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Building Dynamic Capabilities: Innovation Driven by Individual-, Firm-, and Network-Level Effects

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Following the dynamic capabilities perspective, we suggest that antecedents to innovation can be found at the individual, firm, and network levels. Thus, we challenge two assumptions common in prior research: (1) that significant variance exists at the focal level of analysis, whereas other levels of analysis are assumed to be homogeneous, and (2) that the focal level of analysis is independent from other levels of analysis. Accordingly, we advance a set of hypotheses to simultaneously assess the direct effects of antecedents at the individual, firm, and network levels on innovation output. We then investigate whether a firm's antecedents to innovation lie across different levels. To accomplish this, we propose two competing interaction hypotheses. We juxtapose the hypothesis that the individual-, firm-, and network-level antecedents to innovation are substitutes versus the proposition that these innovation mechanisms are complements. We test our multilevel theoretical model using an unusually comprehensive and detailed panel data set that documents the innovation attempts of global pharmaceutical companies within biotechnology over a 22-year time period (1980–2001). We find evidence that the antecedents to innovation lie across different levels of analysis and can have compensating or reinforcing effects on firm-level innovative output.

Key words: dynamic capabilities; organizational learning; innovation; multilevel theory; longitudinal panel data; pharmaceutical and biotechnology industries

Introduction

The recent extension of the resource-based view into dynamic markets provides a fresh perspective for analyzing how firms develop new capabilities to cope with shifting markets. This theoretical perspective posits that a firm's ability to "integrate, build, and reconfigure internal and external competences to address rapidly changing environments" lies at the center of its capability to innovate (Teece et al. 1997, p. 516). Dynamic capabilities facilitate not only the ability of an organization to recognize a potential technological shift, but also its ability to adapt to change through innovation (Hill and Rothaermel 2003). Eisenhardt and Martin (2000, p. 1107) suggest that antecedents to dynamic capabilities, which they describe as "processes to integrate, reconfigure, gain, and release resources—to match and even create market change," can be found at the individual, firm, or network level (see also Zollo and Winter 2002).

Assuming that firms can draw on antecedents across different levels to build dynamic capabilities, several important but underexplored questions arise, such as: Where is the locus of the antecedents to firm-level dynamic capabilities? Does the locus lie within the individual, within the firm, or within networks? If so, which levels are relatively more important? Or, does the locus of the antecedents to dynamic capabilities lie within the intersection of any of these levels? In other words, does the locus lie across multiple levels of analysis? If the locus of the antecedents to dynamic capabilities lies across multiple levels of analysis, are the different mechanisms to innovate complements or substitutes?

Extant research generally focuses on only one level of analysis while neglecting other levels of analysis, thus opening the door for spurious findings due to unobserved heterogeneity. When studying the dynamics of technological innovation, for example, researchers generally analyze incumbent firms as a more or less homogeneous group of firms or as an industry, thus neglecting to investigate firm-differential performance (Christensen 1997, Foster 1986, Henderson and Clark 1990, Tushman and Anderson 1986). Likewise, when analyzing firm-differential performance, researchers invoke constructs like resources, competencies, capabilities, processes, and routines (Barney 1991, Henderson and Cockburn 1994, Nelson and Winter 1982, Peteraf 1993), while neglecting individual-level heterogeneity. Finally, the handful of researchers that highlight individual-level heterogeneity as an antecedent to firm-level heterogeneity (Lacetera et al. 2004; Zucker and Darby 1997a; Zucker et al. 1998, 2002a) generally discount firm- and network-level effects.

Recent theoretical contributions (Felin and Foss 2005, Felin and Hesterly 2007, Klein et al. 1994, Dansereau et al. 1999), however, have identified two serious problems with the dominant unilevel research approach, which we find particularly salient to our research question concerning the locus of antecedents to dynamic

capabilities. First, concentrating on only one level of analysis implicitly assumes that most of the heterogeneity is located at the chosen level, whereas alternate levels of analysis are considered to be more or less homogeneous. Studies of firm-level heterogeneity assume, for example, that significant variation occurs at the firm level of analysis, whereas individuals are more or less homogeneous or randomly distributed across firms. Second, when focusing on one level of analysis, researchers implicitly assume that the focal level of analysis is more or less independent from interactions with other lower- or higher-order levels of analysis. Firm-level heterogeneity, for example, is assumed to be relatively independent from individual- or network-level effects. Taken together, the assumptions of homogeneity in, and independence from, alternate levels of analysis are serious concerns that could lead to spurious empirical findings.

