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RESEARCH NOTES AND COMMENTARIES

WHEN ARE ASSETS COMPLEMENTARY? STAR SCIENTISTS, STRATEGIC ALLIANCES, AND INNOVATION IN THE PHARMACEUTICAL INDUSTRY

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To answer the question of when are assets complementary, we investigate specific resource combinations along the value chain, focusing on two mechanisms that are central to combining resources for innovation in the pharmaceutical industry: recruitment and retention of star scientists, and 2) engagement in strategic alliances. We propose that resource combinations that focus on the same parts of the value chain are substitutes due to knowledge redundancies. Conversely, we hypothesize that resource combinations that link different parts of the value chain are complements due to integration of nonredundant knowledge. To test these hypotheses, we empirically track the innovative performance of 108 global pharmaceutical firms over three decades (1974–2003).

INTRODUCTION

A growing body of research considers the question of where a firm draws its boundaries (Parmigiani and Mitchell, 2009; Williamson, 1991). Recently, researchers have advanced a nuanced approach to more accurately depict the complexity and velocity of today's business environment (Parmigiani, 2007). This stream of research illustrates that it is often the case that organizations choose to simultaneously or concurrently make, buy, or ally to attain like inputs (Parmigiani and Mitchell, 2009; Rothaermel, Hitt, and Jobe, 2006). This literature discusses concurrent sourcing as an alternative to the traditional dichotomy of make versus buy boundary decisions. If indeed organizations are using concurrent sourcing (referred to as tapered integration or dual distribution of inputs in the original literature, see Harrigan, 1986), the question remains whether it is efficacious for them to be doing so. More specifically, within the realm of innovation, are organizations facilitating or hampering their innovating efforts by leveraging different sources of knowledge concurrently?

We attempt to answer the question of when combinations of value chain activities are substitutive or complementary by investigating the effect of specific activity combinations on a firm's innovative performance. Specifically, we focus herein

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on the interactions between two mechanisms that are central to innovation in the pharmaceutical industry: the recruitment and retention of *star scientists,* and 2) engagement in *strategic alliances*. These two different mechanisms are representative of activities firms use to access knowledge and build new capabilities (Cockburn and Henderson, 2001; Ettlie and Pavlou, 2006; Gulati, 1998; Helfat, 1997; Helfat and Peteraf, 2003). Although some of these mechanisms have been studied in isolation (Gardner, 2005; Rothaermel, 2001; Zucker and Darby, 1997), there is a dearth of research regarding the contingency effects of these mechanisms on innovative performance.

We posit that strategic alliances and intellectual human capital are used to access and combine different types of knowledge along the value chain. While an upstream- downstream lens has been applied to strategic alliances (Baum, Calabrese, and Silverman, 2000; Koza and Lewin, 1998; Rothaermel and Deeds, 2004), we suggest that it can also be useful to better understand a firm's intellectual human capital. Our analysis of the degree to which the human capital is used to access upstream knowledge is based on a noted bifurcation of star versus non-star scientists (Rothaermel and Hess, 2007; Zucker and Darby, 1996). The importance of applying these categorizations is reflective of the knowledge that is needed to facilitate innovation at different points along the value chain. We propose that resource combinations that focus on the same value chain activities provide redundant knowledge and, thus, are substitutes. Conversely, we hypothesize that the resource combinations that link different value chain activities are complements, because they bring together different types of knowledge needed to complete the innovation process. To test these hypotheses, we empirically track the innovative performance of 108 global pharmaceutical firms over three decades (1974–2003).

THEORY AND HYPOTHESES

In high-velocity industries, the source of new knowledge is often external to incumbent firms (Powell, Koput, and Smith-Doerr, 1996). The increasing complexity and multidisciplinary nature of the innovation process forces pharmaceutical firms to concurrently access external knowledge to support both upstream and downstream value chain activities (Arora and Gambardella, 1990; Rothaermel and Hess, 2007). In these types of environments, a firm's innovative performance appears to be affected by its ability to create and manage connections with other organizations. Prior research investigating this connectivity has primarily focused on the role strategic alliances play in developing an organization's ability to access sources of external knowledge (Ettlie and Pavlou, 2006; Gulati, 1999; Hagedoorn, 1993; Rothaermel and Deeds, 2004).

It is important to note, however, that a firm's connectivity is also related to the firm's scope of collaborations—both formal (strategic alliances) and informal (interpersonal) relationships. Analysis of an organization's connectivity to the external environment requires knowledge not only of its strategic alliances but also of its intellectual human capital, which fosters, as indicated by the CEO of Centocor (a biotechnology firm): '. . .dozens of handshake deals and informal collaborations, as well as probably hundreds of collaborations by our company's scientists with colleagues elsewhere' (Powell *et al*., 1996: 120). Within high-velocity industries, prior research has identified both strategic alliances and intellectual human capital as antecedents to innovation (Rothaermel and Hess, 2007). Given this importance, it is critical that we further explore the interactions between these activities, because they are used simultaneously as firms pursue innovation.

Strategic alliances

Strategic alliances are a well-established means by which firms gain access to the external knowledge environment (Arora and Gambardella, 1990; Gulati, 1998; Rothaermel, 2001). In their conceptual treatment, Koza and Lewin (1998) established that firms enter into different types of alliances depending on the type of knowledge that they are seeking to acquire. Firms can enter into upstream alliances for the purpose of exploring for new opportunities, while downstream alliances are undertaken to exploit an existing capability (Rothaermel *et al*., 2004). This functional view is based on the position of an alliance along the value chain. Upstream alliances tend to be primarily focused on generating new basic knowledge, while downstream alliances are often focused on generating knowledge that is more applied in nature (i.e., focused on leveraging production and marketing

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activities, see Grant and Baden-Fuller, 2004; Lavie and Rosenkopf, 2006).

Firms conduct upstream research alliances to discover something new, allowing the partners to share and acquire tacit knowledge. These types of alliances are usually undertaken with universities and other research institutions and are often characterized by high uncertainty and frequent failure (Rothaermel *et al.*, 2004). On the other hand, firms that conduct downstream alliances to leverage complementary assets combine explicit knowledge (Teece, 1992). Downstream alliances generally join the drug development efforts of new ventures with larger, more well-established firms that provide manufacturing capabilities, regulatory know-how, market knowledge and access (Rothaermel *et al.*, 2004). Several empirical studies, across different types of firms, industries, and time frames, provide robust support for the viability of applying an upstream-downstream lens to strategic alliances (Lavie and Rosenkopf, 2006; Park, Chen, and Gallagher, 2002; Rothaermel, 2001; Rothaermel and Deeds, 2004). Following this line of research, we dichotomize a firm's strategic alliances into upstream and downstream to reflect their intent to leverage different types of knowledge along the value chain.

