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The downside of prominence in a network of marketing alliances

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ABSTRACT

The authors investigate how a firm's position in a network of marketing alliances affects performance for firms experiencing different levels of uncertainty. A more prominent position—having many, well-connected marketing alliances—is typically theorized to improve the performance of a firm. However, we find that a prominent network position can instead hurt performance when uncertainty is high. Practically, these results can help both researchers and practitioners identify when the risks of marketing alliances outweigh the rewards. Theoretically, they provide a plausible explanation for past research that failed to detect a positive relationship between marketing alliances and firm performance.

1. Introduction

There is a growing stream of research in marketing focused on the study of strategic alliances and how they add value (Anderson, Håkansson, & Johanson, 1994; Bucklin & Sengupta, 1993; Luo, Rindfleisch, & Tse, 2007; Rindfleisch & Moorman, 2001). This trend coincides with the recognition that many firms have shifted from hierarchical forms of governance to the more flexible and disaggregated structure provided by strategic partnerships (Achrol & Kotler, 1999). This is especially evident in technology-intensive (TI) industries like software and biotechnology where the number of firms engaging in strategic alliances has grown steadily since the 1980s (John, Weiss, & Dutta, 1999; Lavie, 2007) giving researchers both the impetus, and the data to conduct research on this phenomenon.

In the current work, we focus specifically on marketing alliances, which are defined as formal agreements between two or more firms that focus on downstream value chain activities (Das, Sen, & Sengupta, 1998; Rindfleisch & Moorman, 2001; Swaminathan & Moorman, 2009). In many cases, firms form these alliances with more than one downstream partner (Fang, Lee, Palmatier, & Guo, 2016). Similarly, these downstream partners can form alliances with more than one upstream firm (Thomaz & Swaminathan, 2015). Collectively, this web of marketing alliances forms a network wherein a given alliance acts as a conduit for the flow of information and resources between otherwise unconnected firms. Consequently, each firms' unique position in this network can affect its performance over time (Mazzola, Perrone, & Handfield, 2018; Thomaz & Swaminathan, 2015).

Although the majority of research in marketing looks at (dyadic) relationships rather than the whole network, findings document a largely positive association between the use of marketing alliances and firm performance (Kalaignanam, Shankar, & Varadarajan, 2007; Swaminathan & Moorman, 2009). We argue that this view is overly optimistic and by studying these relationships from a network perspective, we can uncover important boundary conditions. To do so, we look at both prominent and entrepreneurial positions in a network of marketing alliances and hypothesize that any benefits associated with these network positions are contingent on expectations about a firm's prospects for the future—a contingency we refer to as firm-specific uncertainty.

To test this theory, we look at biotechnology firms during the industry's formative years and examine how firms' position in a network of marketing alliances affects performance under different levels of firm-specific uncertainty. Our results indicate that the value of a prominent position depends on the level of firm-specific uncertainty—-when uncertainty is high, prominence can actually hurt performance. Surprisingly, we do not find any effect of entrepreneurial positioning in a network of marketing alliances on firm performance.

Our research makes three primary contributions. First, we show that there are risks associated with marketing alliances, but these risks are apparent only when looking at the entire network of relationships. Second, we identify a new moderator of the relationship between marketing alliances and firm performance and show that performance can actually suffer when firm-specific uncertainty is high. For researchers looking to understand the mechanisms driving the alliance-performance relationship, our moderator provides an empirical means to identify the circumstances when the risks of network prominence

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outweigh the rewards. Third, our results offer a plausible explanation for research that has failed to detect any effect of marketing alliances on firm performance over the longer term (see e.g., Das et al., 1998; Koh & Venkatraman, 1991; Swaminathan & Moorman, 2009).

In the sections that follow, we begin with a discussion of network position and the potential benefits of holding either a prominent or entrepreneurial position within a network of marketing alliances. We then consider how firm-specific uncertainty can moderate these relationships. A brief description of the research context is followed by our model, results, and a discussion of how our findings contribute to both theory and practice.

2. Theory and hypotheses

Marketing alliances are used by firms to access resources and capabilities (Thomaz & Swaminathan, 2015) and to signal quality (Swaminathan & Moorman, 2009; Wolff, 2001)—strategies manifest in the position a firm occupies within an alliance network (Koka & Prescott, 2008). In essence, the broader alliance network serves as a reservoir of available benefits, and a firm's position defines the volume and character of benefits it has access to. Nevertheless, different positions confer different benefits and very few researchers have examined how these benefits accrue in a network defined by marketing alliances.

Given the lack of theory specific to networks of marketing alliances, we begin our exposition by looking at the established literature on strategic alliances. Within this body of work, two distinct structural constructs tend to dominate. The first emphasizes benefits that accumulate due to a firm's prominence within a network (Podolny, 2001; Powell, Koput, & Smith-Doerr, 1996). The second draws on Burt's (1992) theory of structural holes to identify benefits arising from an entrepreneurial network position. It is unclear that these constructs operate the same way for marketing alliances that they do for strategic alliances more generally; however, the volume of evidence accrued in the strategic management literature offers a logical point of departure for hypothesis development in the context of marketing.

2.1. Network prominence

A prominent network position confers benefits via two mechanisms. First, prominent firms have more (and better) access to information than those less prominent in the network. Second, prominent firms are more visible, which leads to perceptions of quality and the opportunity to shape industry norms. Both of these mechanisms can lead to greater relative performance; however, the means by which this occurs in a marketing context requires some elaboration.

Marketing alliances form in order to facilitate downstream value chain activities. Thus, an information advantage that stems from a prominent position is likely to derive from more or better information about these downstream activities. Market intelligence, including customer preferences, commercialization opportunities, and competitive threats are all types of information that could originate from a downstream partner. While many firms may have access to similar information, a prominent firm is more likely to get the information earlier, with more redundancy, and from more reliable sources (Ahuja, 2000; Koka & Prescott, 2002; Mazzola, Perrone, & Kamuriwo, 2016).