To address the threats of homogeneity and independence, we develop a multilevel theoretical model that accounts for potential heterogeneity in and across three distinct levels when explaining and predicting innovation: the *individual level*, representing internal investments such as employee hiring; the *firm level*, representing internal investments such as research and development (R&D); and the *network level*, representing external investments such as alliances or acquisitions.

The integrative theoretical model advanced here enables us to not only assess the effect of each innovation antecedent while explicitly controlling for potentially confounding lower- or higher-order levels of analysis, but also to assess if and how the different innovation antecedents across the three levels of analysis interact with one another. First, to challenge the assumption of homogeneity across levels of analysis, we develop direct effects hypotheses pertaining to each of the three levels of analysis. Second, to assess the validity of the assumption of independence across levels, we advance two competing interaction hypotheses concerning the potential complementary or substitutive nature of innovation antecedents in the intersections across different levels of analysis: individual-firm, individual-network, and firm-network.

We selected the global pharmaceutical industry as the research setting to empirically test our integrative theoretical model across multiple levels of analysis, because this industry experienced a radical technological transformation with the advent of biotechnology based on genetic engineering, genomics, and other novel research. We document the attempts of incumbent pharmaceutical companies to build the capabilities necessary to innovate within biotechnology. Methodologically, we make a contribution by developing and analyzing a unique panel data set that approaches the population of observations across different levels of analysis and categories. To empirically test our hypotheses, we leverage fine-grained longitudinal data on over 900 acquisitions, 4,000 alliances, 13,200 biotechnology patents, 110,000 non-biotechnology patents, 135,000 scientists, 480,000 journal publications, and 9.2 million journal citations.

Theory and Hypotheses Development

Individual-Level Effects

Intellectual Human Capital. Unilevel research implicitly assumes not only that nonfocal levels of analysis are homogeneous, but does not generally consider the importance of nonfocal levels when predicting heterogeneity at the focal level of analysis (Felin and Foss 2005, Felin and Hesterly 2007). By investigating individual-level effects as a critical antecedent to firm-level innovation, we question the legitimacy of the assumption of homogeneity across levels. We posit that intellectual human capital can be heterogeneously distributed across firms and therefore must be accounted for when investigating firm-level innovation. We consider intellectual human capital to be highly skilled and talented employees like research scientists, who hold advanced graduate degrees and doctorates. In our sample of global pharmaceutical companies, about 0.5% of all employees fall in this category, as research scientists that publish in academic journals.

To understand the role of intellectual human capital in a firm's ability to build new capabilities, researchers have highlighted the emergence of tacit knowledge resulting from the interaction of highly skilled human capital (Almeida et al. 2002, Kogut and Zander 1992). As an example, Henderson and Cockburn (1994) find that locally embedded knowledge and skills among intellectual human capital may be a unique source of innovative competence for the firm. More specifically, the disciplinary focus of groups of scientists within a firm creates deeply embedded knowledge that is not easily codified, and thus is difficult to transfer or imitate. For instance, pharmaceutical firms often develop expertise in specific areas, such as Eli Lilly's focus on diabetic therapy or Hoffman-La Roche's expertise in the area of antianxiety drugs. In a similar fashion, Leonard-Barton (1992) indicates that the tacit knowledge developed by skilled engineers with a specific production process over an extended period of time may develop into a source of innovation. Taken together, the specificity of the external and internal learning necessary for a firm to innovate favors those firms that invest in and maintain significant levels of intellectual human capital.

A firm's innovative performance is at least partially a function of the value of its human capital (Hitt et al. 2001). Thus, organizations are expected to invest more in acquiring, retaining, and training intellectual human capital as the value of their human resources increases (Gardner 2005). Such a case has emerged within the realm of the biopharmaceutical industry, where changes

in drug discovery and development have enhanced the need for the input of scientists who are skilled in a wide variety of disciplines, some of which, like molecular biochemistry, are newly emerging (Cockburn et al. 2000, Henderson and Cockburn 1994).