Star scientists

In the pharmaceutical industry, star scientists provide critical connectivity to universities and other sources of upstream knowledge (Arora and Gambardella, 1990). Star scientists are important boundary spanners, because a difference in coding schemes exists, specifically between large public firms and academic institutions and other high-tech start-ups. This mismatch creates the possibility of communication difficulties (Allen and Cohen, 1969). It can be alleviated, however, by the use of individuals 'who are capable of translating between two coding schemes either through personal contact or knowledge of the literature, and who can act as bridges linking the organization to other organizations and workers in the field' (Allen and Cohen, 1969: 13). The variations in coding schemes between different knowledge communities is of concern because without boundary spanners that function as translators, the firm would potentially be unable to assimilate tacit information into codified knowledge that can lead to future innovation.

Further, in high-velocity knowledge environments, boundary spanners are not only able to keep the pulse of shifts in technology, but in many cases may actually hold key knowledge themselves. Prior research has identified the spread of biotechnology through the scientific community as one case in point. Specifically, Zucker, Darby, and Brewer (1998: 291) suggest that for at least 10 to 15 years the repository for key knowledge associated with biotechnology was with a 'small initial group of discoverers, their coworkers, and others who learned the knowledge from working at the bench-science level with those possessing the requisite know-how.'

We suggest that star scientists provide an incumbent firm with access to upstream knowledge not only through their own research but also by being part of a broader scientific community. In support for this notion, Furukawa and Goto (2006) found that the stars in science were responsible for a disproportional large number of publications in scientific journals, and were thus engaging in the creation of new (upstream) knowledge. Our own data illustrate a similar trend. We find that the top one percent of authors (employed by one of the pharmaceutical companies in our sample) account for almost 40 percent of all publications (with at least one coauthor affiliated with a pharmaceutical company). Engaging star scientists in the open literature in turn lays a critical foundation for subsequent innovation (Henderson and Cockburn, 1994), because it builds and maintains a firm's absorptive capacity, understood as the firm's ability to recognize, value, and exploit new external knowledge (Cohen and Levinthal, 1990).

Contingency effects: star scientists and strategic alliances

Two resource combinations are complementary when the marginal return to one resource increases in the presence of the other (Milgrom and Roberts, 1995). While there is potential for synergies between sets of resources, there is also a potential for a substitutive relationship, if doing more of an activity to leverage a specific resource reduces the marginal benefit of another (Arora and Ceccagnoli, 2006; Cassiman and Veugelers, 2006).

Our central argument is that the complementary or substitutive relationship between bundles

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of resources is a function of the types of knowledge being combined. We suggest that activities that link different segments of the value chain are complementary, while those that focus on the same value chain activity are substitutive. It is important to note that our focus is on understanding the relationship between the different upstream and downstream value chain activities of an organization. The contingency effects we stipulate occur *after* a firm has established a threshold of minimum activity in each category.[1] The two contingency effects we are focusing on are combining 1) *star scientists and upstream alliances,* and 2) *star scientists and downstream alliances* in a firm's pursuit of innovation.

Although there are clearly some important differences between star scientists engaging in knowledge creation and dissemination and firms pursuing upstream research alliances, there is also some element of equifinality present with respect to the type of knowledge generated in each activity. This implies that investments in different innovation activities can lead to similar outcomes. Although an equifinality argument is necessary for a substitutive relationship to occur, it is not sufficient. More specifically, for a substitutive relationship to occur, using one activity must also marginally decrease the benefit of using another. In the case of pharmaceutical firms, this is exactly what we suggest happens when upstream alliances and star scientists are simultaneously employed for the purpose of gaining access to tacit knowledge.

The premise of this argument stems from the potential diseconomies of scope associated with using different governance mechanisms. Specifically, given the high velocity of the knowledge environments in which they operate, access to external communities of practice is critical (Arora and Gambardella, 1990). Over time, firms within these communities of practice develop relationship-specific knowledge that cannot be easily replicated with other firms outside the specific community (Brown and Duguid, 2001; Kogut and Zander, 1992). Such firm-specific research and development (R&D) activities have been empirically demonstrated in the petroleum industry (Helfat, 1994a; Helfat, 1994b). Further, early decisions affect outcomes in the distant future due to time compression diseconomies (Dierickx and Cool, 1989). Given this, the longer a firm participates in a community of practice, the more social capital, trust, tacit knowledge, and bargaining power it will accumulate with the other members of the community (Brown and Duguid, 2001; Reed and DeFillippi, 1990). These mechanisms indicate that marginal transaction costs diminish with the level of involvement a pharmaceutical firm has with a given community of practice.

The key point for our argument is that for pharmaceutical firms, the members of the communities of practice tend to be different, depending on whether they relate to the firm's network of alliance partners (primarily small biotechnology firms) or the networks of individual scientists (Gambardella, 1992). Over time, firms tend to develop a competence to facilitate communication with and participation within a specific community. For example, Merck prefers to leverage their own star scientists when exploring for new therapeutic areas, whereas Lilly tends to rely more on upstream alliances (Galambos and Sturchio, 1998).

It is important to note that our arguments here relate solely to the R&D process in the pharmaceutical industry. Specifically, in other industries in which this process is not as clearly structured, star scientists may serve a complementary role in the innovation process by suggesting potential alliance targets and helping to facilitate the knowledge-sharing process between partners. Nonetheless, we suggest that within the pharmaceutical industry, the transaction costs of participating in multiple communities of practice at the same stage in the knowledge conversion process will outweigh these potential benefits.

Hypothesis 1: Different upstream activities are substitutes, such that the interaction between

[1] It is theoretically possible that a firm sources *all* of its knowledge internally through combining internal exploration by star scientists with internal exploitation by staff scientists. Alternatively, it is theoretically possible that a firm sources *all* of its knowledge externally through combining upstream alliances with downstream alliances. Although these are theoretically possible combinations, they tend to be *not probable*, because the vast majority of firms, across many different industries, have moved to an open innovation system, combining internal and external R&D (Chesbrough, 2003). Specifically, in our sample of global pharmaceutical companies, 75 of the 108 (69%) of the sample firms have followed a system of open innovation by simultaneously employing at least one star scientist and one staff scientist, combined with the pursuit of at least one upstream and one downstream alliance during a single year. This figure jumps to 99 percent of the firms when the window is increased to a three-year time period.

