusion promotes the collective processing of knowledge and joint problem-solving (Powell et al., 1996). We thus anticipate improved innovation output and reduced uncertainty about product development (Ahuja, 2000), such that greater network density increases stock returns, insulates the firm’s stock from market downturns, and reduces firm-specific idiosyncratic risk. Accordingly, we predict:

**H4.** The greater a firm’s network density, the (a) higher its stock returns, (b) lower its systematic risk, and (c) lower its idiosyncratic risk.
Similar to network closeness centrality, dense networks offer three key advantages that moderate the relationship between product alliance activity and stock returns and risks. First, increased information-sharing in a dense network creates cooperation norms and incentives, and encourages shared behavioral expectations (Antia & Frazier, 2001). Such behavioral norms encourage the sharing of tacit knowledge that is critical for product alliance success (Ahuja, 2000). In addition to know-how, a dense network improves resource access and facilitates investments in relationship-specific investments (Walker et al., 1997). Second, dense ties reduce information asymmetries in product alliances and facilitate partner selection, because they provide quality information about a partner firm’s capabilities that can be easily diffused. This helps to address the hidden information problem (Swaminathan & Moorman, 2009). Third, high network density creates system-level trust among network members and deters partner opportunism through collective monitoring and sanctioning (Rindfleisch & Heide, 1997). The social costs of opportunism in a dense network are higher, which obviates the need to devote resources to alliance coordination (Swaminathan & Moorman, 2009) and mitigates the hidden action problem. Thus, dense networks encourage resource- and knowledge-sharing, reduce the risk associated with sharing tacit knowledge, mitigate partner firm opportunism, and lower coordination and monitoring costs.

Thus, we predict:

**H5.** Greater network density strengthens (weakens) (a) the positive (negative) relationship between product alliance activity and stock returns, (b) the negative (positive) relationship between product alliance activity and systematic risk, and (c) the negative (positive) relationship between product alliance activity and idiosyncratic risk.

4. **Method**

4.1. *Empirical context*
We test our hypotheses in the context of product alliances in the biopharmaceutical sector, where product development is a central goal for most firms (Grewal, Chakravarty, Ding, & Liechty, 2008). In the past decade, biopharmaceutical firms have launched 300 new drugs (Phrma, 2011), at an average cost of $1 billion—up from $100 million in 1990 (Tufts Center for the Study of Drug Development, 2008)—incurred over 10 to 12 years. Product development is highly risky; in fact, only one in 50,000 chemical entities generated in the earliest stages of development ultimately qualifies as a new drug candidate that will be retained in later stages. High costs and high failure rates motivate firms to engage in product alliances to improve the efficiency of their product development and introduction efforts. Because of the importance of product alliances in the biopharmaceutical industry, considerable information is available with respect to industry-wide product alliance activity (Wuyts et al., 2004). Such information enables us to create time-varying networks of interfirm relations and to rigorously examine product alliance activity.

4.2. Data and sample

We applied three inclusion criteria to build our dataset. First, a given firm must function in either the biotech (NAICS-325414) or pharmaceutical (NAICS-325412) industry. Second, we required that each firm be publicly listed. Third, firm-identifying information had to be available on each firm in both Compustat and CRSP. Integrating data across these sources yielded a sample of 597 publicly listed biopharmaceutical firms.

We separately obtained product alliance activity data about these firms from Recap.com, which provides reliable, comprehensive data about alliances among public and private biopharmaceutical firms (Rao, Chandy, & Prabhu, 2008; Wuyts & Dutta, 2008). The biotech industry first emerged in the mid-1970s, and product alliance propensity increased soon
thereafter to ensure effective access to new technology and consumer markets. Interestingly, surge in alliance formation occurred after 1985. To illustrate, 35 product alliances were formed between 1973 and 1984; 102 product alliances emerged between 1985 and 1989. For the 597 publicly listed firms retained for inclusion in this study, we constructed an unbalanced panel dataset with time-varying product alliance activity information.

Next, we carefully constructed networks to include all alliances reported in Recap. The census of alliances revealed ego networks that included both public and private firms, even though only public firms appear in our analyses. Due to lags, leads, and missing values, we obtained complete data on various study measures for 359 firms, 2,394 firm-year observations, and 1,381 product alliances formed between 1985 and 2004. On average, the sample included seven years’ observation for firms with at least one and a maximum of 20 observations.

4.3. Measures

In Table 2, we summarize our construct operationalizations and corresponding data sources. 

> Insert Table 2 --

**Endogenous variables.** We measured *stock return* as the difference between the compounded monthly holding period returns for firm $i$ over a calendar year $t$ ($R_{it}$), less the risk-free rate of return ($R_{ft}$) for year $t$ (Bharadwaj, Tuli, & Bonfrer, 2011; Srinivasan, Pauwels, Silva-Risso, & Hanssens, 2009).

We measured *systematic* and *idiosyncratic risk* using the four-factor Fama-French benchmark model (1992, 1996),

$$R_{it} - R_{ft} = \beta_{0i} + \beta_{1i}(R_{md} - R_{ft}) + \beta_{2i} SMB_d + \beta_{3i} HML_d + \beta_{4i} UMD_d + \epsilon_{id}$$

(1)

where the subscripts $i$ and $d$ indicate firm $i$ on day $d$; $R_{it}$ is the stock return; $R_{ft}$ is the risk-free rate of return; and, $R_{md}$ is the average market rate of return. The first factor represents the market
risk factor, or $R_{id} - R_{rf,d}$. The other factors refer to the size, or the difference in returns between large and small firms ($SMB_d$); value, which is the difference in returns between high and low book-to-market stocks ($HML_d$); and, momentum, or the difference in average returns between two high prior return and two low prior return portfolios ($UMD_d$). The momentum factor uses value-weighted portfolios based on size and prior month’s returns.\textsuperscript{3} To estimate the four-factor model, we collected daily ($d$) stock price data for firm $i$ from CRSP and data on the four factors from Kenneth French’s website (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html#Research). We estimated Equation 1 for each firm $i$ and calendar year $t$. The coefficient $\beta_{1i}$ reflects systematic risk; idiosyncratic risk is captured by the variance of the daily firm residual $\varepsilon_{id}$, obtained from Equation 1 (Rego, Billett, & Morgan, 2009; Tuli & Bharadwaj, 2009).

Following Kalaignanam et al. (2007), we operationalized *product alliance activity* as the number of product alliances undertaken by firm $i$ in year $t$. Within the biopharmaceutical industry, firms engage in alliances to discover, develop, and launch new drugs. We included discovery and development alliances—that is, product alliance activity efforts geared toward developing new products. However, we excluded alliances that entailed only the marketing or distribution of biopharmaceutical products.