HYPOTHESIS 1A. *A firm's innovative output is a positive function of its intellectual human capital.*

Star Scientists. Numerous empirical and qualitative studies provide convincing evidence that not all intellectual human capital is created equally, giving rise to the idea that significant heterogeneity exists within highly specialized intellectual human capital. Lotka (1926) was one of the first to note a highly skewed distribution pertaining to research output among scientists. When studying scientific publications in chemistry, he found that only about 5% of scientists were responsible for more than 50% of the total scientific research output. A similar skewed distribution in research output is also reflected in the patenting activity in U.S. and Japanese semiconductor firms (Narin and Breitzman 1995) and the patenting output in German companies in the chemical, mechanical, and electronic industries (Ernst et al. 2000).

Therefore, we suggest that intellectual human capital can be conceptualized as consisting of two components: star scientists and nonstar scientists. We understand a star scientist to be someone who is, by an order of magnitude, both more productive in and more influential on a specific research field than the average (nonstar) scientist active in this field. In particular, we hypothesize that there exists a positive and significant relationship between a firm's star scientists and its innovative output, above and beyond the effects of nonstar scientists.

Within the context of entrepreneurial biotechnology ventures, star scientists have been shown to affect the geographic location of firm entry into new technologies (Zucker et al. 1998) and to exert significant positive effects on a wide range of firm-level measures, such as the number of products on the market, publishing propensity, and network connections (Audretsch and Stephan 1996, Zucker et al. 2002b). Ties to stars have also been shown to shorten the time to initial public offering (IPO) and to increase the amount of IPO proceeds (Darby and Zucker 2001). Thus, the assumption of lower-level homogeneity inherent in most firm-level and alliance research is even more questionable when considering star scientists as part of a firm's intellectual human capital.

Star scientists assume gate-keeping and boundary-spanning roles—critical functions in a firm's ability to innovate (Allen 1977, Allen and Cohen 1969, Tushman 1977, Tushman and Katz 1980). Gatekeepers are the few key individuals within a firm who are capable of understanding and translating contrasting coding schemes. Boundary spanners are able to bridge organizational and environmental boundaries to act as an information filter by evaluating, streamlining, and organizing knowledge flows from external sources. Gatekeepers and boundary spanners thus facilitate an organization's ability to collect, assimilate, and apply external information in a two-step process. They are able to gather and understand external information and then translate and disseminate this information into terms that are meaningful and useful to other organization members.

A firm's star scientists not only function as technological boundary spanners and gatekeepers, but also as the organization's information and knowledge core. Other important pathways through which star scientists can improve the innovative output of firms include: (1) positive spillovers to other researchers through the changing of behavioral and cultural norms, such as legitimizing a stronger focus on basic research; (2) changing the strategic direction of the firm's research and human resource policies; and (3) recruiting other like-minded scientists (Lacetera et al. 2004).

We propose that star scientists can be recruited from the labor market, and that they can be a source of firm-level heterogeneity in innovation. This assertion is true if firms have different ex ante expectations of the rent-generating potential of a star scientist. Our hypothesis, therefore, follows Barney's (1986) treatment of strategic factor markets, which relaxes the strong assumption of perfectly competitive factor markets, and in turn posits that strategic factor markets are characterized by an element of imperfection. Some preliminary evidence for this assumption is found in the recent work by Stephan et al. (2004), who show that in the case of biotechnology IPOs, Nobel laureate scientists allow significant rents to accrue to the firms who hired them, because their total compensation packages were considerably less than the stock price premium they created based on their outstanding scientific reputations.

HYPOTHESIS 1B. *A firm's innovative output is a positive function of its* star *scientists, controlling for* nonstar *scientists.*

Firm-Level Effects

We posit that heterogeneity in internal R&D capability across firms partly explains innovative performance differentials. Rosenberg (1990) underscores the importance of internal R&D by stressing that a firm needs a significant internal research capability to recognize, understand, appraise, and apply internal knowledge that has been placed on the shelf. Another important by-product of an internal R&D capability is the creation of firm-specific knowledge that enables a firm to take advantage of knowledge generated externally (Cohen and Levinthal 1989). Tilton (1971), for example, observes this phenomenon in the semiconductor industry. He concludes that continued investments in internal R&D created an in-house research capability that enabled these firms to

keep abreast of the latest developments in semiconductor research, to develop new technology internally, and also to recognize, appraise, and assimilate new technology developed elsewhere.