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star scientists *and* ***upstream alliances*** *is negative and thus decreases a firm's innovative performance at the margin.*[2]

Successful innovation requires that a firm combines upstream and downstream value chain activities (Teece, 1986). By combining these activities, firms are not only able to capture greater economic rents, but also to enhance the potential for uncovering synergies within the innovation process. Specifically, we suggest that firms that are able to integrate upstream knowledge generated by star scientists with downstream alliances are able to elicit complementarities. This resource combination allows firms to leverage distinctly different parts of knowledge to complete the innovation process. In downstream alliances, drug discovery and early-stage development is completed by the new venture, before the drug is 'handed-off' to the pharmaceutical company for large-scale manufacturing, pre- and clinical trials, regulatory management by the Food and Drug Administration, and finally distribution and sales (Pisano and Mang, 1993). Thus, combining star scientists and downstream alliances constitutes a matching of complementary assets because it links different types of knowledge to complete the value chain.

We further hypothesize that the value in combining upstream and downstream activities will outweigh the costs associated with using different mechanisms as outlined above. Support for this can be found in the research examining the importance of organizations simultaneously pursuing disparate innovative activities (e.g., Tushman and O'Reilly, 1996). Such research has highlighted the importance of being ambidextrous, or being able to balance the exploration and exploitation of knowledge. Although we do not suggest that there is a precise matching between the constructs of upstream/downstream and exploration/exploitation, the locus on knowledge (i.e., upstream or downstream) is often reflective of the motivation of the accessing organization (i.e., exploration or exploitation). Within the setting of our study, star scientists are embedded in the greater scientific community. These relationships are often premised on the exploration for new projects with the highest potential (Stephan, 1996). Likewise, pharmaceutical firms tend to use their downstream connections for the purpose of exploiting or commercializing knowledge that is held within the firm (Rothaermel, 2001). Thus, pursuing these mechanisms simultaneously is likely to be reflective of an organization that is attempting to pursue an ambidextrous innovation strategy.

Hypothesis 2: Upstream and downstream activities are complements, such that the interaction between ***star scientists*** *and* ***downstream alliances*** *is positive and thus increases a firm's innovative performance at the margin.*[3]

METHODOLOGY

Research setting

The global pharmaceutical industry is our research setting. We tracked annual data for 108 incumbent firms over 30 years, beginning in 1974 until the end of 2003. An incumbent pharmaceutical firm is one that was founded prior to the emergence of biotechnology, which commenced with the 1973 breakthrough publication on r-DNA (Cohen *et al.*,

[2] In a more technical fashion, if we define star scientists as $Star_{Upstream}$ and upstream alliances as $All_{Upstream}$ based on their position on innovation value chain, and innovative performance as π, it follows that

$$\pi\left(Star_{Upstream}, All_{Upstream}\right) - \pi\left(\overline{Star_{Upstream}}, All_{Upstream}\right) < \pi\left(Star_{Upstream}, \overline{All_{Upstream}}\right) - \pi\left(\overline{Star_{Upstream}}, \overline{All_{Upstream}}\right),$$

where *prime* indicates that a firm does not engage in that specific activity. The formula states that the innovative performance of firms that engage in upstream research through star scientists *and* upstream alliances simultaneously is lower than for firms that engage in upstream research through either star scientists *or* upstream alliances, holding all else constant (Milgrom and Roberts, 1995).

[3] In a more technical fashion: If we define star scientists as $Star_{Upstream}$ and downstream alliances as $All_{Downstream}$ based on their position on innovation value chain, and innovative performance as π, it follows that

$$\pi\left(Star_{Upstream}, All_{Downstream}\right) - \pi\left(\overline{Star_{Upstream}}, All_{Downstream}\right) > \pi\left(Star_{Upstream}, \overline{All_{Downstream\ t}}\right) - \pi\left(\overline{Star_{Upstream}}, \overline{All_{Downstream}}\right),$$

where *prime* indicates that a firm does not engage in that specific activity. The formula states that the innovative performance of firms that combine upstream research through star scientists with downstream alliances is higher than for firms that engage in upstream research through either star scientists *or* downstream research through downstream alliances alone, holding all else constant (Milgrom and Roberts, 1995).

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1973). The sample comprises pharmaceutical companies that engage in research, discovery, development, and commercialization of new drugs that are placed inside the human body (*in vivo*). To track the innovation of the incumbent pharmaceutical companies, we collected fine-grained longitudinal data on 900 acquisitions, 3,100 alliances, 4,000 new drug introductions, 147,000 patents, 171,000 publishing scientists, 672,000 journal publications, and 9.9 million journal citations.

Dependent variables

We view new product development as a process of discovering new knowledge with the intent of transforming and embodying it in a final product (Madhavan and Grover, 1998). To capture the effect of both upstream and downstream knowledge, we use two dependent variables that represent different knowledge stages along the innovative process: citation-weighted patents and new drugs in development.

Citation-weighted patents

Although simple patent counts are a frequently used indicator of innovative output, they are inherently limited in the extent to which they can capture differences in patent quality (Griliches, Pakes, and Hall, 1987). Patents that are highly cited tend to be perceived as the more important inventions (Albert *et al*., 1991; Stuart, 1998). We collected forward citation-weighted patent information (*citation-weighted patents*) for the sample firms following the procedure detailed in Hall, Jaffe, and Trajtenberg (2005). We obtained these data primarily through the National Bureau of Economic Research patent data provided by Hall, Jaffe, and Trajtenberg (2001). In addition, we used the United States Patent and Trademark Office (USPTO) patent database to both cross-check the validity of the data, and to update them. We created a five-year citation-weighting window, and were able to do this for 86 firms between the years 1974–2001.[4]

New drugs in development

To proxy for the firm's ability to combine different types of knowledge along the innovation value chain, we counted the number of new drugs annually that entered a firm's pipeline at the preclinical stage of development (*new drugs*). These are so-called lead candidates, because they have overcome significant uncertainty: only 2.5 percent of all drug compounds tested become lead candidates to enter preclinical testing in the laboratory and on animals before moving to phase I clinical trials where they are tested on humans (Giovannetti and Morrison, 2000). We chose this new product development measure to reduce concerns associated with the time lags between dependent and independent variables caused by the lengthy drug development and approval process (Galambos *et al*., 1998). The average firm in our sample introduced just over six lead drug candidates into their pipeline per year. We obtained these data from *PharmaProjects,* a comprehensive database tracking new drug development in the pharmaceutical industry.