*Exogenous variables.* Consistent with prior research (c.f., Gulati, 1999), the network of past alliances features all interfirm relations for five years prior to the focal period. For example, for product alliances formed in 1985, we considered the alliance network for 1980–1984. Accordingly, we constructed adjacency matrices for alliances of biopharmaceutical firms

\textsuperscript{3} For details, see http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_mom_factor.html.
between 1980 and 2004. We computed network measures, referring to the firm’s ego network, using UCINET 5 for Windows (Borgatti, Everett, & Freeman, 1999).

*Network closeness centrality* is the ratio of the minimum ties needed to reach all firms in firm i’s network to the count of the actual number of ties that firm i must use to reach all other firms in the network (Freeman, 1979). In Fig. 1, for example, Firm A needs at least seven ties to reach all firms in the network, and the actual number of ties it uses to reach all firms is 11; so, its closeness centrality score is 63.63 per cent. We measured the firm’s ego *network density* as the ratio of alliances among firm i’s alliance partners to the total count of potential alliances among all alliance partners (Swaminathan & Moorman, 2009). For Firm A, the ego network includes D, E, F, and G, and there is only one alliance among these alliance partners, whereas the potential alliances are six. Therefore, Firm A’s network density is 16.66 per cent. We took a semi-log measure of network density in the empirical specification to reduce skewness.

*Control variables.* We included *R&D intensity* to control for the firm’s ability to expend resources on product development and thereby improve its stock returns and reduce systematic and idiosyncratic risk. Similar to Luo and Bhattacharya (2009), we controlled for a comprehensive list of drivers of stock returns and systematic and idiosyncratic risk. We measured *profitability* as the return on assets, which affects the level and volatility of future cash flows. *Leverage* was a ratio of long- and short-term debt to the book value of equity. In addition, we controlled for the *market-to-book ratio*, or the ratio of the market value of equity to the book value of equity, which allows us to account for intangible factors that might affect the level and volatility of firm cash flows.

We measured *dividends paid* as a dummy variable, equal to 1 if a firm pays dividends and 0 otherwise. Dividend-paying firms expect improved cash flows and stability, which affects firm
stock returns, systematic risk, and idiosyncratic risk. Finally, we also controlled for *sales growth*, measured as the ratio of the difference in sales between years $t$ and $t-1$ and sales in year $t-1$.

*Liquidity* was the ratio of current assets to current liabilities. Table 3 contains the relevant summary statistics and correlations for all of the variables included in our analysis.

--- Insert Table 3---

4.4. Model estimation

We tested our hypotheses regarding the effects of product alliance activity, network characteristics, and various firm-specific controls on stock returns, systematic risk, and idiosyncratic risk using Equations 2, 3, and 4, respectively. The efficient market hypothesis suggests that stock prices reflect all known information about the future cash flows of a firm, and as a result, only new information emerging due to unanticipated changes in product alliance activity and network characteristics will affect stock returns and risks. Thus, the right-hand side variables in each of these equations represent the unanticipated changes to the predictor variables, derived from the residuals of a first-order autoregressive model with clustered standard errors. This approach is consistent with recent studies that assess the impact of marketing metrics on shareholder value (Aaker & Jacobson, 1994; Osinga, Leeflang, Srinivasan, & Wieringa, 2011).

$$SR_{it} = \beta_{s0} + \beta_{s1}UPA_{it} + \beta_{s2}UCC_{it} + \beta_{s3}UPA_{it}.UCC_{it} + \beta_{s4}UND_{it} + \beta_{s5}UPA_{it}.UND_{it} + \beta_{s6}URDint_{it} + \beta_{s7}UPft_{it} + \beta_{s8}ULev_{it} + \beta_{s9}UMktbk_{it} + \beta_{s10}UDiv_{it} + \beta_{s11}USalesg_{it} + \beta_{s12}ULiq_{it} + \beta_{s13}(R_{mt} - R_{it}) + \beta_{s14}SMB_{t} + \beta_{s15}HML_{t} + \beta_{s16}UMD_{t} + \mu_{it}, \quad (2)$$

where the prefix $U =$ the unanticipated predictor variables; $SR =$ stock return; $PA =$ product alliance activity; $CC =$ network closeness centrality; $ND =$ network density; $PA.CC$ and $PA.ND =$ the multiplicative interaction terms between product alliances and network closeness centrality and network density, respectively; $RDint =$ R&D intensity; $Pft =$ profitability; $Lev =$ leverage;
$Mktbk$ = market-to-book ratio; $Div$ = dividend paid; $Salesg$ = sales growth; and $Liq$ = liquidity.

The notations $R_m$, $R_f$, SMB, HML, and UMD are as noted for Equation 1. In each case, the subscripts $i$ and $t$ indicate the firm and calendar year, respectively.

\[
SYSR_{it} = \beta_{syr0} + \beta_{syr1}UPA_{it} + \beta_{syr2}UCC_{it} + \beta_{syr3}UPA_{it}\cdot UCC_{it} + \beta_{syr4}UND_{it} + \beta_{syr5}UPA_{it}\cdot UND_{it} + \beta_{syr6}URDint_{it} + \beta_{syr7}UPft_{it} + \beta_{syr8}ULev_{it} + \beta_{syr9}UMktbk_{it} + \beta_{syr10}UDiv_{it} + \beta_{syr11}USalesg_{it} + \beta_{syr12}ULiq_{it} + \mu_{it}, \quad (3)
\]

\[
IR_{it} = \beta_{ir0} + \beta_{ir1}UPA_{it} + \beta_{ir2}UCC_{it} + \beta_{ir3}UPA_{it}\cdot UCC_{it} + \beta_{ir4}UND_{it} + \beta_{ir5}UPA_{it}\cdot UND_{it} + \beta_{ir6}URDint_{it} + \beta_{ir7}UPft_{it} + \beta_{ir8}ULev_{it} + \beta_{ir9}UMktbk_{it} + \beta_{ir10}UDiv_{it} + \beta_{ir11}USalesg_{it} + \beta_{ir12}ULiq_{it} + \mu_{it}, \quad (4)
\]

where $SYSR$ = systematic risk in Equation 3, and $IR$ = idiosyncratic risk in Equation 4, with all other notations as noted for Equation 2. We standardized the variables to estimate these equations. To create the interaction terms, we used the cross-product of the standardized unanticipated product alliances, unanticipated network closeness centrality, and unanticipated network density.

Unanticipated product alliance activity is endogenous in our analyses because the decision to engage in an alliance represents a strategic choice by the firm. The endogenous nature of product alliance formation violates the strict exogeneity assumption of ordinary least square (OLS) estimation, making such estimates biased and inconsistent (Albers, 2012; Wooldridge, 2002). Although the unanticipated nature of product alliance formation represents unexpected information for the stock market, it represents a deliberate choice for the firm.