A more prominent position also means higher visibility (Podolny, 2005). It is often the case that several firms are working on the same or similar problem. Yet, these firms may only have a general sense of the capabilities of their rivals. Network prominence can act as a signal of technological authority in a given domain (Podolny, 2001; Stuart, Hoang, & Hybels, 1999). This is especially true when a firm maintains alliances with large and prestigious industry partners (Shane & Stuart, 2002; Swaminathan & Moorman, 2009). This consolidation may dissuade rivals from competing directly with the focal firm since scarce industry resources (i.e. financing) are already tied up in a similar technology.

Affiliations can also serve as a source of legitimacy, ensuring that prominent firms continue to have access to the best resources at the lowest cost. For instance, commenting on the biotechnology industry, Wolff (2001, p. 64) writes, “the fact that an established drug company with its experienced scientific and managerial staff has examined a biotech venture and found it worthy of receiving millions of dollars in payments over many years is a strong endorsement of its potential.” These endorsements from big industry players give firms a stronger bargaining position. This stronger position can make it less costly to acquire additional resources like financing, and easier to create and enforce the terms of a commercialization agreement. Thus, we argue that all else equal, a more prominent position in a network of marketing alliances will help firm performance.

H1. Ceteris paribus, a prominent position in a network of marketing alliances will have a positive impact on firm performance.

2.2. Entrepreneurial position

Firms that occupy an entrepreneurial position are generally theorized to benefit from access to disparate—often unconnected—parts of a network. This assertion is based on observations that real-world networks are not uniform. Rather, they are characterized by clusters of firms that share connections with each other. This creates what Burt (1992) refers to as a structural hole—a portion of the network that bridges between dense clusters of firms.

Entrepreneurial network positions (like a structural hole) offer benefits in the form of rents from brokerage activities (Burt, 1992) and the opportunity to synthesize diverse information (Koka & Prescott, 2002). Brokerage benefits are realized when a focal firm can serve as an intermediary between otherwise unconnected firms. Because entrepreneurial network positions bridge otherwise disconnected portions of the network, they are ripe with opportunities to benefit from information and resource transfers. Diversity benefits arise when a firm in an entrepreneurial position has access to non-redundant and diverse information. Non-redundancy is beneficial as a means to compare the validity of information received by any one alliance partner. It is also beneficial as a source of novel information since disparate parts of a network are typically occupied by firms with different characteristics. Moreover, firms that bridge otherwise disconnected clusters have a unique opportunity to control the flow of information. When a new or novel piece of information from one area of the network is received, the bridging firm can decide to either pass on, or withhold that information from other parts of the network.

In the context of marketing alliances, it is unclear what value the ability to broker between unconnected downstream partners provides to the focal firm. However, the benefits of information diversity may be more relevant. For instance, access to diverse information is theorized to enable novel combinations of knowledge that ultimately result in unique market offerings. If a firm has downstream partners that operate in different areas of the market, it is plausible that the focal firm could synthesize information about these two segments to create something uniquely valuable. For these reasons, we hypothesize that firms which occupy an entrepreneurial position, will have some advantages over those that do not.

H2. Ceteris paribus, an entrepreneurial position in a network of marketing alliances will have a positive impact on firm performance.

2.3. Firm-specific uncertainty

Uncertainty is the difficulty firms have in predicting the future, which comes from partial, unstable, or otherwise incomplete knowledge about the state of the world in which they operate (Beckman, Haunschild, & Phillips, 2004). Uncertainty, in general, has been shown to impact a variety of firm behavior and outcomes related to marketing and strategy (Achrol and Stern, 1988; Sorescu & Spanjol, 2008). For our purpose, however, we need to distinguish the uncertainty that is unique to each particular firm—the firm-specific uncertainty—from uncertainty that is common to all firms in an industry (Beckman et al., 2004; Thomaz & Swaminathan, 2015).

Firm-specific uncertainty can stem from a variety of different factors, but most often from sources internal to a firm. For example, firm-specific uncertainty may be due to differences in employee turnover (particularly among key scientists and engineers), products at various stages of development, status of intellectual property (whether or not protected via patents or publication), and nature of funding. Firm-specific uncertainty can also be driven by heterogeneity in endowed resources or technical capabilities (Beckman et al., 2004; McGrath, 1997).

We argue that firms facing higher levels of firm-specific uncertainty are more susceptible to the risks of a prominent position in a network of marketing alliances. When a firm is more prominent in a network, competing firms are more likely to learn about the specific nature of that firm's work. Lavie (2006) refers to the appropriation hazard this represents as “outbound spillover rents.” If firms lack the capabilities to manage resource flows, prominence can place intellectual property at risk of appropriation (Xiong & Bharadwaj, 2011). This is especially true in networks of marketing alliances where the details of a technology are inevitably revealed through the process of commercialization (Teece, 1986). When a firm's future is uncertain, these ‘outbound spillovers’ are more likely to contain negative information, which can increase competition (if the firm is viewed as vulnerable) or hinder firms' efforts to secure additional resources like investment capital.

Prominent firms also have more (and better connected) marketing alliances, and while many obligations are specific to a given contract, the allocation of internal human resources, attention, and support are fungible (Wathne & Heide, 2000). When a prominent firm is facing an uncertain future, its alliance partners may provision less of their fungible resources to that firm (i.e. engage in passive opportunism). In a general sense, firms that are more prominent are more exposed—both in terms of knowledge appropriation and the commitment of internal resources (Lavie, 2007; Noordhoff, Kyriakopoulos, Moorman, Pauwels, & Dellaert, 2011). Thus, we argue that higher levels of firm-specific uncertainty will negatively moderate the relationship between network prominence and firm performance.