Independent variables

Star scientists

We followed the process described in detail by Lacetera, Cockburn, and Henderson (2004) and Rothaermel and Hess (2007) to identify star scientists. Using several sources including the *BioScan* and *Recap* databases, we identified a population of 125 pharmaceutical firms.[5] We then searched the *Web of Science ISI* database to identify journal publications that appeared between 1974 and 2005,[6] had a keyword related to science research (excluding social science research and nonhuman

[4] We collected patent citation data until the end of 2006. While the sample sizes for the regression models employing the citation-weighted patents (86 firms) and new drug development (56 firms) are by necessity less than the 108 firms in the initial sample frame, we are confident that this does not introduce a systemic sample selection bias, because the industry structure of the global pharmaceutical industry is fairly oligopolistic and has become more concentrated over time. We tracked the pharmaceutical sales of 52 sample firms that were not diversified outside pharmaceuticals. These focused pharmaceutical companies represent only 44 percent of the initial sample, but account for 75 percent of the total sales for pharmaceuticals worldwide (*IMS Health,* 2008). Moreover, we also explicitly control for this concentration effect trough tracking horizontal mergers between pharmaceutical firms in the sample.

[5] All 108 firms in the initial sample were included in the sample drawn to construct the measures for intellectual human capital. There were 17 horizontal mergers over the study period, which we explicitly controlled for.

[6] Note that our time period to identify stars is by design two years longer than the study period (1973–2003) to account, to some extent, for a 'rising star' effect associated with the potential right censoring of the data.

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focused research, e.g., agricultural), and could be unambiguously connected with one of the pharmaceutical firms in the sample. From the population of over 672,000 publications, we collected the following information: author's name, author's affiliation(s), journal name, article title, keywords, publication year, and number of times cited. We then compiled a list of authors with an aggregate number of publications and times cited for each year. This query yielded the records of over 171,000 authors who on average published 3.9 papers and that were cited 66.3 times. We then tied back each author to the pharmaceutical firms in our sample based on the authors' affiliations as indicated in the journal article(s).

We followed Rothaermel and Hess (2007) by identifying star scientists as researchers who had *both* published *and* been cited at a rate of three standard deviations above the mean.[7] To qualify for this elite group of star scientists, an individual must have published more than 28 papers during the study period and had to be cited at least 861 times. Based on this intersection, we identified 1,071 *star scientists*. These individuals represent only 0.63 percent of the total population of scientists in this sample, but produced 12.2 percent of all publications and garnered 22.1 percent of all citations. This made star scientists 19 times more productive in terms of research output and 35 times more impactful in terms of influencing other scientists' research. The average pharmaceutical firm employed about 23 star scientists (and 211 non-star scientists) in a given year. We explicitly control for non-star scientists (*non-star scientists*).

Strategic alliances

To document the alliances that the pharmaceutical firms had entered with different partners, we tracked each firm's alliances with universities, research institutions, and biotechnology firms (Powell *et al*., 1996). To obtain the most accurate alliance data as possible, we used various issues of the *BioScan* industry directory and the *Recap* database.[8] The average sample firm entered approximately one alliance per year.

We content analyzed each alliance description to decompose a firm's total strategic alliances into upstream and downstream agreements. Following a well-established coding procedure in prior research (Koza and Lewin, 1998; Lavie and Rosenkopf, 2006; Park *et al*., 2002; Rothaermel, 2001), we coded grants, research and R&D alliances as *upstream alliances*, because they focus on the basic research oriented upstream knowledge discovery activities of the value chain. We identified manufacturing, licensing, development, and supply alliances as *downstream alliances*, because they focus on the downstream knowledge-leveraging activities of the value chain. Accordingly, we identified 2,041 upstream alliances and 1,061 downstream alliances.[9]

To control for differential strengths of alliances ties, we collected information for each alliance to determine whether it was based on an equity exchange, which is considered to be a stronger tie (Gulati, 1995). While non-equity alliances are contract-based cooperative agreements to exchange knowledge and resources, equity alliances are based on taking an equity stake in a partner, exchanging equity, or setting up a third organization as a joint venture. We calculated a variable equal to the percentage of total alliances that are equity agreements (*% equity alliances*). About 12 percent of all alliances were equity based.

Additional control variables

We include a detailed set of additional control variables to account for potential heterogeneity at the drug, firm, network, and industry level. These controls are well established and validated

[7] In addition to examining stars at three standard deviations (sd) above the mean for both publications and citations, additional sensitivity analysis indicates that our results are robust to equating stardom with two and four sd above the mean, but not one sd.

[8] *BioScan* and *Recap* are fairly consistent in their reporting. We found their intersource reliability to be greater than 0.90 when documenting alliances. *BioScan* and *Recap* appear to be the two most comprehensive publicly available data sources documenting alliance activity in the global biopharmaceutical industry, and they have been used frequently in prior research, although not together, but in isolation (e.g., Shan, Walker, and Kogut, 1994; Lane and Lubatkin, 1998; Powell *et al*., 1996).

[9] Research assistants that were blind to each other and the theory to be tested coded the alliance data. In addition, in an attempt to ensure the accuracy of this coding, two additional research assistants independently coded each 100 randomly selected alliance agreements. The interrater reliability was 98 percent, and thus well above the recommended threshold of 70 percent (Cohen *et al*. 2003).

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by prior research, and include: a pharmaceutical family tree to control for horizontal merger (*merged firm*); whether a firm's strategy is focused solely on drug development (e.g., Merck) or a diversified product line (e.g., Johnson and Johnson) (*diversified*); nationality (*US, EU*, or *Japan*); financial performance (*net income*); total patent propensity (*total patents*), R&D expense (*R&D expense*); acquisitions focused on research and development (*R&D acquisitions*); the percentage of new products focused on cancer treatments (*% cancer drugs*); and temporal effects (*year dummies*). We collected financial data from a number of sources including *Compustat* and annual financial reports. All financial data are inflation adjusted in constant 2000 U.S. dollars.

Estimation procedure

The dependent variables (citation-weighted patents and new drug indications) are count variables, and thus take on only nonnegative integer values. A negative binomial estimation provides a better fit for count data than the more restrictive Poisson model.[10] Negative binomial regression accounts for an omitted variable bias, while simultaneously estimating heterogeneity (Cameron and Trivedi, 1986; Hausman, Hall, and Griliches, 1984). Moreover, based on econometric theory, the use of either a fixed- or a random-effects specification permits one to reduce the threat for unobserved heterogeneity (Greene, 2003). We applied a Hausman (1978) specification test, and its results revealed that there was not a systematic variation between the random- and fixed-effects estimations. Taken together, we applied the following random-effects negative binomial model:[11]

$$P(nit/\varepsilon) = e^{-\lambda it-1\exp(\varepsilon)}\lambda i^{nit-1}/nit-1!,$$

where n is a nonnegative integer count variable capturing each pharmaceutical firm's innovative output. Accordingly, $P(nit/\varepsilon)$ indicates the probability that pharmaceutical firm i develops the expected number n of these outputs in year t.[12]

As illustrated in Table 1, all of the bivariate correlations are below the recommended 0.70 threshold. To assess the threat of multicolinearity, we calculated the variance inflation factors (VIFs) for each coefficient. The maximum estimated VIF for was 5.8, well below the recommended ceiling of 10 (for a discussion of these issues see Cohen *et al*., 2003). In an attempt to compensate for a potential simultaneity bias and to allow for potential claims of causality, we lagged the financial measures (net income, revenues, and R&D expenditures) as well as alliances and acquisitions by one year (Gulati, 1999; Hall, Griliches, and Hausman, 1986; Stuart, 1998). We did not lag our measures of star scientists because of the close temporal link between the date at which an article was published (this was the basis for our measure of star scientists) and the innovative output associated with the publication (Murray, 2002). Moreover, we submit that through the application of the Hausman-specification test and the resulting random-effects specification, in combination with an extensive set of control variables and various robustness tests, we have attempted to address the issue of endogeneity (Hamilton and Nickerson, 2003). As detailed below, we also conducted a split-sample regression to assess the robustness of our interaction results.