We turned to prior work on alliance formation to find suitable instruments for the endogenous covariate—unanticipated product alliance activity. Resource-rich firms are more likely to engage in additional unanticipated product alliances (Gulati, 1995; Gulati, 1999).
Therefore, we used a one-year lagged measure of assets and its squared term (to account for nonlinearity) as instruments for product alliance activity. Further, firms with product alliance experience—measured as a count of all product alliances engaged by firm \( i \) up to year \( t-1 \)—are more likely to engage in additional product alliances (Eisenhardt & Schoonhoven, 1996). We undertook a semi-log transformation of product alliance experience to account for its diminishing effect (Santoro & McGill, 2005). We thus used three instruments to account for the endogenous nature of unanticipated product alliance activity, assets, the squared term of assets, and product alliance experience, in the regressions for stock returns, systematic risk, and idiosyncratic risk.

Even though unanticipated network closeness centrality and unanticipated network density are exogenous, the interaction of unanticipated product alliance activity with each of the network variables is endogenous by definition. To create instruments for these interaction terms, we created multiplicative interactions between the instrumented alliance variable and each of the network variables\(^4\). The instrumented alliance variable represents the fitted values obtained from regressing unanticipated product alliance activity on all exogenous variables (including assets, the squared term of assets, and product alliance experience; see Equation 2; Wooldridge, 2010, pp.267-268; Beaver, Landsman, & Owens, 2012). This is akin to estimating the first-stage regression in a two-step generalized method of moments (GMM) estimation.

\[
UPA_{it} = \beta_{sh0} + \beta_{sh1} UCC_{it} + \beta_{sh2} UND_{it} + \beta_{sh3} URD_{it} + \beta_{sh4} UPf_{it} + \beta_{sh5} ULev_{it} + \beta_{sh6} UMktbk_{it} + \beta_{sh7} UDiv_{it} + \beta_{sh8} USales_{gtit} + \beta_{sh9} ULiq_{it} + \beta_{sh10} (R_{mt} - R_{ft}) + \beta_{sh11} SMB_{it} + \beta_{sh12} HML_{it} + \beta_{sh13} UMD_{it} + \beta_{sh14} At_{it-1} + \beta_{sh15} (At_{it-1})^2 + \beta_{sh16} Exp_{it-1} + \epsilon_{it},
\] (5)

where \( At = \) assets; \( Exp = \) product alliance experience, with all other notations as noted for Equation 2. We estimated Equation 5 using OLS and then obtained the fitted values of

\(^4\) We thank the AE for specific guidance on the appropriate instrumentation strategy for the endogenous interaction terms.
unanticipated product alliance activity (i.e., the instrumented alliance variable $\text{UPA}_{n}^{\text{hat}}$; Wooldridge 2010, p.276). We then computed the cross product of the instrumented alliance variable with unanticipated network centrality ($\text{UPA}_{n}^{\text{hat}} \times \text{UCC}_{n}$) and unanticipated network density ($\text{UPA}_{n}^{\text{hat}} \times \text{UND}_{n}$); and used these cross products as instruments for the interaction terms in the stock returns model (Equation 2).

Similarly, for systematic and idiosyncratic risk models, we estimated Equation 5, again, using all the right-hand side variables, except the Fama-French four factors. Then, we calculated the fitted values of unanticipated product alliance activity and created corresponding cross products of the instrumented alliance variable with the network variables ($\text{UPA}_{n}^{\text{hat}} \times \text{UCC}_{n}$ and $\text{UPA}_{n}^{\text{hat}} \times \text{UND}_{n}$). These were used as instruments for the interaction terms in the systematic risk (Equation 3) and idiosyncratic risk models (Equation 4).

We estimated Equations 2, 3, and 4 using the generalized method of moments estimator with standard errors clustered by firm, where unanticipated product alliance activity and the interaction terms were endogenous. The endogenous variables were instrumented with assets, the squared term of assets, product alliance experience, and the cross product of the instrumented alliance variable with each of the network variables. In the case with $L$ instruments ($Z$), there were $L$ moment conditions, or orthogonality conditions, such that the instruments were uncorrelated with the error term, or $E(Z_{i} \mu_{i}) = 0$. Under these conditions, GMM is appropriate for model estimation. The parameter estimates were robust to heteroskedasticity and autocorrelation (Baum, Schaffer, & Stillman, 2003). In the empirical specification, we also corrected for the intragroup correlation among firms with multiple years of observation, using cluster-robust standard errors. Finally, to address multicollinearity concerns, we checked the variance inflation

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5 We tested for the presence of heteroskedasticity using the Pagan-Hall (1983) test. We could reject the null hypothesis that the error term was homoskedastic at $p < .001$. 
factor and found it to be well below the standard cutoff of 10, suggesting that our results were unaffected by multicollinearity.

4.5. Instrument validity

We used the difference of two Sargan-Hansen statistics (C statistic) to determine whether we could treat the proposed endogenous regressors as exogenous, where the test statistic was distributed as a chi-square with degrees of freedom equal to 3 for the number of endogenous regressors. We rejected a null hypothesis of exogeneity at $p < .01$ for stock returns, systematic risk, and idiosyncratic risk. With the Anderson-Rubin (1949) Wald test, we rejected the joint null hypothesis, which would imply that the endogenous regressors were relevant for stock returns ($p < .01$), systematic risk ($p < .01$), and idiosyncratic risk ($p < .01$). We then used three tests to assess instrument validity. First, the $F$-statistic for each of the first-stage equations was well above the rule-of-thumb of 10; the lowest value was 10.9 for the interaction between product alliance activity and network closeness centrality (Staiger & Stock, 1997). The $F$-statistic comes from a conditional homoskedastic model, which is a reasonable test of instrument strength, even though the second-stage estimation emerged from a model with conditional heteroskedasticity. Second, using Hansen’s (1982) test of overidentifying restrictions, we tested the null hypothesis that the excluded instruments were correctly excluded from the second-stage regression and uncorrelated with the error term in the second-stage regression. We could not reject this joint null hypothesis for stock returns ($p = .15$), systematic risk ($p = .13$), or idiosyncratic risk ($p = .14$). Third, using the Sargan $C$ test, we tested the exogeneity of the excluded instrument variables to assess whether the instruments were uncorrelated with the error

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6 We separately checked the exogeneity of network closeness centrality and network density. We could not reject the null hypothesis of exogeneity for either closeness centrality or network density, respectively: stock returns ($p = .10$ and .17), systematic risk ($p = .55$ and .31), or idiosyncratic risk ($p = .23$ and .74). Thus, we treated them as exogenous predictors.
term in the second-stage regression (i.e., the null is no serial correlation in error terms). We could not reject this null hypothesis for stock returns ($p = .54$), systematic risk ($p = .39$), or idiosyncratic risk ($p = .11$). These tests provided evidence of instrument validity.