H3. Under high levels of firm-specific uncertainty, firms that are prominent in a network of marketing alliances will exhibit lower relative performance.

In contrast, firms in an entrepreneurial position may have some advantages when facing firm-specific uncertainty. As famously argued by Levinthal and March (1993), the impetus to exploit vs. explore is driven by circumstance, and the ability to explore is more important in unsettled times. Extending this insight to the literature on inter-organizational networks, a variety of scholars (see e.g., Uzzi, 1996; Ahuja & Carley, 1999; Koka & Prescott, 2008) have argued that access to heterogeneous alliance partners can help firms outperform their peers when facing some environmental change.

The factors undergirding this relative performance advantage are twofold. First, entrenched firms—like those occupying a prominent position—can find it difficult to extricate themselves from their current (perhaps poorly performing) relationships. This occurs because of the social pressure to remain part of the current clique—removing an alliance is more difficult when other, existing alliance partners are also tied to that firm (Uzzi, 1996). Second, access to diverse information can help managers explore a variety of solutions to a given problem. Rather than retrench with existing partners, managers can focus the firm's resources on relationships that are performing relatively well or use their access to disparate regions of the network to find unique solutions to the current uncertainty.

The current work is unique in that we are focused exclusively on marketing alliances and firm-specific (rather than environmental) uncertainty. Nonetheless, similar logic may apply. Consider for instance the firm-specific uncertainty created by the turnover of key personnel or unexpected problems with the commercialization process. Broader reach into the network can help firms find new resources (like a new CEO) or acquire information about unique commercialization opportunities that a more entrenched firm can't access. In either case, a firm located in an entrepreneurial network position is more likely to fare better than a firm with more homogenous alliance partners. Thus, we argue that an entrepreneurial network position will help firms facing high levels of firm-specific uncertainty.

H4. Under high levels of firm-specific uncertainty, firms that are more entrepreneurially positioned in a network of marketing alliances will exhibit higher relative performance.

3. Method

3.1. Research setting

Our research setting is the biotechnology industry during the period 1988–2004. We chose this time period for two reasons. First, it spans the years between studies with conflicting results on the value of marketing alliances (Das et al., 1998; Kalaignanam et al., 2007; Koh & Venkatraman, 1991; Swaminathan & Moorman, 2009). Second, it represents a period in the industry with sparse analyst coverage and unreliable financial data—there were few individuals capable of evaluating the science, much less its commercial value (Powell et al., 2005; Wolff, 2001). These features of the industry amplified the importance of strategic alliances as an indicator of firm potential (Podolny, 2001; Shane & Stuart, 2002). The fact that significant investment has occurred in this context confirms the importance of network models in information and investment. Moreover, the data we describe below is based on formal contractual agreements and not informal ties, handshake deals, or social embedding, hence they afford a strict test of whether network relationships influence performance outcomes.[1]

The science underlying the field of biotechnology had its origins in university laboratories. These promising discoveries were initially exploited by a handful of science-based start-up firms founded in the mid-to-late 1970s. The year 1980 marked a sea change, with the U.S. Supreme Court ruling in the *Diamond v. Chakrabaty* case that genetically engineered life forms were patentable. Congress passed the Bayh-Dole Act in the same year, which allowed universities, nonprofit research institutes, and small businesses to retain the intellectual property rights to discoveries funded by federal research grants (Mowery, Sampat, and Zedonis, 2001). And Genentech—which along with Cetus was then the most visible biotech company—had its initial public offering, drawing great interest on Wall Street, with a single day stock price run up exceeding any previous one-day jump. Over the next two decades, hundreds of small, science-based biotech firms were founded, mostly in the United States but more recently in Canada, Australia, Britain, and Europe.

In fields such as biotech, where knowledge is advancing rapidly and the sources of knowledge are widely dispersed, organizations enter into an array of alliances to gain different competencies and knowledge (Powell et al., 1996). In so doing, firms develop portfolios of

[1] There is clearly an important difference between formal and informal organizational linkages. Contractual relationships are crafted with considerable care and typically entail milestones or covenants dictating certain types of expected performance. Informal linkages more typically involve unwritten understandings, quid pro quos, and tacit agreements. Moreover, informal relationships are often entangled in ongoing friendships among employees of organizations. Such interpersonal ties are often less calculative and voluntaristic than formal ties. Our focus here is on direct organization to organization relationships that involve the transfer of resources and/or information.

relationships that permit access both to developments in science and skill in bringing new products to markets. Thus, the field is not only multi-disciplinary, it is multi-institutional as well. In addition to research universities and both start-up and established firms, government agencies, nonprofit research institutes, and leading hospitals have played key roles in conducting and funding research, while venture capitalists and law firms have played essential parts as talent scouts, advisors, consultants, and financiers (Black & Gilson, 1998; Lerner and Merges, 1998), and chemical, pharmaceutical, health-care, and conglomerate corporations have sought to bring the science to consumers.

3.2. Data

We use the dataset collected by Powell et al. (1996), extended through 2004 and supplemented with stock market data obtained from the Wharton Research Data Service (WRDS). The dataset on firm demographics and inter-organizational agreements has been described in detail elsewhere (see Powell et al., 2005), but a few remarks are still warranted. The database focuses on dedicated human biotech firms, omitting companies involved in veterinary and agricultural biotech (which draw on different scientific capabilities and operate in a much different regulatory climate). The reference source for information on a firm's ownership, financial history, formal contractual linkages to collaborators, products, and current research was the proprietary industry directory BioScan. Firm characteristics reported in BioScan include founding data, employment levels, financial history, and, for firms that exit, whether they were acquired or failed. The data on alliances cover the time frame and purpose of the relationship.