RESULTS

Tables 2–3 present the regression results using the two different dependent variables. In each case, we first estimated a baseline model including the control variables and direct effects only. Next, we added the interaction effects. With the exception of Model 1b, each subsequent model represents a significant improvement over the respective baseline models at $p < 0.05$, or smaller. Models 1a and 2a each contain all the controls, Models 1b and 2b additionally contain all direct effects as

[10] In an attempt to address the concern of endogeneity, we also applied a conditional fixed-effects Poisson estimation. The results were robust.

[11] To assess how sensitive our results are to the reported random-effects specification, we additionally applied a conditional fixed-effects estimation. While the hypothesized results remained robust, in Model 1c (citation-weighted patents) there was a reversion in the findings, such that the coefficient for star scientists became negative and significant ($p < 0.05$) and the squared-star coefficient was positive and significant ($p < 0.05$). This result clearly does not fit with the rest of the estimations and we hypothesize may be a function of the fact that the citation-weighted panel has a reduced number of time periods without a corresponding reduction in sample size. Thus, fixed effects may be picking up more random error in these models.

[12] The results are robust to applying a zero-inflated Poisson estimation.

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Table 1. Descriptive statistics and correlations

Variables		Mean	St.Dev	Min	Max	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.
DV	**1.** Citation-weighted patents	84.76	174.65	1.00	2603.00															
	2. New drugs	6.01	10.42	0.00	89.00	0.036														
Control	**3.** Merged firm	0.15	0.36	0.00	1.00	0.396	0.290													
	4. Diversified	0.46	0.50	0.00	1.00	0.120	0.168	0.132												
	5. US	0.30	0.46	0.00	1.00	0.321	−0.099	−0.063	0.150											
	6. EU	0.34	0.48	0.00	1.00	−0.058	0.257	0.254	−0.059	−0.600										
	7. Net income*	710.78	1575.00	−6680.33	28 596.29	0.493	0.000	0.203	0.033	0.221	0.062									
	8. % equity alliances	0.12	0.47	0.00	10.00	−0.033	0.024	0.030	0.116	−0.059	0.109	−0.045								
	9. % cancer drugs	0.11	0.21	0.00	1.00	0.348	0.021	0.398	0.031	0.312	−0.160	0.398	−0.092							
	10. Total patents	41.47	73.44	−21.00	688.00	0.481	−0.139	0.336	−0.317	0.009	0.197	0.225	−0.106	0.251						
	11. R&D expense*	627.91	1473.25	0.00	33 433.23	0.373	−0.028	0.244	−0.362	−0.099	0.345	0.245	−0.064	0.201	0.664					
	12. R&D acquisitions	0.28	1.20	0.00	30.00	0.454	0.008	0.272	−0.126	0.368	−0.217	0.387	0.028	0.522	0.153	0.131				
	13. Non-star scientists	211.18	325.72	0.00	2134.00	0.596	0.184	0.442	0.162	0.482	−0.241	0.324	−0.045	0.612	0.339	0.283	0.495			
IV	**14.** Upstream alliances	0.60	1.45	0.00	17.00	0.164	−0.042	0.151	−0.199	0.346	−0.106	0.363	−0.072	0.377	0.239	0.230	0.413	0.284		
	15. Downstream alliances	0.31	0.96	0.00	13.00	0.093	−0.199	0.031	−0.003	0.267	−0.087	0.123	−0.051	0.099	0.112	0.025	0.106	0.041	0.486	
	16. Star scientists	23.02	52.31	0.00	145.00	0.570	0.127	0.453	0.354	0.418	−0.299	0.287	−0.039	0.498	0.104	0.033	0.397	0.652	0.169	0.024

* Inflation adjusted in constant 2000 U.S. dollars.
(n = 1, 163 for citation-weighted patent models; n = 465 for new product development models).

Table 2. Regression results for random-effect negative binomial estimation: citation-weighted patents

	Forward citation-weighted patents					
	Model 1a		Model 1b		Model 1c	
	beta	s.e.	beta	s.e.	beta	s.e.
Year effects	*Included*		*Included*		*Included*	
Constant	−1.2168	(0.5770)	−1.2052	(0.5772)	−1.1763	(0.5768)
Merged firm	0.0837	(0.0696)	0.0719	(0.0703)	0.0794	(0.0692)
Diversified	0.0930	(0.0947)	0.0819	(0.0967)	0.0711	(0.0969)
US firm	0.2549*	(0.1277)	0.2517*	(0.1289)	0.2452	(0.1285)
EU firm	0.1122	(0.1298)	0.1173	(0.1313)	0.1026	(0.1313)
Net income	−0.0171	(0.0400)	−0.0231	(0.0404)	−0.0194	(0.0404)
% equity alliances	0.0268	(0.0159)	0.0265*	(0.0159)	0.0257	(0.0159)
Total patents	0.2055***	(0.0245)	0.2092***	(0.0249)	0.2099***	(0.0250)
R&D expense	0.1369***	(0.0241)	0.1377***	(0.0243)	0.1421***	(0.0241)
R&D acquisitions	−0.0002	(0.0168)	−0.0004	(0.0172)	−0.0058	(0.0174)
Non-star scientists	0.1503***	(0.0336)	0.1462***	(0.0363)	0.1490***	(0.0368)
Upstream alliances	0.0131	(0.0161)	0.0098	(0.0337)	0.0171	(0.0327)
Upstream alliances²			0.0014	(0.0241)	0.0138	(0.0226)
Downstream alliances	0.0057	(0.0145)	0.0506*	(0.0290)	0.0492*	(0.0292)
Downstream alliances²			−0.0430*	(0.0248)	−0.0444*	(0.0246)
Star scientists	−0.0221	(0.0234)	0.0128	(0.0350)	0.0272	(0.0363)
Star scientists²			−0.0322*	(0.0187)	−0.0143	(0.0201)
Star scientists × upstream alliances					−0.0159**	(0.0062)
Star scientists × downstream alliances					0.0029	(0.0060)
Log likelihood	−4606.01		−4490.13		−4486.66	
Chi square	503.1***		503.8***		513.9***	
Improvement over base ($\Delta\chi^2$)			0.70		10.80*	

n = 1,163
* p < 0.05; ** p < 0.01; *** p < 0.001; Huber-White robust standard errors in parentheses.

well as squared effects for the variables of theoretical interest in this study, while we added the interaction effects in Models 1c and 2c.