5. Results

5.1. Hypotheses testing

Table 4 contains the results of the GMM with standard errors clustered by firm. Columns 5, 6, and 7 show the results of the full model for each of the dependent variables, stock returns, systematic risk, and idiosyncratic risk, respectively. The firms’ product alliance activity related negatively to stock returns ($\beta_{s1} = -.170$, $p < .05$) and idiosyncratic risk ($\beta_{ir1} = -.523$, $p < .05$), in support of H1a\textsubscript{alt} and H1c, respectively. However, product alliance activity exerted no effect on systematic risk ($\beta_{sysr1} = .021$, n.s.); so, we could not reject either H1b or H1b\textsubscript{alt}. In support of H2a, network closeness centrality was positively associated with stock returns ($\beta_{s2} = .034$, $p < .1$), but had no effect on systematic risk ($\beta_{sysr2} = .034$, n.s.) or on idiosyncratic risk ($\beta_{ir2} = -.020$, n.s.); so, we could not reject H2b or H2c. We found no support for H3a, predicting that network closeness centrality served as a significant moderator of the relationship between product alliance activity and stock returns ($\beta_{s3} = .012$, n.s.). In support of H3b and H3c, the moderating effects of network closeness centrality on the relationship between product alliance activity and systematic risk ($\beta_{sysr3} = -1.704$, $p < .01$) and idiosyncratic risk ($\beta_{ir3} = -1.676$, $p < .01$) were negative and significant.

--- Insert Table 4 ---

Contrary to H4a, network density had a negative and significant effect on stock returns ($\beta_{s4} = -.050$, $p < .05$). Network density had no effect on systematic risk ($\beta_{sysr4} = .017$, n.s.) or on idiosyncratic risk ($\beta_{ir4} = -.038$, n.s.), providing no support for either H4b or H4c, respectively. As
noted in H5a, network density’s role as a moderator of the relationship between product alliance activity and stock returns was significant ($\beta_{55} = .112, p < .05$). Contrary to H5b and H5c, network density’s interaction with product alliance activity increased both systematic risk ($\beta_{sys5} = .665, p < .01$) and idiosyncratic risk ($\beta_{ir5} = 1.151, p < .01$), respectively.

We assessed the effects of the control variables on stock returns, consistent with Bharadwaj et al. (2011), we found that the market factor ($\beta_{s13} = .238, p < .01$) and the SMB factor ($\beta_{s14} = .154, p < .01$) increased stock returns. In the full model, the value factor (HML) was a statistically insignificant predictor of stock returns ($\beta_{s15} = -.044, \text{n.s.}$), and the value effect was likely captured by firm-specific marketing actions included in the full model. This finding is similar to Srinivasan et al. (2009), where the inclusion of marketing variables made the size effect (SMB) statistically insignificant. Finally, consistent with Osinga et al. (2011) and Srinivasan et al. (2009), we found that the momentum factor (UMD) was not significant ($\beta_{s16} = .015, \text{n.s.}$).

Profitability ($\beta_{s7} = .106, p < .01$) and liquidity ($\beta_{s12} = .086, p < .01$) increased stock returns, while R&D intensity ($\beta_{s6} = -.016, p < .01$) reduced them. The other control variables—leverage ($\beta_{s8} = .007, \text{n.s.}$), market-to-book ratio ($\beta_{s9} = .007, \text{n.s.}$), dividends paid ($\beta_{s10} = -.028, \text{n.s.}$), and sales growth ($\beta_{s11} = .052, \text{n.s.}$)—exerted no effect on stock returns. Among the control variables, R&D intensity ($\beta_{sys6} = -.006, \text{n.s.}$), profitability ($\beta_{sys7} = .008, \text{n.s.}$), leverage ($\beta_{sys8} = .044, \text{n.s.}$), market-to-book ratio ($\beta_{sys9} = .013, \text{n.s.}$), dividends paid ($\beta_{sys10} = .001, \text{n.s.}$), sales growth ($\beta_{sys11} = .080, \text{n.s.}$), and liquidity ($\beta_{sys12} = .034, \text{n.s.}$) had no effect on systematic risk. Furthermore, R&D intensity ($\beta_{ir6} = -.014, \text{n.s.}$), leverage ($\beta_{ir8} = .034, \text{n.s.}$), market-to-book ratio ($\beta_{ir9} = -.001, \text{n.s.}$), dividends paid ($\beta_{ir10} = -.057, \text{n.s.}$), and liquidity ($\beta_{ir12} = .012, \text{n.s.}$) exerted no effects on
idiosyncratic risk. However, profitability ($\beta_{ir7} = -.169, p < .01$) reduced firm idiosyncratic risk, while sales growth ($\beta_{ir11} = .114, p < .1$) increased it.

For ease of interpretation, we provide graphical representations of the interactions in Figures 2 and 3. Following Aiken and West (1991), we conducted a simple slope analysis to assess the significant effects in the interactions between unanticipated product alliance activity and unanticipated network closeness centrality. We examined the effects of network closeness centrality at the mean +/-1 standard deviation to represent high and low unanticipated network closeness centrality. As displayed in Fig. 2, in the presence of high centrality, the negative slopes of product alliance activity were -1.78 ($p < .01$) for systematic risk and -2.30 ($p < .01$) for idiosyncratic risk. In stark contrast for firms with low network closeness centrality, product alliance activity increased systematic risk (1.71, $p < .05$) and had no effect on idiosyncratic risk (1.14, n.s.). We used a similar approach to assess the effect of unanticipated product alliance activity at different levels of unanticipated network density. As shown in Fig. 3, in the presence of high network density, product alliance activity had no effect on stock returns (-.02, n.s.), and it increased systematic risk (.85, $p < .05$) and idiosyncratic risk (.91, $p < .05$). In contrast, in the low network density case, product alliance activity reduced stock returns (-.29, $p < .05$), systematic risk (-.74, $p < .01$), and idiosyncratic risk (-1.84, $p < .05$).

--- Insert Figs. 2 and 3 ---

5.2. Robustness checks

We re-estimated Equations 2, 3, and 4 to assess the robustness of our results. First, we removed potential outliers, given that the results could be driven by a few firm-years in which some firms engaged in many product alliances. To alleviate such concerns, we removed those firm-years for which product alliance activity fell into the top fifth percentile. We also conducted
a residual analysis to remove observations with the five highest and lowest residuals; the results did not change substantively. Second, the tests of our hypotheses used a 20-year observation period. To assess the robustness of these findings, we determined whether the results were sensitive to the estimation window by estimating Equations 2, 3, and 4 for two separate time intervals (i.e., 1990-2004 and 1995-2004) and achieved robust results for both.

Third, we conducted additional analyses to explore the possibility of nonlinear effects of product alliance activity, and found its squared term to be nonsignificant. To assess the robustness of our choice of instruments, we also instrumented product alliance activity with two-year lag of assets, the squared term of assets, and product alliance experience. Following the procedure outlined in Section 4.4, we created corresponding multiplicative interactions between the instrumented alliance variable and each of the network variables as additional excluded instruments. The results remained robust, regardless of instruments used. Furthermore, the results remained robust to potential outliers, alternate observation windows, alternate specifications, and choice of instruments. These checks attest to the robustness of the results reported in Section 5.1.