Following work by Powell et al. (2005), Rothaermel and Deeds (2004), Santoro and McGill (2005), and others, we sample companies that are publicly-held, independently operated, profit-seeking entities involved in human therapeutic and diagnostic applications of biotechnology. The resulting sample covers 401 firms, of which 85 were in existence in 1988 and 245 in 2004. In this time-frame, some firms were created and entered the database, and others exited, due to failure, departure from the industry, or acquisition. We designed the study as a pooled time-series analysis covering the years 1988–2004; however, we tracked alliance formation as far back as 1967 to account for contracts already active in 1988.

Firms in our sample varied widely in their number of active alliances within a given year—several dedicated biotech firms maintained only a few marketing alliances while others were active in more than fifty. On average, firms grew their strategic alliance portfolios from about four alliances in 1988 to almost ten by the year 1999. The years 2000 through 2004 saw a modest decline in the number of overall alliances as firms succumbed to the financial pressures characteristic of that time period. While the overall number of marketing alliances as a share of total alliances rose to approximately 45% in 1990, they then dropped to roughly 20% by the year 1996. However, there was a brief increase in 2000 as firms sought the financial stability of partnerships with large pharmaceuticals. The decline in the percentage of marketing alliances reflects efforts by larger biotech firms to vertically integrate downstream and thus capture a larger share of the revenue derived from commercializing their technology.

Financial data was obtained from Compustat and the Center for Research in Security Prices (CRSP) databases, a widely used electronic data service. However, use of this data constrained the size of our panel; of the 401 firms identified in Bioscan, 145 are excluded from the primary analysis because of missing data, or because they were public for only one year during the sampling window. Missing data occurred most often for shares outstanding and for international firms, which was either unavailable in some of the earlier years or simply not reported. Seventeen additional firms are excluded because of missing alliance variables.

3.3. Dependent variable

3.3.1. Annual market returns

We chose annual market returns as our operationalization of performance for two main reasons. First, this is the dependent variable used by the most relevant studies of marketing alliances (see e.g., Kalaignanam et al., 2007; Swaminathan & Moorman, 2009; Thomaz & Swaminathan, 2015). Thus, we have a more reliable basis for comparison of our results. Second, it helps to overcome certain well-known limitations in other accounting measures, which often discount a firm's intangible assets (see e.g. Brush, Bromiley, & Hendrickx, 2000). Intangible assets are pervasive for nearly all biotech firms during the period of our study and many firms relied heavily on venture capital, NIH grants, and long-term discovery contracts with large pharmaceuticals to fund their operations—distribution of funds was often periodic rather than performance-based. Moreover, as a discipline based primarily on science-driven discovery, human capital is often the most valuable resource within a firm.

We calculated annual market returns for each firm by capturing the annual change in market value of the firm's common shares. This measure is based on investors' expectations of future performance and typically calculated by multiplying the firm's stock price by the number of common shares outstanding. In a risky environment like biotech, this measure can be volatile. Thus, we calculated the annual market value by taking the mean of the 12 end-of-month daily values for the relevant year (Lavie, 2007). Change in market value was calculated by dividing the market value at time t + 1 by the market value at time t. This ratio was then log transformed to achieve the desired statistical properties under assumptions of linearity, homoscedasticity, and independence (Lavie, 2007; Podolny, Stuart, & Hannan, 1996; Stuart, 2000). Given a covariate matrix X_{it}, change in market value can be expressed by a power function of the form:

$$\ln(MV_{it}) = \alpha \ln(MV_{i,t-1}) + \beta X_{i,t-1} + e_{it} \tag{1}$$

3.4. Independent variables

3.4.1. Network prominence

Following prior research (Powell et al., 1996; Powell et al., 2005; Swaminathan & Moorman, 2009), alliances were coded as marketing if they included a downstream, commerce-related component in the agreement. From these ties, we formed a network representing all marketing alliance activity that included at least one dedicated biotech firm.[2] Prominence was then operationalized using Bonacich's (1972, 1987) eigenvector measure, which considers not only the number of other firms connected to the focal firm (whether directly or indirectly), but also how well those others are connected (Freeman, 1979).

3.4.2. Entrepreneurial network position

We operationalized entrepreneurial network position using Burt's (1992) structural holes construct. We used the calculation available in the Python Networkx library to construct the variable for use in estimation. This is the most common measure used by network researchers (i.e., Koka & Prescott, 2008) and effectively captures the degree to which a firm's alliance partners are unconnected. That is, does the firm occupy a structural hole?

[2] While we only consider publically-traded dedicated biotech firms in our panel, all parties to an alliance including universities, hospitals the government, venture firms and other biotechs enter as partners and thus as part of the centrality and alliance counts. We do not have records of marketing ties between non-DBF's which could introduce a potential source of bias into our results. However, most marketing alliances occurred between two DBFs or one DBF and one large pharmaceutical company. We have information on the DBF ties, and large pharmaceuticals are unlikely to have alliances with other pharmaceuticals.

3.4.3. Firm-specific uncertainty

In accordance with prior work (Beckman et al., 2004; Gulati, Lavie, & Singh, 2009; Sorescu & Spanjol, 2008), we operationalize firm-specific uncertainty as the standardized monthly volatility of the focal firm's common stock. The monthly volatility is calculated as the coefficient of variation for firm i's annual monthly closing price:

$$\frac{\mathrm{StdDev}(\mathrm{MonthlyPrice}_{it})}{\mathrm{Mean}(\mathrm{MonthlyPrice}_{it})} \tag{2}$$

where $t = 1988, \ldots, 2004$. The index i identifies each firm in the sample. By dividing the standard deviation of a firm's monthly closing price by its mean, we allow for comparisons across firms with different price ranges.