Hypothesis 1 posits that innovative activities that represent attempts to access upstream knowledge are substitutes. We thus expect the interaction between star scientists and upstream alliances to be negative (and statistically significant).[13] We find support for Hypothesis 1. The interactions between star scientists and upstream alliances are negative and statistically significant in Model 1c ($p < 0.05$) when predicting citation-weighted patents, and in Model 2c ($p < 0.05$) when predicting new product development.

In Hypothesis 2, we suggest that innovation activities that link different aspects of the value chain complement one another. We thus expect the interaction between star scientists and downstream alliances to be positive (and statistically significant). We find support for this hypothesis when predicting new drugs in development. The interaction between star scientists and downstream alliances is positive and statistically significant in Model 2c ($p < 0.05$) when predicting new drugs in development. The coefficient for the interaction between star scientists and downstream alliances does not reach significance, however, when predicting citation-weighted patents (Model 1c). The lack of significance in the interaction between star scientists and downstream alliances when predicting citation-weighted patents is not

[13] Complements and substitutes correspond to interactions in moderated regression analysis because their combined effects differ from the sum of their separate parts. Specifically, complements are represented by positive interaction effects reflecting their synergizing behavior, while substitutes are represented by negative interaction effects reflecting their compensating behavior (see Cohen *et al.*, 2003: 255–260).

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Table 3. Regression results for random-effect negative binomial estimation: new drugs in development

	New drugs in development					
	Model 2a		Model 2b		Model 2c	
	beta	s.e.	beta	s.e.	beta	s.e.
Year effects	*Included*		*Included*		*Included*	
Constant	2.8135	(0.2304)	2.8190	(0.2336)	2.8907	(0.2387)
Merged firm	0.2820*	(0.1318)	0.2950*	(0.1304)	0.2903*	(0.1297)
Diversified	0.0730	(0.1515)	0.0457	(0.1482)	0.0195	(0.1484)
US firm	0.2453	(0.2027)	0.2158	(0.1989)	0.2346	(0.1978)
EU firm	0.0303	(0.1979)	0.0595	(0.1973)	0.0903	(0.1965)
Net income	0.0372	(0.0353)	0.0390	(0.0340)	0.0447	(0.0346)
% equity alliances	−0.0552	(0.0376)	−0.0595	(0.0375)	−0.0605	(0.0376)
% cancer drugs	0.0047	(0.0082)	0.0039	(0.0081)	0.0236*	(0.0142)
R&D expense	0.0484	(0.0436)	0.0503	(0.0417)	0.0579	(0.0439)
R&D acquisitions	0.0104	(0.0215)	0.0131	(0.0209)	0.0126	(0.0208)
Non-star scientists	0.1152***	(0.0377)	0.0966**	(0.0371)	0.0742*	(0.0408)
Upstream alliances	−0.0468	(0.0286)	−0.0110	(0.0498)	0.0029	(0.0501)
Upstream alliances^2			−0.0249	(0.0333)	−0.0348	(0.0332)
Downstream alliances	0.0389*	(0.0192)	0.0019	(0.0398)	−0.0078	(0.0410)
Downstream alliances^2			0.0264	(0.0241)	0.0169	(0.0246)
Star scientists	−0.0673*	(0.0273)	0.1629*	(0.0835)	0.1810*	(0.0856)
Star scientists^2			−0.1533**	(0.0552)	−0.1499**	(0.0583)
Star scientists × upstream alliances					−0.0264*	(0.0141)
Star scientists × downstream alliances					0.0139*	(0.0075)
Log likelihood	−999.5		−975.10		−972.90	
Chi square	807.7***		857.1***		879.5***	
Improvement over base ($\Delta\chi^2$)			49.40***		71.80**	

n = 465

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$; Huber-White robust standard errors in parentheses.

entirely unexpected. Although new knowledge is often developed during the refinement of downstream practices, the bulk of an organization's patents are related to the search for new knowledge that is most often found in upstream partners (Baum *et al*., 2000; Rothaermel and Deeds, 2004).

Some of the results for the direct effects are also noteworthy. Specifically, we find that there seems to be a positive, yet diminishing effect of downstream alliances (Model 1b) and star scientists (Model 2b). The diminishing returns effect to downstream alliances echoes results in prior work (Rothaermel, 2001). Additionally, the effect of non-star scientists was positive and significant in predicting both citation-weighted patents and new drugs in development. These findings also resonate with prior work (Furukawa and Goto, 2006; Rothaermel and Hess, 2007).

As a robustness check, we applied a split-sample approach recommended by Shaver (2007) for testing interaction effects in nonlinear estimations. We split the sample along the mean of intellectual human capital (IHC), which is 224 scientists for a given year at a given firm. We found support at $p < 0.05$ for Hypothesis 1 in both subsamples and for Hypothesis 2 only in the high IHC subsample.

DISCUSSION

Through applying the upstream/downstream framework, we encapsulate the innovative activities of individuals and in doing so attempt to synthesize literature investigating individual talent with the literature on concurrent sourcing (Parmigiani, 2007; Parmigiani and Mitchell, 2009). By analyzing a dichotomy of individuals based on star versus

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average employees within the value chain framework, we demonstrate that pursuing certain activities concurrently can result in improved innovative performance, despite their inherent differences and unique managerial challenges. As hypothesized, the benefits of completing the knowledge value chain outweigh the costs associated with being able to develop the disparate competencies associated with both alliances and human resource management. Pursuing the various stages of the value chain simultaneously provides the basis for unique resource combinations that can be the source of superior performance. Our empirical finding validates Peteraf's (1993: 187) theoretical insight offered in her treatise on the resource-based view: '... a brilliant, Nobel prize winning scientist may be a unique resource, but unless he has firm-specific ties, his perfect mobility makes him an unlikely source of sustainable advantage.' This implies that any performance effects of star scientists on firm innovation are *contingent* upon the stars' connections to other firm-specific resources (Groysberg, Lee, and Nanda, 2008).