5.3. Does endogeneity matter?

Following the recommendations provided in Albers (2012), we compared the results of our endogeneity-corrected model with a model that treated product alliance activity as an exogenous variable. A panel data feasible generalized least squares (FGLS) estimate accounted for the panel structure of the data, autocorrelation, and heteroskedasticity but not for endogeneity (see Table 5). We compared this approach with estimates obtained using the GMM with standard errors clustered by firm (Table 4). Some notable differences arose in the results between these two models.
In particular, the FGLS estimate significantly underestimated the risk pursuant to product alliance activity because it failed to capture the downside of product alliance activity with a decrease in stock returns. The endogeneity-corrected analytical approach suggested a decidedly more cautious approach to product alliance activity. Using the GMM estimation, we found that network closeness centrality and network density moderated the relationship between product alliance activity and stock risk. However, the FGLS estimates largely failed to capture such effects.

Finally, the results for the exogenous variables of interest, network closeness centrality, and network density also varied across the two estimation techniques. The GMM estimates indicated that closeness centrality increased stock returns; however, the endogeneity-corrected analytical approach detected no direct effect of network closeness centrality or of network density on stock risk. The FGLS estimate seemed to suggest that network closeness centrality decreases systematic risk. In addition, network closeness centrality increases idiosyncratic risk while network density reduces it. In summary, failing to account for the endogenous nature of product alliance activity would cause the endogeneity bias to affect the magnitude and direction of not just the endogenous regressors but also of their interactions with the exogenous predictors.

--- Insert Table 5 ---

6. Discussion

6.1 Theoretical implications.

We developed and tested hypotheses predicting the impact of product alliances on the broader network they engender on all three aspects of shareholder value—stock returns, systematic risk, and idiosyncratic risk. In doing so, we build on and extend our understanding of product alliances, networks, and the literature on marketing metrics.
The present study helps to reconcile divergent views on the financial implications of firms’ product alliance activity. The alliance literature is rife with both fans and critics, who support and discourage product alliance activity, respectively. On the one hand, proponents of alliances emphasize access to complementary resources and lower costs of product development that accrue from partnering (Rindfleisch & Moorman, 2001). On the other hand, detractors of alliances highlight the concomitant risks of partner incompetence and opportunism (Mohr & Spekman, 1994). Our findings suggest that both viewpoints are valid, depending on the particular financial outcome examined to draw conclusions about the effectiveness of product alliances.

In support of a more bearish outlook on product alliance formation, we find that product alliance activity reduces stock returns. At first glance, our finding of negative effects of product alliance activity on stock returns seems to stand in stark contrast to prior studies that suggest the opposite outcome (Kalaignanam et al., 2007; Das, Sen, & Sengupta, 1998). A closer examination, however, reveals that the short-term positive returns captured by prior work either uses event study methodology (see Das, Sen, & Sengupta, 1998) or examines product alliance formation over a shorter time period (see Boyd & Spekman, 2008). The immediate positive response may be due to short-run overreactions in the market that dissipate in the long run (Ben-Zion, Galil, Rosenboim, & Shabtay, 2011). Our study assesses the longer-term value accruing to product alliance activity, given the cost and “sticky” nature of such important relationships.

In support of product alliance proponents, we find that product alliance activity reduces idiosyncratic risk. In our study we respond to prior research’s criticism that “risk is as crucial as trust and opportunism, [yet] it has not received equal attention from researchers” (Lee et al., 2008, p. 198). We also address calls “to provide a valuable contribution by exploring a broader scope of consequences” of product alliance activity (Rindfleisch & Moorman, 2003, p. 433).
In assessing how networks created by firms’ product alliance activity can affect their risk-return outcomes, our work also contributes to a better understanding of interorganizational network effects. We examined the effectiveness of positional (network closeness centrality) and structural (network density) characteristics on shareholder value metrics. We expected centrally positioned firms to benefit both directly and through product alliance formation with improved stock returns and lower stock risks. Consistent with this expectation, we find a direct and positive effect of network centrality on firms’ stock returns. Centrally positioned firms are better able to mitigate risk associated with product alliance activity by shielding the firm’s stock from market downturns (systematic risk) and by reducing the uncertainty of future cash flows (idiosyncratic risk). Thus, with centrally positioned firms the risk-lowering impact of product alliance activity is more pronounced, perhaps because of the ability of these firms to leverage their positions in central networks. Ours is the first study, to the best of our knowledge, to provide evidence of centrality’s salutary effect on stock returns and stock risk. We are thus able to provide a comprehensive assessment of network closeness centrality on both stock returns and stock risks, addressing calls to “investigate the role of other types of network centrality [network closeness centrality]” on shareholder value (Swaminathan & Moorman, 2009, p. 64).

In contrast to the positive outcomes accruing to network closeness centrality, the impact of network density is mixed. Our finding of negative returns for dense networks suggests that access to redundant and homogenous information shared among firms that are embedded in dense networks serves to dilute scarce management resources (Bae & Gargiulo, 2004; Burt, 1997). This finding is consistent with the assertion that redundant information secured from dense networks does not constitute a source of competitive advantage (Gnyawali & Madhavan, 2001). Although product alliance activity reduces stock returns, consistent with our expectations,
network density tempers these negative returns. This result is consonant with extant research on the upside of dense networks, where firms’ product alliance activity grants access to tacit, fine-grained information and also enforces behavioral norms (Coleman, 1988; Soh, 2010).

Contrary to our hypotheses, however, we find that firms embedded in sparse networks are better able to mitigate the risks associated with product alliance activity. This suggests that firms embedded in dense networks may not be in a position to identify emerging threats in the marketplace when engaging in product alliance activity, and risk being blind-sided by access to homogenous information. Altogether our research highlights both the promise and the pitfalls of densely embedded firms undertaking product alliance activity (Zaheer & Bell, 2005), providing evidence of a trade-off between risk and return.

Finally, our research contributes to evolving research on marketing metrics. By relating interfirm relationships to firms’ stock returns and stock risks, we extend nascent efforts to determine the effect of marketing strategies on CEO-relevant metrics. Several prior studies have assessed a host of customer relevant metrics—including brand quality (Bharadwaj et al., 2011), advertising (Osinga et al., 2011), and customer satisfaction (Tuli & Bharadwaj, 2009)—on shareholder value. We extend this stream of work by examining the effects of business relations—alliances and networks—on all aspects of shareholder value. As Srinivasan and Hanssens (2009, p. 299) note, idiosyncratic risk represents an important subject for marketing researchers to address because it “induces higher costs of capital financing, thus damaging firm valuation in the long run.” Our research thus benefits individual investors, financial analysts, and financial agencies alike, who all track stock risk metrics when making investment decisions.