3.5. Control variables

3.5.1. Firm controls

Since many traditional measures of firm performance carried little weight during the period of our study (Rothaermel & Deeds, 2004; Wolff, 2001), other firm-level variables may have been used by investors to proxy for a firm's ability to capitalize on its marketing alliances. We include several within-firm controls to account for this possibility. Specifically we measure firm age, alliance experience, firm size and the number of non-marketing alliances, and the number of marketing alliances with pharmaceutical (vs. other) firms. Firm age could signal a firm's reliability as a partner given their ability to survive a volatile industry and is measured as the number of years since the firm's founding date. Alliance experience is measured as the number of years since a firm's first alliance (regardless of type). Over time, firms can become more proficient at managing alliances (Gulati et al., 2009). Annual market returns could also be affected by a firm's total alliance activity if, for instance, many alliances allow greater access to industry information (Powell et al., 1996). Without this control, our marketing alliances variables could proxy for a propensity towards alliance activity in general. This would make interpretation of the marketing-specific parameters troublesome (Stuart, 2000). Firm size (i.e. number of employees) is also included to account for the reduction in uncertainty as firms grow and diversify.

The number of marketing alliances to pharmaceutical (vs. other) firms can control for the alternative explanation that indirect ties proxy for firm capability. This would mean that the appropriation hazard is stemming from direct rather than indirect ties. Since pharmaceutical companies are not likely to be direct competitors, our parameter estimates are conditioned on the amount of potential direct competitors in a firm's marketing alliance portfolio. Finally, we include an indicator variable for whether a firm is located in California given the importance of certain geographic locations to the formation of alliances (see e.g. Owen-Smith & Powell, 2004).

3.5.2. Financial controls

As mentioned previously, financial measures of firm performance in biotech did not carry much information during the period covered in this study. However, to support this argument and to account for other possible within-firm changes that might affect stock returns, we collected all available annual financial measures from Compustat. In our sample, the majority of these measures are often highly correlated (> 0.80) and their inclusion resulted in significant missing values, especially for the earlier years. For these reasons, we do not include the majority of them in our analysis; however, three theoretically relevant financial measures are included in the most complete model for comparison. The log of *total revenue* may indicate early successes (and thus future potential) and can be a non-employee-based proxy for firm size. *R&D intensity* was calculated as the log of the ratio of R&D expenditures to total sales. This is potentially important given the performance implications of a strong marketing-to-research collaboration (Dutta, Narasimhan, & Rajiv, 1999). Finally, we control for *operating profit* (revenue minus operating expenses) since slack financial resources may give firms the ability to engage in more alliance activity (Eisenhardt & Schoonhoven, 1996).

3.5.3. Selection correction

When estimating changes in annual market returns that result from firm strategies or events, a potential econometric bias may arise because of sample selection. As a rule, selection bias occurs when the criterion for inclusion in a sample is not independent of the outcome variables. In this study, a potential bias could occur if sample attrition is somehow related to our key theoretical constructs. For instance, we observe that exit rates differ significantly based on number of marketing alliances. This could bias our estimates if exit is due to a merger with a previously aligned firm.

Following work by Kalaignanam et al. (2007), we use the generalized version of a Heckman selection model that uses predicted probabilities of firm exit to create a selection correction variable λ, given by

$$\lambda_{it} = \phi[\phi^{-1}(F_i(t))]/(1 - F_i(t)), \tag{3}$$

where $F_i(t)$ is the cumulative hazard function for firm i at time t, and Φ is the standard normal density function. A variable that indicates whether a firm is headquartered in a foreign country is included to account for the requirement that at least one variable in the selection model is correlated with failure but not with market returns. Results show that number of marketing alliances is a positive predictor of firm exit ($z = 2.60, p < .01$) and network centrality is a negative predictor of firm exit ($z = -2.24, p < .05$). The correction variable λ_{it} (where t is the observation year), is predicted from this model and included in our main analysis. Descriptive statistics are provided in Table 1 and pairwise correlations are provided in Table 2.

3.6. Statistical method

Eq. (1) can be estimated using ordinary least squares (OLS) while yielding unbiased and efficient estimates under the standard independence, linearity and homoscedasticity assumptions. However, there are two major econometric challenges in testing the proposed effects. The first issue is that prior stock market performance may affect both itself (state dependence) and alliance formation (reverse causality), meaning that several of our explanatory variables can be endogenous. The second issue is that unobservable, time-invariant firm characteristics may be correlated with the explanatory variables.

A variety of marketing studies have used vector-autoregression (VAR) models to address endogenous time-series variables; however, VAR models do not account for cross-sectional variability and are most

Table 1
Descriptive statistics.

Variable	Obs	Mean	Std. Dev.	Min	Max
Firm performance	1727	5.22	1.58	−0.11	11.29
Firm-specific uncertainty	1620	0.28	0.17	0.00	1.36
Network prominence	1727	0.04	0.04	0.00	0.33
Entrepreneurial position	1727	0.45	0.32	0.02	1.00
# of biotech firms	1727	113	31	50	158
# of marketing alliances with pharmaceuticals	1727	5	5	0	32
# of marketing alliances with other firm types	1727	5	5	0	57
# of non-marketing alliances	1727	10	8	0	68
Firm age	1727	12.76	7.71	1	83
Alliance experience	1726	9.46	4.74	0	28
Firm size	1727	286.51	763.80	1	8342
Headquartered in California	1727	0.32	0.47	0	1
Revenue	1725	95.33	466.11	−21.80	10,550.00
R&D intensity	1492	15.02	155.89	−1.69	5400.00
Operating profit	1725	7.58	193.87	−322.75	4636.00

Table 2
Pairwise correlations.