As a corollary to this, we find that the pursuit of redundant mechanisms simultaneously (e.g., both activities represent upstream activities), results in a marginal decrease in innovative performance. This substitutability may be reflective of an organization that is overly focused on either upstream or downstream activities, which is indeed a commonly observed phenomenon (Levinthal and March, 1993). Repeated failure, for example, tends to drive organizations toward extensive exploration for upstream knowledge (failure trap). The dynamic of failure turns organizations into 'frenzies of experimentation, change, and innovation' (Levinthal and March, 1993: 105). Firms that engage in such activities at the expense of the downstream portion of the value chain incur the substantial costs of experimentation without reaping the commensurate benefits thereof (March, 1991). These firms, for example, may pursue too many distinctly different scientific avenues without developing the competences required to exploit any new knowledge gained, and thus fail to transform it into commercially viable products, processes, or services, negating any capability development effect (Helfat and Raubitschek, 2000).

As this study represents an initial attempt to understand the relationship between different innovative activities, one limitation is related to the research setting. We suggest that the pharmaceutical industry represents an interesting and appropriate setting for investigating the knowledge acquisition and assimilation associated with upstream and downstream activities. Given the idiosyncrasies associated with the pharmaceutical industry in terms of the importance of scientific knowledge and new product development, however, future studies are needed to enhance the external validity of our findings. Our split-sample analysis detailed above also highlights the importance of understanding the differences between the behaviors of different types of firms. Specifically, our finding regarding the substitutive relationship between star scientists and upstream alliances may be a function of the research setting. The knowledge-driven nature of the pharmaceutical industry is such that organizations expend significant resources on the development of their alliance management capability and human resources. These expenditures are likely to augment the potential transaction costs associated with using multiple activities simultaneously. That is, in other industries, star scientists may help organizations choose their upstream alliance partners, thus acting in a complementary rather than substitutive manner. This is what one would expect based on the congruence hypothesis (Burnes and Stalker, 1961).

In conclusion, we submit that this study extends our understanding of the importance of considering not only the heterogeneity of a firm's intellectual human capital but also the relationship between key innovative activities along the knowledge value chain.

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REFERENCES

Albert MB, Avery D, Narin F, McAllister P. 1991. Direct validation of citation counts as indicators of industrially important patents. *Research Policy* **20**(3): 251–259.

Allen T, Cohen SI. 1969. Information flow in R&D laboratories. *Administrative Science Quarterly* **14**: 12–19.

Arora A, Ceccagnoli M. 2006. Patent protection, complementary assets, and firms' incentives for technology licensing. *Management Science* **52**(2): 293–318.

Arora A, Gambardella A. 1990. Complementarity and external linkages: the strategies of the large firms in biotechnology. *Journal of Industrial Economics* **38**: 361–379.

Baum JAC, Calabrese T, Silverman BS. 2000. Don't go it alone: alliance network composition and startups' performance in Canadian biotechnology. *Strategic Management Journal*, March Special Issue **21**: 267–294.

Brown JS, Duguid P. 2001. Knowledge and organization: a social-practice perspective. *Organization Science* **12**(2): 198–213.

Burnes T, Stalker G. 1961. *The Management of Innovation*. Tavistock: London, UK.

Cameron AC, Trivedi PK. 1986. Econometric models based on count data: comparisons and applications of some estimators and tests. *Journal of Applied Econometrics* **1**(1): 29–53.

Cassiman B, Veugelers R. 2006. In search of complementarity in innovation strategy: internal R&D and external knowledge acquisition. *Management Science* **52**(1): 68–82.

Chesbrough HW. 2003. *Open Innovation: The New Imperative for Creating and Profiting from Technology* Harvard Business School Press: Boston, MA.

Cockburn IM, Henderson RM. 2001. Scale and scope in drug development: unpacking the advantages of size in pharmaceutical research. *Journal of Health Economics* **20**(6): 1033–1057.

Cohen J, Cohen P, West SG, Aiken LS. 2003. *Applied Multiple Regression Correlation Analysis for the Behavioral Sciences* (3rd edn). Erlbaum: Mahwah, NJ.

Cohen SN, Chang ACY, Boyer HW, Helling RB. 1973. Construction of biologically functional bacterial plasmids *in vitro*. *Proceedings of the National Academy of Sciences* **70**(11): 3240–3244.

Cohen WM, Levinthal DA. 1990. Absorptive capacity: a new perspective on learning and innovation. *Administrative Science Quarterly* **35**: 128–152.

Dierickx I, Cool K. 1989. Asset stock accumulation and sustainability of competitive advantage. *Management Science* **35**(12): 1504–1513.

Ettlie JE, Pavlou PA. 2006. Technology-based new product development partnerships. *Decision Sciences* **37**(2): 117–147.

Furukawa R, Goto A. 2006. The role of corporate scientists in innovation. *Research Policy* **35**(1): 24–36.

Galambos L, Sturchio J. 1998. Pharmaceutical firms and the transition to biotechnology: a study in strategic innovation. *Business History Review* **72**: 250–278.

Gambardella A. 1992. Competitive advantage from in-house scientific research: the US pharmaceutical industry in the 1980s. *Research Policy* **21**(5): 391–407.

Gardner T. 2005. Interfirm competition for human resources: evidence from the software industry. *Academy of Management Journal* **48**(2): 237–256.

Giovannetti G, Morrison S. 2000. *Convergence: The biotechnology Industry Report*. Ernst & Young: Palo Alto, CA.

Grant R, Baden-Fuller C. 2004. A knowledge accessing theory of strategic alliances. *Journal of Management Studies* **41**(1): 61–84.

Greene WH. 2003. *Econometric Analysis*. Prentice Hall: Upper Saddle River, NJ.

Griliches Z, Pakes A, Hall BH. 1987. The value of patents as indicators of inventive activity. In *Economic Policy and Technological Performance*, Dasgupta P, Stoneman P (eds). Cambridge University Press: Cambridge, UK: 97–124.

Groysberg B, Lee L, Nanda A. 2008. Can they take it with them? The portability of star knowledge workers' performance. *Management Science* **54**(7): 1213–1230.

Gulati R. 1995. Does familiarity breed trust? The implications of repeated ties for contractual choice in alliances *Academy of Management Journal* **38**: 85–112.

DOI: 10.1002/smj

Gulati R. 1998. Alliances and networks. *Strategic Management Journal*, April Special Issue **19**: 293–317.

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

Hagedoorn J. 1993. Understanding the rationale of strategic technology partnering: interorganizational modes of cooperation and sectoral differences. *Strategic Management Journal* **14**(95): 371–385.

Hall BH, Griliches Z, Hausman JA. 1986. Patents and R&D: is there a lag? *International Economic Review* **27**(2): 265–283.

Hall BH, Jaffe A, Trajtenberg M. 2001. The NBER patent citations data file: lessons, insights, and methodological tools. Working paper no. 8498. National Bureau of Economic Research: Cambridge, MA.