6.2 Managerial implications.
Managers are generally highly optimistic about engaging in product alliances, fully anticipating access to newly available resources and capabilities and the consequent returns to their deployment. Our research suggests such optimism may be misplaced, and that exclusively focusing on returns ignores the risk that also accompanies product alliance activity. Our findings strongly indicate that managers must pay attention to the effects of product alliance activity on both stock returns and stock risks. Whereas product alliance activity can reduce stock risks, it also results in a corresponding decrease in stock returns. These findings are sobering, given that “innovators who try to go it alone face incredibly long odds” and “even the smartest people tend to underestimate the amount of time and cost it will take to hone a new idea and persuade the world to give it a try” (Mandel, 2008). Our results imply a grimmer reality than has been depicted previously, and portray a Hobbesian choice for managers interested in product alliances: product alliance activity is likely to reduce cash flow volatility (idiosyncratic risk), while also reducing the value of cash flows (stock returns).

We do not mean to offer a universal “doom and gloom” prediction for product alliances. In fact, our research suggests that firms engaging in product alliances are not destined to experience lower returns. Firms should look beyond their focal alliance partners to the extended network of relationships to improve stock returns. Occupying a central position in an alliance network further mitigates the risks (systematic and idiosyncratic) associated with product alliance formation. The leverage afforded by not only direct ties with partner firms, but also by indirect links to their partners’ partners, provides access to information that facilitates partner selection and alliance governance. Our findings encourage forward-thinking managers to strategically leverage their extended alliance networks in an effort to further their risk-reduction objectives.
We make two clear recommendations, based on our examination of network density and product alliance activity. First, a manager for whom stock returns are a top priority is advised to engage in product alliances only if his firm is embedded in dense networks. Second, we advise managers seeking to mitigate the lower returns accruing from their product alliance activity to look to the extended alliance network. Specifically, our results point to a hitherto undiscovered vested interest on the part of managers to not only bolster their own ties, but also to encourage firms in their network to engage in product alliances among themselves.

Managers valuing risk reduction, on the other hand, should shy away from acting as “matchmakers” among firms in the extended alliance network. Instead, their alliance-partner selection efforts should assess not only the internal resources of potential partners, but also their ability to access network resources accruing from potential partners’ position in an alliance network. Thus, managers may improve their firm’s probability of success by partnering with firms that are centrally positioned in their alliance networks. Depending on their specific objectives, managers who engage in product alliances are better off focusing on being central (in the interest of lower risk) or encouraging ties among firms in their alliance networks (to mitigate lower returns). Our findings strike a cautionary note: product alliance activities and the networks they engender constitute neither a panacea for all ills nor a pitfall to avoid at all times. In Table 6 we summarize the recommendations of our findings for practicing managers.

*** Insert Table 6 here ***

6.3 Limitations.

As with any research, our efforts are fraught with some limitations. First, we employ a stock market-based performance metrics, which has some inherent limitations. These metrics adopt the efficient market hypothesis, a dominant paradigm in finance, which postulates that the firm’s
stock price reflects all publicly available information (Fama, 1965). Although these assumptions do not always hold completely, shareholder value-based metrics are generally well-accepted measures of firm performance in research that examines the impacts of alliances and networks (Boyd & Spekman, 2008; Kalaignanam et al., 2007). However, our choice of a stock market-based performance metric limited our sample and our analyses to publicly listed firms; thus implications of this study might not apply to private firms. Second, as currently assessed, product alliance activity does not describe the type of alliance. We leave the issue of incorporating richer information on alliance type to future research. Third, we tested our hypotheses in a single industrial context: the biopharmaceutical industry. Although restricting research to a single industry helps improve internal validity by minimizing sources of extraneous variance (Swaminathan & Moorman, 2009), future research examining strategic alliances would be enriched by exploring these issues in a multi-industry context.

6.4 Further research

We provide strong evidence that product alliances lower idiosyncratic risk. However, prior research indicates that incremental innovation has no effect on idiosyncratic risk, but breakthrough innovation increases it (Sorescu & Spanjol, 2008). Additional research is needed to reconcile these disparate conclusions. Researchers might explore how innovation type (incremental versus radical) moderates the product alliance activity/stock risk relationship. Perhaps product alliance activity is more appropriate for radical innovations because it mitigates innovation risks, but it is detrimental for incremental innovation attempts. Similarly, explicating the moderating role of innovation type in the relationship between product alliance activity and stock returns could enhance our understanding of the impact of product alliance activity on shareholder value.
While we examined the role of product alliances, a thorough examination of effects associated with marketing alliances would also be useful—especially as they pertain to stock risk. Further research could examine other aspects of alliance activity and network, too, such as the strength of ties or the diversity of capabilities (Houston, Hutt, Moorman, Reingen, Rindfleisch, Swaminathan, & Walker, 2004). We examined networks that evolved from formal product alliances, yet many firms engage in informal ties that provide similar informational advantages and may improve firm performance. Data limitations hindered exploration of informal alliances, but we hope future research finds a way to explore the effects of both formal and informal relationship networks on stock returns and risk. Finally, as noted, we focused on publicly listed, biopharmaceutical firms; additional research could consider other risk metrics that apply to both private and public firms.
References


Fig. 1
Network characteristics

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</tr>
<tr>
<td>H</td>
<td>33.33</td>
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</table>

Notes: Lines represent alliances between firms.
Fig. 2
Interaction effects: Unanticipated product alliance activity and unanticipated network closeness centrality

![Interaction effects diagram]
Fig. 3
Interactions effects: Unanticipated product alliance activity and unanticipated network density
Fig. 3 (contd.)
Interactions effects: Unanticipated product alliance activity and unanticipated network density
Table 1
Research overview—Product alliances, networks, and shareholder value

<table>
<thead>
<tr>
<th>Study</th>
<th>Sample</th>
<th>Relational versus agency-theoretic view</th>
<th>Assesses the effect of product alliance activity on stock returns?</th>
<th>Assesses the effect of product alliance activity on stock risks?</th>
<th>Considered network effects on stock returns and stock risks?</th>
</tr>
</thead>
<tbody>
<tr>
<td>Boyd &amp; Spekman (2008)</td>
<td>73 product alliances for pharmaceutical, electronic equipment manufacturing, and software development</td>
<td>Relational</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>Das, Sen, &amp; Sengupta (1998)</td>
<td>119 (49 R&amp;D and 70 marketing) alliances in 18 industries</td>
<td>Relational</td>
<td>Yes</td>
<td>Yes (on total risk)</td>
<td>No</td>
</tr>
<tr>
<td>Kalaignanam, Shankar, &amp; Varadarajan (2007)</td>
<td>167 product alliances in the computer and office equipment, prepackaged software, and communication equipment industries</td>
<td>Relational</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>Park &amp; Mezias (2005)</td>
<td>408 alliances in the e-commerce industry</td>
<td>Relational</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>Park, Mezias, &amp; Song (2004)</td>
<td>272 alliances (technology and marketing alliances) in the e-commerce industry</td>
<td>Relational</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
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<tr>
<td>Swaminathan &amp; Moorman (2009)</td>
<td>230 marketing alliances in the computer software industry</td>
<td>Relational</td>
<td>Yes</td>
<td>No</td>
<td>Yes (on stock returns)</td>
</tr>
<tr>
<td><strong>This research</strong></td>
<td><strong>2,394 firm-year observations, 359 firms, and 1,381 product alliances in the biopharmaceutical industry</strong></td>
<td><strong>Relational and agency-theoretic</strong></td>
<td><strong>Yes</strong></td>
<td><strong>Yes</strong></td>
<td><strong>Yes</strong></td>
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</table>