		1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	Performance	1													
2	Uncertainty	−0.0595	1												
3	Prominence	0.3792	−0.0668	1											
4	Entrepreneurial	−0.25	0.0784	−0.4006	1										
5	# of biotech firms	0.2238	0.0471	−0.0922	0.0612	1									
6	Pharma alliances	0.4407	−0.1037	0.7952	−0.5322	−0.0565	1								
7	Other alliances	0.0919	0.0022	0.3941	−0.1284	0.0906	0.119	1							
8	Non-mktg. alliances	0.349	−0.0372	0.6402	−0.2384	0.1608	0.514	0.6622	1						
9	Ln(firm age)	0.2642	0.0088	0.0404	−0.1718	0.1805	0.1698	−0.0472	0.0651	1					
10	Ln(alliance exp.)	0.3125	0.072	0.1582	−0.2157	0.2675	0.2397	0.0576	0.2397	0.7592	1				
11	Ln(firm size)	0.6715	−0.169	0.4963	−0.3679	0.0773	0.555	0.1199	0.4063	0.3107	0.2944	1			
12	California	0.118	−0.0343	0.1442	0.0361	0.0261	0.1252	0.0177	0.1334	−0.0721	−0.0671	0.1586	1		
13	Ln(revenue)	0.6583	−0.1784	0.4375	−0.3486	0.0774	0.5113	0.0778	0.3752	0.2913	0.2824	0.7636	0.1047	1	
14	R&D intensity	−0.0379	−0.0125	−0.0525	0.045	−0.028	−0.0562	−0.02	−0.0642	−0.0125	−0.0311	−0.0605	−0.0087	−0.1307	1
15	Operating profit	0.3096	−0.1038	0.1144	−0.1216	0.0096	0.1314	−0.0013	0.1096	0.1381	0.1326	0.3142	0.0991	0.3539	−0.0119

appropriate when the number of cross-section units is much smaller than the number of time points. In our data, the cross-sectional units (firms) are much larger than the number of time points (years). To address this issue, marketing researchers (e.g. Tuli, Bharadwaj, & Kohli, 2010; Xiong & Bharadwaj, 2013; and others) have used the Arellano-Bond General Method of Moments (GMM) approach to obtain consistent and unbiased estimates (Wooldridge, 2002). This method uses lags of the endogenous regressors as instruments, and first-differencing to addresses any bias imposed by unobserved, time-invariant firm characteristics.

Given these considerations, we estimate a model using the Arellano-Bond two-step system GMM (Arellano & Bond, 1991; Arellano & Bover, 1995) with lags of the dependent variable as instruments. Lags of two time periods produced the most efficient estimations while keeping the number of instruments below the number of groups (firms), thus reducing the risk of over-identification. Moreover, the AR(2) test of serial correlation is insignificant (see e.g. Arellano & Bond, 1991). Values for this test are included at the bottom of Table 1 for reference.

Some of our data are left-censored. Any effect of censoring on the estimate of a firm's average returns is controlled by the fixed firm effects. The same is true of sample attrition. To the extent that left-censored firms may follow a different within-firm process, our findings are likely to be suppressed, since we miss the period of early growth for such firms. Nevertheless, we do have firms of all ages and sizes represented in our sample. Right-censoring due to failure, merger, or other exit from biotechnology is controlled for with our selection model. Right-censoring due to sample attrition (losing observation for firms that remain independent and active in biotech) occurs very rarely, and so is not likely to bias our results.

The processes we are studying involve the co-evolution of firms and networks. This focus leads to an additional source of statistical non-independence across our observations. We need to control for effects that vary over time but are constant across firms, such as the overall number of outside partners, the density of the industry's network, government budgets for biomedical research, or the economic circumstances of pharmaceutical companies. To do so, we include a dummy variable for each year. While fixed year effects may be theoretically crude, they allow for the complete statistical control of factors that change over time at the industry/field level.

Correlations between most explanatory variables are below the values that should cause concern; however, several of our models use an interaction term, which can sometimes bias the standard errors by introducing additional multicolinearity. In addition, the number of marketing alliances is highly correlated with network centrality since eigenvector centrality uses number of direct connections as part of its formula. Mean centering variables accounted for this bias and fixed any observed problems in conditioning or variance inflation.

The above considerations are captured in Eq. (4),

$$\begin{aligned}\ln(\mathrm{MV}_{i,t+1}) &= \alpha\ln(\mathrm{MV}_{it}) + \beta_1\mathrm{FSU}_{it} + \beta_2\mathrm{P}_{it} + \beta_3(\mathrm{FSU}\times\mathrm{P})_{it} + \beta_4 H_{it} + \beta_5\\ &\quad(\mathrm{FSU}\times\mathrm{H})_{it} + \delta'\mathrm{X}_{it} + \gamma\lambda_{it} + \theta'\mathrm{T}_t + (\mu_i + e_{i,t+1}),\end{aligned} \tag{4}$$

where MV_{it} is the market value of firm i at time t, FSU_{it} is the firm-specific uncertainty, P_{it} is the firm's network prominence, H_{it} is the degree to which a firm occupies a structural hole, and β_3 and β_5 capture the hypothesized effects of uncertainty by prominence and uncertainty by entrepreneurial position interactions. X_{it} is a vector of control variables, λ_{it} is the selection correction for firm exit, T_t are time fixed effects, μ_i is the firm fixed-effect and e_{it} is the observation-specific error.

4. Results

Coefficient estimates from an Arellano-Bond two-step system GMM estimation of our model (Eq. (4)) are found in Table 3. We follow a hierarchical approach in which we introduce controls and independent

Table 3
Panel results for firm performance as dependent variable.