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

Hamilton BH, Nickerson JA. 2003. Correcting for endogeneity in strategic management research. *Strategic Organization* **1**(1): 51–78.

Harrigan K. 1986. Matching vertical integration strategies to competitive conditions. *Strategic Management Journal* **7**(6): 535–555.

Hausman JA. 1978. Specification tests in econometrics. *Econometrica* **46**(6): 1251–1271.

Hausman J, Hall BH, Griliches Z. 1984. Econometric models for count data with an application to the patents-R&D relationship. *Econometrica* **52**(4): 909–938.

Helfat CE. 1994a. Evolutionary trajectories in petroleum firm R&D. *Management Science* **40**(12): 1720–1747.

Helfat CE. 1994b. Firm specificity in corporate applied R&D. *Organization Science* **5**: 173–173.

Helfat CE. 1997. Know-how and asset complementarity and dynamic capability accumulation: the case of R&D. *Strategic Management Journal* **18**(5): 339–360.

Helfat CE, Peteraf MA. 2003. The dynamic resource-based view: capability lifecycles. *Strategic Management Journal*, October Special Issue **24**: 997–1010.

Helfat CE, Raubitschek RS. 2000. Product sequencing: co-evolution of knowledge, capabilities and products. *Strategic Management Journal,* October–November Special Issue **21**: 961–979.

Henderson RM, Cockburn IM. 1994. Measuring competence? Exploring firm effects in pharmaceutical research. *Strategic Management Journal*, Winter Special Issue **15**: 63–84.

IMS-Health. 2008. *Global Pharmaceutical Sales 2000–2007.* Available at: http://www.imshealth.com/deployedfiles/imshealth/Global/Content/StaticFile/Top_Line_Data/GlobalSales.pdf (15 September 2008).

Kogut B, Zander U. 1992. Knowledge of the firm, combinative capabilities and the replication of technology. *Organization Science* **3**(3): 383–397.

Koza MP, Lewin AY. 1998. The co-evolution of strategic alliances. *Organization Science* **9**(3): 255–264.

Lacetera N, Cockburn IM, Henderson RM. 2004. Do firms change capabilities by hiring new people? A study of the adoption of science-based drug discovery. In *Business Strategy over the Industry Lifecycle: Advances in Strategic Management,* Baum JAC, McGahan AM (eds). Elsevier: Oxford, UK; 133–159.

Lane PJ, Lubatkin MH. 1998. Relative absorptive capacity and interorganizational learning. *Strategic Management Journal* **19**(5): 461–477.

Lavie D, Rosenkopf L. 2006. Balancing exploration and exploitation in alliance formation. *Academy of Management Journal* **49**(6): 797–818.

Levinthal DA, March JG. 1993. The myopia of learning. *Strategic Management Journal*, Winter Special Issue **14**: 95–112.

Madhavan R, Grover R. 1998. From embedded knowledge to embodied knowledge: new product development as knowledge management. *Journal of Marketing* **62**(4): 1–12.

March JG. 1991. Exploration and exploitation in organizational learning. *Organization Science* **2**(1): 71–87.

Milgrom P, Roberts J. 1995. Complementarities and fit strategy, structure, and organizational change in manufacturing. *Journal of Accounting and Economics* **19**(2–3): 179–208.

Murray F. 2002. Innovation as co-evolution of scientific and technological networks: exploring tissue engineering. *Research Policy* **31**: 1389–1403.

Park SH, Chen R, Gallagher S. 2002. Firm resources as moderators of the relationship between market growth and strategic alliances in semiconductor start-ups. *Academy of Management Journal* **45**(3): 527–545.

Parmigiani A. 2007. Why do firms both make and buy? An investigation of concurrent sourcing. *Strategic Management Journal* **28**(3): 285–311.

Parmigiani A, Mitchell W. 2009. Complementarity, capabilities, and the boundaries of the firm: the impact of within-firm and interfirm expertise on concurrent sourcing of complementary components. *Strategic Management Journal* **30**(10): 1065–1091.

Peteraf MA. 1993. The cornerstones of competitive advantage: a resource-based view. *Strategic Management Journal* **14**(3): 179–191.

Pisano G, Mang P. 1993. Collaborative product development and the market for know–how: strategies and structures in the biotechnology industry. In *Research on Technological Innovation, Management and Policy.* Rosenbloom R, Burgelman R (eds). JAI. Press: Greenwich, CT; 109–136.

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

Reed R, DeFillippi RJ. 1990. Causal ambiguity, barriers to imitation, and sustainable competitive advantage. *Academy of Management Review* **15**: 88–102.

Rothaermel FT. 2001. Incumbent's advantage through exploiting complementary assets via interfirm cooperation. *Strategic Management Journal*, June–July Special Issue **22**: 687–699.

Rothaermel FT, Deeds DL. 2004. Exploration and exploitation alliances in biotechnology: a system of new product development *Strategic Management Journal* **25**(3): 201–221.

Rothaermel FT, Hess AM. 2007. Building dynamic capabilities: innovation driven by individual, firm, and network level effects. *Organization Science* **18**(6): 898–921.

Rothaermel FT, Hitt MA, Jobe LA. 2006. Balancing vertical integration and strategic outsourcing: effects on product portfolio, product success, and firm performance. *Strategic Management Journal* **27**(11): 1033–1056.

Shan W, Walker G, Kogut B. 1994. Interfirm cooperation and startup innovation in the biotechnology industry. *Strategic Management Journal* **15**(5): 387–394.

Shaver J. 2007. Interpreting empirical results in strategy and management research. *Research Methodology in Strategy and Management* **4**: 273–293.

Stephan P. 1996. The economics of science. *Journal of Economic Literature* **34**(3): 1199–1235.

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

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

Teece D. 1992. Competition, cooperation, and innovation: organizational arrangements for regimes of rapid technological progress. *Journal of Economic Behavior and Organization* **18**(1): 1–25.

Tushman M, O'Reilly CA. 1996. Ambidextrous organizations: managing evolutionary and revolutionary change. *California Management Review* **38**(4): 8–30.

Williamson O. 1991. Comparative economic organization: the analysis of discrete structural alternatives. *Administrative Science Quarterly* **36**(2): 269–296.

Zucker LG, Darby MR. 1996. Costly information: firm transformation, exit, or persistent failure. *American Behavioral Scientist* **39**(8): 959–974.

Zucker LG, Darby MR. 1997. Individual action and the demand for institutions: star scientists and institutional transformation. *American Behavioral Scientist* **40**(4): 502–513.

Zucker LG, Darby MR, Brewer MB. 1998. Intellectual human capital and the birth of U.S. biotechnology enterprises. *American Economic Review* **88**(1): 290–306.

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