This research: Forthcoming IJRM Volume 32 #1 (2015)
<table>
<thead>
<tr>
<th>Conceptual Variable</th>
<th>Notation</th>
<th>Measured Variable</th>
<th>Data Source</th>
</tr>
</thead>
</table>

**Endogenous: Dependent Variable**

- **Stock returns** SR
  - Difference between compounded holding period return for firm \(i\) over calendar year \(t\) less the risk free rate of return for year \(t\).
  - CRSP, French’s website

- **Systematic risk** SYSR \(\beta_{it}\)
  - Obtained from Equation 1 for each firm \(i\) year \(t\).
  - CRSP, French’s website

- **Idiosyncratic risk** IR
  - Variance of daily firm residual \(\varepsilon_{id}\), obtained from Equation 1 for each firm \(i\) year \(t\).
  - CRSP, French’s website

**Endogenous: Hypothesized Variable**

- **Product alliance activity** PA
  - Number of product alliances undertaken by firm \(i\) in year \(t\).
  - Recap.com

**Exogenous: Hypothesized Variables**

- **Network closeness centrality** CC
  - Ratio of minimum ties to reach all firms in firm \(i\)’s network to the count of the actual number of ties firm \(i\) uses to reach all other firms, expressed as a percentage.
  - Recap.com

- **Network density** ND
  - Ratio of alliances among firm \(i\)’s alliance partners to the total count of potential alliances among all alliance partners, expressed as a percentage.
  - Recap.com

**Exogenous: Control Variables**

- **R&D intensity** RDint
  - Ratio of R&D expenses to sales.
  - COMPUSTAT

- **Profitability** Pft
  - Return on assets, or ratio of net income to assets.
  - COMPUSTAT

- **Leverage** Lev
  - Ratio of total debt to book value of equity.
  - COMPUSTAT

- **Market-to-book ratio** Mktbk
  - Ratio of market value of equity to the book value of equity.
  - COMPUSTAT

- **Dividend paid** Div
  - Dummy equal to 1 if firm pays dividends in year \(t\) and 0 otherwise.
  - COMPUSTAT

- **Sales growth** Salesg
  - Ratio of the difference in sales between years \(t\) and \(t-1\) and sales in year \(t-1\).
  - COMPUSTAT

- **Liquidity** Liq
  - Ratio of current assets to current liabilities.
  - COMPUSTAT

- **Market factor** \(R_{mt}-R_{ft}\)
  - Market returns less returns on a risk-free investment.
  - Kenneth French’s website

- **SMB** SMB
  - Difference in returns between portfolios of large and small firms.
  - Kenneth French’s website

- **HML** HML
  - Difference in returns between portfolios of high and low book-to-market equity firms.
  - Kenneth French’s website

- **UMD** UMD
  - Difference in returns between portfolios of with high and low prior return portfolios.
  - Kenneth French’s website
Table 3
Summary statistics and correlation matrix (n = 2,394)

<table>
<thead>
<tr>
<th></th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
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<th>10</th>
<th>11</th>
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<tr>
<td>Mean</td>
<td>1.29</td>
<td>1.13</td>
<td>0.04</td>
<td>0.04</td>
<td>0.17</td>
<td>0.02</td>
<td>-1.37</td>
<td>0.03</td>
<td>-0.16</td>
<td>-0.56</td>
<td>0.01</td>
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<td>-0.27</td>
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<tr>
<td>SD</td>
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<td>0.87</td>
<td>0.02</td>
<td>1.08</td>
<td>5.28</td>
<td>0.55</td>
<td>133.4</td>
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<td>5.43</td>
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<td>Maximum</td>
<td>13.27</td>
<td>22.17</td>
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<td>21.75</td>
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<td></td>
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<td>2. Systematic risk</td>
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<td>3. Idiosyncratic risk</td>
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<td>4. (U)Product alliance activity</td>
<td>0.02</td>
<td>-0.01</td>
<td>-0.12</td>
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<tr>
<td>5. (U)Network closeness centrality</td>
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<td>-0.02</td>
<td>-0.10</td>
<td>0.05</td>
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<td>6. (U)Network density</td>
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<td>7. (U)R&amp;D intensity</td>
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<td>0.03</td>
<td>-0.02</td>
<td>0.01</td>
<td>0.01</td>
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<td>8. (U)Profitability</td>
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<td>-0.01</td>
<td>-0.23</td>
<td>0.07</td>
<td>0.06</td>
<td>-0.02</td>
<td>-0.06</td>
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<td>9. (U)Leverage</td>
<td>0.01</td>
<td>-0.01</td>
<td>-0.05</td>
<td>0.04</td>
<td>-0.01</td>
<td>-0.02</td>
<td>-0.01</td>
<td>0.03</td>
<td>1.00</td>
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<tr>
<td>10. (U)Market-to-book ratio</td>
<td>0.02</td>
<td>0.02</td>
<td>-0.01</td>
<td>0.02</td>
<td>0.01</td>
<td></td>
<td>-0.01</td>
<td>-0.01</td>
<td>0.55</td>
<td>1.00</td>
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<tr>
<td>11. (U)Dividend paid</td>
<td>-0.04</td>
<td>-0.05</td>
<td>-0.11</td>
<td>0.02</td>
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<td>-0.03</td>
<td>0.02</td>
<td>-0.01</td>
<td>1.00</td>
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<td></td>
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<tr>
<td>12. (U)Sales growth</td>
<td>0.05</td>
<td>0.02</td>
<td>0.01</td>
<td>0.03</td>
<td>0.04</td>
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<td>1.00</td>
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<tr>
<td>13. (U)Liquidity</td>
<td>0.11</td>
<td>0.07</td>
<td>0.06</td>
<td>0.02</td>
<td>0.03</td>
<td>-0.05</td>
<td>-0.01</td>
<td>0.14</td>
<td>0.00</td>
<td>-0.01</td>
<td>-0.03</td>
<td>0.02</td>
<td>1.00</td>
</tr>
</tbody>
</table>

Note: All correlations greater than .03 (absolute value) are significantly different from 0 at the $p < .05$ level.
The prefix (U) reflects the unanticipated values of the predictors.
### Table 4
Generalized method of moments with standard errors clustered by firm (n = 2,394)