	(1)	(2)	(3)	(4)	(5)
Explanatory variables					
Firm-specific uncertainty	−0.432	−0.416	−0.381	−0.404	−0.247
	(0.456)	(0.460)	(0.453)	(0.455)	(0.469)
Network prominence	−1.449	−1.480	−1.389	−1.462	−2.350**
	(0.940)	(0.975)	(0.949)	(0.979)	(1.020)
Entrepreneurial position	0.132	0.111	0.127	0.109	−0.0131
	(0.142)	(0.143)	(0.140)	(0.143)	(0.146)
Network prominence x uncertainty		−4.860***		−4.688***	−5.786***
		(1.347)		(1.433)	(1.401)
Entrepreneurial position x uncertainty			0.451	0.0800	−0.362
			(0.415)	(0.437)	(0.414)
Control variables					
Lagged annual returns	0.473***	0.479***	0.474***	0.478***	0.442***
	(0.0784)	(0.0777)	(0.0786)	(0.0776)	(0.0801)
Second lag of annual returns	−0.195***	−0.199***	−0.195***	−0.198***	−0.196***
	(0.0354)	(0.0352)	(0.0350)	(0.0350)	(0.0413)
# of biotech firms	0.0125*	0.0119*	0.0125*	0.0120*	0.0118*
	(0.00645)	(0.00628)	(0.00642)	(0.00627)	(0.00625)
# of marketing alliances with pharmaceuticals	0.00952	0.00511	0.00877	0.00465	0.000604
	(0.0229)	(0.0231)	(0.0227)	(0.0230)	(0.0233)
# of marketing alliances with other firm types	0.0199	0.0183	0.0193	0.0182	0.0194
	(0.0160)	(0.0160)	(0.0160)	(0.0159)	(0.0163)
# of non-marketing alliances	0.0694	0.0862	0.0748	0.0865	0.111
	(0.0973)	(0.0974)	(0.0978)	(0.0977)	(0.102)
Ln(firm age)	−1.471*	−1.432*	−1.480*	−1.437*	−1.138
	(0.789)	(0.782)	(0.782)	(0.782)	(0.751)
Ln(alliance experience)	−0.163	−0.175	−0.164	−0.173	−0.138
	(0.618)	(0.615)	(0.611)	(0.614)	(0.621)
Ln(firm size)	−0.163	−0.165	−0.167	−0.165	−0.0820
	(0.157)	(0.157)	(0.156)	(0.157)	(0.162)
Headquartered in California	0.0114	0.0158	0.0100	0.0161	0.207
	(0.276)	(0.269)	(0.267)	(0.269)	(0.296)
Selection correction (firm exit)	−29.22	−30.39	−29.31	−30.06	−28.27
	(27.75)	(27.39)	(27.59)	(27.39)	(28.03)
Ln(revenue)					−0.0688
					(0.0427)
R&D intensity					4.40e-05
					(5.38e-05)
Operating profit					0.000237
					(0.000162)
Observations	1028	1028	1028	1028	936
Number of firms	169	169	169	169	161
p-Value of AR(2) test	0.76	0.66	0.60	0.63	0.77

Entries are coefficients, and the Windmeijer robust estimators of standard errors.
*** $p < .01$.
** $p < .05$.
* $p < .1$.

variables in subsequent models. Windmeijer (2005) robust standard errors account for heteroskedasticity and finite sample bias, and are presented just below the estimates in parentheses. Also presented for each model are the number of records, and the number of firms involved for those records. Year dummies are included in all models, but are omitted from the displayed results for clarity. Several additional specifications were tested as reported in Appendix A, and all results remain qualitatively the same.

Model 1 in Table 3 shows just the main effects. Neither parameter estimate is a statistically significant predictor of annual market returns. Thus, we do not find direct support for either Hypothesis 1 or Hypothesis 2. However, model 2 introduces the interaction between network prominence and firm-specific uncertainty, which is statistically significant in model 3 ($t = -2.84, p < .01$). This provides strong evidence and support for Hypothesis 3. Model 3 introduces the interaction between entrepreneurial position and firm-specific uncertainty, which is not significant. This is also the case in Model 4, which includes both interactions. Thus, Hypothesis 4 is not supported. Model 5 adds three theoretically relevant financial measures. While several observations are dropped due to missing data, the impact and significance of the hypothesized interaction with network prominence holds.

5. Discussion

We predicted that a prominent position in a network of marketing alliances would have a positive impact on firm performance (Hypothesis 1), that an entrepreneurial position would also have a positive impact on firm performance (Hypothesis 2) and that these relationships would be moderated by firm-specific uncertainty (Hypotheses 3 and 4). We did not find direct support for the main effect of prominence on performance, which mirrors findings by Swaminathan and Moorman (2009). However, we do find that the prominence-performance relationship is negative when firm-specific uncertainty is high. This result provides support for Hypothesis 3, that prominence can be a liability when firm-specific uncertainty is high. Surprisingly, we do not find any relationship between an entrepreneurial position and firm performance in this context.

5.1. Contributions to marketing alliance research

We make three primary contributions to the literature on marketing alliances. First, we offer evidence of a downside to marketing alliances. While others have shown that marketing alliances can lead to an increase in risk (i.e. Thomaz & Swaminathan, 2015), we are the first to show a negative effect on performance. Second, we introduce a new moderator for the relationship between network prominence and performance, which can be used by researchers to study the benefits of marketing alliances with greater nuance. Third, our results offer a plausible explanation for prior studies that struggled to detect a main effect of marketing alliances on firm performance (see e.g., Das et al., 1998; Koh & Venkatraman, 1991; Krasnikov & Jayachandran, 2008).

We also make a methodological contribution related to the measurement of short-term versus long-term value of marketing alliances. For instance, Swaminathan and Moorman (2009) find a positive relationship between the formation of strategic marketing alliances and firm performance. However, when they check the robustness of their findings over the longer term, the initially positive relationship becomes undetectable (Swaminathan & Moorman, 2009, p. 67). By analyzing marketing alliances in a network context, we allow for a broader view of a firm's marketing strategy. Indeed, many marketing alliances last several years and their value may change over time. Our approach provides the opportunity to relate marketing strategy to market returns over a longer period of time.