<table>
<thead>
<tr>
<th>Independent variables</th>
<th>Stock returns Main effects model</th>
<th>Systematic risk Main effects model</th>
<th>Idiosyncratic risk Main effects model</th>
<th>Stock returns Full model</th>
<th>Systematic risk Full model</th>
<th>Idiosyncratic risk full model</th>
</tr>
</thead>
<tbody>
<tr>
<td>(U)Product alliance activity</td>
<td>-.139 (.017)***</td>
<td>-.474 (.081)***</td>
<td>-.360 (.142)***</td>
<td>-.170 (.074)**</td>
<td>.021 (.205)</td>
<td>-.523 (.232)***</td>
</tr>
<tr>
<td>(U)Network closeness centrality</td>
<td>.033 (.019)*</td>
<td>-.003 (.042)</td>
<td>-.074 (.020)***</td>
<td>.034 (.020)</td>
<td>.034 (.093)</td>
<td>-.020 (.089)</td>
</tr>
<tr>
<td>(U)Product alliance activity \times</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(U)Network closeness centrality</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(U)Network density</td>
<td>-.049 (.019)***</td>
<td>.038 (.021)</td>
<td>-.021 (.021)</td>
<td>-.050 (.019)**</td>
<td>.017 (.049)</td>
<td>-.038 (.076)</td>
</tr>
<tr>
<td>(U)Product alliance activity \times</td>
<td></td>
<td></td>
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<td></td>
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<td>(U)Network density</td>
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<td>Control Variables</td>
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<tr>
<td>(U)R&amp;D intensity</td>
<td>-.016 (.006)***</td>
<td>.006 (.011)</td>
<td>.005 (.017)</td>
<td>-.016 (.006)**</td>
<td>-.006 (.015)</td>
<td>-.014 (.016)</td>
</tr>
<tr>
<td>(U)Profitability</td>
<td>.107 (.020)***</td>
<td>.005 (.040)</td>
<td>-.217 (.045)***</td>
<td>.106 (.021)***</td>
<td>.008 (.053)</td>
<td>-.169 (.055)***</td>
</tr>
<tr>
<td>(U)Leverage</td>
<td>.005 (.015)</td>
<td>.007 (.027)</td>
<td>-.038 (.021)*</td>
<td>.007 (.017)</td>
<td>.044 (.049)</td>
<td>.034 (.062)</td>
</tr>
<tr>
<td>(U)Market-to-book ratio</td>
<td>.008 (.016)</td>
<td>.025 (.016)</td>
<td>.022 (.022)</td>
<td>.007 (.016)</td>
<td>.013 (.023)</td>
<td>-.001 (.028)</td>
</tr>
<tr>
<td>(U)Dividend paid</td>
<td>-.026 (.019)</td>
<td>-.031 (.022)</td>
<td>-.108 (.024)***</td>
<td>-.028 (.019)</td>
<td>.001 (.034)</td>
<td>-.057 (.040)</td>
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<tr>
<td>(U)Sales growth</td>
<td>.038 (.034)</td>
<td>.032 (.009)***</td>
<td>.042 (.027)</td>
<td>.052 (.035)</td>
<td>.080 (.054)</td>
<td>.114 (.065)*</td>
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<tr>
<td>(U)Liquidity</td>
<td>.085 (.027)***</td>
<td>.063 (.025)***</td>
<td>.079 (.022)***</td>
<td>.086 (.027)***</td>
<td>.034 (.036)</td>
<td>.012 (.038)</td>
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<td>Market factor</td>
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<td>.238 (.022)***</td>
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<tr>
<td>SMB</td>
<td>.149 (.022)***</td>
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<td>.154 (.024)***</td>
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<tr>
<td>HML</td>
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<td></td>
<td>-.044 (.027)</td>
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<tr>
<td>UMD</td>
<td>.007 (.025)</td>
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<td>.015 (.025)</td>
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<tr>
<td>Constant</td>
<td>-.008 (.016)</td>
<td>-.002 (.031)</td>
<td>-.2.25 x 10^-9 (.039)</td>
<td>-.016 (.018)</td>
<td>.055 (.062)</td>
<td>.049 (.068)</td>
</tr>
</tbody>
</table>

Notes: Standard errors are in parentheses.

* p < .1, ** p < .05, *** p < .01 (two-tailed).

Variable corrected for endogeneity.
Table 5
Feasible generalized least squares (n = 2,354)

<table>
<thead>
<tr>
<th>Independent variables</th>
<th>Stock returns</th>
<th>Systematic risk</th>
<th>Idiosyncratic risk</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Full model</td>
<td>Full model</td>
<td>full model</td>
</tr>
<tr>
<td>(U)Product alliance activity</td>
<td>.001 (.010)</td>
<td>-.005 (.011)</td>
<td>-.016 (.009)*</td>
</tr>
<tr>
<td>(U)Network closeness centrality</td>
<td>.004 (.011)</td>
<td>-.021 (.012)*</td>
<td>.018 (.009)**</td>
</tr>
<tr>
<td>(U)Product alliance activity × (U)Network closeness centrality</td>
<td>.011 (.012)</td>
<td>.003 (.014)</td>
<td>.015 (.012)</td>
</tr>
<tr>
<td>(U)Network density</td>
<td>-.035 (.010)***</td>
<td>.015 (.012)</td>
<td>-.017 (.007)**</td>
</tr>
<tr>
<td>(U)Product alliance activity × (U)Network density</td>
<td>.022 (.008)**</td>
<td>.001 (.008)</td>
<td>-.002 (.006)</td>
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<tr>
<td>(U)Network density</td>
<td>-.007 (.014)</td>
<td>.008 (.012)</td>
<td>.013 (.008)*</td>
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<tr>
<td>(U)R&amp;D intensity</td>
<td>-.028 (.012)**</td>
<td>.033 (.014)**</td>
<td>-.027 (.009)**</td>
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<tr>
<td>(U)Leverage</td>
<td>-.007 (.015)</td>
<td>.014 (.020)</td>
<td>-.052 (.011)***</td>
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<tr>
<td>(U)Profitability</td>
<td>.094 (.012)***</td>
<td>-.024 (.014)*</td>
<td>-.074 (.012)***</td>
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<td>(U)Market-to-book ratio</td>
<td>-.006 (.012)</td>
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<td>.021 (.014)</td>
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<td>(U)Liquidity</td>
<td>.055 (.014)***</td>
<td>.072 (.014)</td>
<td>.031 (.009)**</td>
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<td>Market factor</td>
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<td>-.057 (.013)***</td>
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<td>.031 (.009)**</td>
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<tr>
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<td>-.057 (.013)***</td>
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<td>UMD</td>
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<td>.072 (.014)</td>
<td>.031 (.009)**</td>
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<tr>
<td>Constant</td>
<td>-.083 (.016)***</td>
<td>-.057 (.013)***</td>
<td>-.138 (.016)***</td>
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Notes: Standard errors are in parentheses.
* p < .1. ** p < .05. *** p < .01 (two-tailed).
<table>
<thead>
<tr>
<th>Firm’s network embeddedness</th>
<th>Manager’s objective</th>
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<td>High network closeness centrality</td>
<td>Increase stock returns</td>
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<tr>
<td>High network density</td>
<td>Increase product alliance formation</td>
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