The focus on short-term reactions in the stock market can also suppress important factors related to performance. For instance, the event study methods employed by prior research looks at the risk-adjusted variation in market returns, which can mask contingencies based on uncertainty (Sorescu & Spanjol, 2008). Moreover, many marketing alliances last years, and their value may fluctuate as the result of new developments that occur while the relationship is still in place. When only measuring the effect of alliance formation, you miss these fluctuations and their effect on firm performance.

5.2. Contributions to marketing practice

Our findings suggest that a portion of the value from marketing alliances stems from benefits associated with the network context within which they are executed. A prominent position in a network of marketing alliances could be beneficial; however, that same position becomes a liability when firm-specific uncertainty is high. Essentially, the value of existing alliances changes as a firm's future becomes more or less certain. Thus, practitioners should be particularly wary of forming new marketing alliances unless they are relatively certain about the future of their company.

In addition, we offer some insight into the mechanisms that drive the prominence-performance relationship, which can provide savvy practitioners insight on how to manage the risks of their firm's network position. For instance, when working on high-risk ventures, managers may want to implement relationship-specific practices that protect information from leaking to competitors. Or, if firms are concerned with information leakage during the process of technology commercialization (i.e., when firms engage in consumer research, testing and technology integration), managers may want to choose a commercialization partner with fewer existing alliances.

5.3. Limitations and future research

In the sample of biotech firms studied herein, we find that there is no main effect of either prominence or entrepreneurial positioning on firm performance, and the effect of prominence on performance is only apparent when the firm-specific uncertainty moderator is included in the model. Despite the robustness of the result to different model specifications and operationalizations of the constructs, there are several features of the chosen context that might not generalize. For instance, the time period under study covers the 15 years during which the biotechnology industry emerged and became part of the mainstream. During this time, firms were mostly not profitable, and literally survived or failed based on their ability to acquire information, secure financing, and attract scarce talent (Wolff, 2001). Under these conditions, the risks of prominence may be more pronounced than they might be in a more mature industry. Thus, replications of this work in other contexts could actually find a main effect of prominence on performance and perhaps a weaker moderation. The natural research question this raises, is how other factors in the environment (industry or otherwise) affect the strength of the prominence-performance relationship and the firm-specific uncertainty moderator.

The null results related to an entrepreneurial network position are perhaps a blessing in disguise. Marketing researchers have been trying to identify characteristics unique to marketing alliances that don't translate perfectly from the broader literature on interorganizational alliances. Here, we have a case where the results are inconsistent with those of (for instance) Koka and Prescott (2008). This may simply be an artifact of the context—e.g., diverse market intelligence is not a driving force in the performance of biotechnology firms. However, it is worth speculating on other explanations as a source of future research. For instance, the fact that marketing alliances deal with downstream value-chain activities may mean that diverse information is less useful or takes longer to have an effect. Much of the research on information diversity links it to a firm's ability to create novel products, but this value would manifest well before a firm seeks to commercialize its product. Alternatively, diverse market feedback could take years to incorporate into a new product development cycle meaning that the performance effect will only manifest after several years. Regardless, there is still much to uncover regarding the role of entrepreneurial positioning in a network of marketing alliances.

6. Conclusion

Our research provides evidence that prominence within a network of marketing alliances can have a downside. Alliance networks provide access to information and legitimacy, but they also present hazards of knowledge appropriation and limits on strategic action. These countervailing forces lead us to conclude that a practiced study of the broader context within which marketing partnerships are conducted is vital in today's interconnected world. We hope our findings and the limitations outlined above, can provide a solid foundation for future research on this important subject.

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Appendix A. Robustness

In addition to the Arellano-Bond GMM approach, we also test first-order autoregressive models and simple cross-time panel regression with both robust and Driscoll-Kraay standard errors. Driscoll-Kraay standard errors can account for both serial and cross-section (or spatial) correlations, which is potentially important given the gradual geographic dispersal of biotech firms during the period of our study (Driscoll & Kraay, 1998). Regardless of specification, the interaction between centrality and uncertainty remains statistically significant and typically with higher t-values since these models do not reduce statistical power by incorporating a large number of instrumental variables.

Moderate variations in the operationalization of most variables does not change our results. For instance, models run using annualized daily stock returns as the performance measure and annualized daily volatility as the uncertainty measure maintain qualitatively the same outcome. However, one substantial concern is the operationalization of our measure for firm-specific uncertainty. Since we are using the standardized volatility of a firm's share price, the effect of uncertainty on market returns could be attributable to changes in industry-wide volatility (see e.g. Morgan and Rego, 2009). To account for this possibility, we derived a sanitized version of the uncertainty measure by using residuals from a regression of uncertainty on time fixed effects, which is possible because our sample effectively covers the population of publicly traded biotech firms. Industry effects only accounted for around 12% of the variation in firm-specific uncertainty. Moreover, the sanitized operationalization improves parameter significance suggesting that our original specification is conservative.

While not part of our initial theorizing, we did perform several post-hoc analyses that point to some of the mechanisms underlying our results. For instance, to better understand the mechanisms underlying the network centrality construct we also took direct measurements of a firm's extended network. To do this, we counted the number of marketing alliances once removed (all partners' partners) and used the count instead of centrality in our models. Not surprisingly, the uncertainty by extended-network-count interaction is negative and statistically significant.

One alternative explanation for our results is that the number of indirect ties is a proxy for partner capability. As such, the benefits and hazards would stem from competition with strong, direct alliances rather than from the exposure they provide to other (indirect) firms in the industry. If this is the case, we would expect the hazard to be higher when a firm's marketing alliances are with other biotech firms—this is opposed to pharmaceutical firms and others who are less likely to have the same research and development capabilities. To test this explanation we constructed a variable that indicated whether a given firm's marketing alliances were > 50% biotech firms. We then ran our models using a three-way interaction with the indicator variable. The parameter estimate on the interaction is not significant, thus providing no evidence that our main result is stronger when the majority of marketing alliances are with biotech firms.

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