Continuing investments in R&D capability are necessary, because R&D effectiveness is path dependent, and thus, failure to invest in internal R&D at a given time may foreclose future options in a particular technology (Cohen and Levinthal 1989). In support of this idea, Helfat (1994a) provides convincing evidence for the hypothesis that ongoing R&D investments create a firm-specific capability whose heterogeneous distribution across firms tends to persist over time (Helfat 1994b). Moreover, Helfat (1997) also demonstrates a positive direct effect of R&D capability on innovative performance in the petroleum industry. Thus, R&D capability has the potential to be the kind of valuable, rare, inimitable, and nonsubstitutable resource that can form the basis for superior innovation performance (Barney 1991, Peteraf 1993).

When confronted with a new technological paradigm, internal R&D capability is especially relevant to innovative performance. Multiple new technologies or different versions of the same underlying technology frequently compete until a new dominant design emerges (Anderson and Tushman 1990). Internal research capability enables the incumbent firm to more accurately assess and appraise the many new technology trajectories that present themselves following radical technological changes. In their multiindustry study, Rothaermel and Hill (2005) show that internal R&D capability has a positive effect on a firm's financial performance. This was especially true for pharmaceutical companies following the emergence of biotechnology because it allowed them to identify promising research areas more readily. Further, R&D capability has become more critical to innovative performance because many industries have become more science driven. Thus, firms are now even more compelled to leverage advances in the fundamental sciences (Cockburn et al. 2000, Narin et al. 1997).

HYPOTHESIS 2. *A firm's innovative output is a positive function of its R&D capability.*

Network-Level Effects

Significant technological breakthroughs are generally exogenous to firms, because no single firm can keep abreast of all technological developments through internal R&D. Powell et al. (1996) provide support for the hypothesis that in industries characterized by complex and rapidly expanding knowledge bases, the locus of innovation lies within a network of learning composed of incumbent firms, new entrants, and research institutions, rather than within the boundaries of individual firms. Thus, to build new capabilities within an emerging technological paradigm, incumbent firms frequently need to leverage their external networks to source new technology. Networks can provide access to knowledge and resources that are not readily available via market exchanges (Gulati 1999, Gulati et al. 2000).

Although the resource-based view tends to focus on the importance of the internal asset base of the firm, researchers have recently posited that network relationships may allow a firm to leverage unique resource combinations. Dyer and Singh (1998) highlight relation-specific assets, knowledge-sharing routines, complementary resources and capabilities, as well as effective governance as antecedents to an interorganizational competitive advantage. The ability to leverage external networks to adapt to a rapidly changing environment is emphasized by Teece et al. (1997) and Eisenhardt and Martin (2000) as one possible manifestation of a dynamic capability. Strategic alliances and acquisitions of new technology ventures are generally considered to be alternatives to the external sourcing of technological knowledge by incumbent firms (Hill and Rothaermel 2003, Higgins and Rodriguez 2006, Vanhaverbeke et al. 2002). Therefore, we investigate how each type of external sourcing strategy affects an existing firm's innovative output.

Strategic Alliances. Strategic alliances are voluntary arrangements between firms to exchange and share knowledge and resources with the intent of developing processes, products, or services (Gulati 1998). It is not surprising that strategic alliances are often highlighted as an important mechanism used by firms to access external technology. Indeed, alliances have become commonplace as firms try to absorb or learn capabilities and knowledge from other firms (Ahuja 2000, Hagedoorn 1993, Powell et al. 1996, Rothaermel 2001). There are multiple pathways by which a firm's alliances with providers of new technology can affect its innovative output. Among other benefits, alliances enable partners to share technological knowledge, take advantage of scale economies in research, and leverage complementary assets (Teece 1992).

Extant empirical research provides evidence for the idea that strategic alliances enhance innovative output. With regard to new technology ventures, prior studies demonstrate that strategic alliances increase patent and new product development rates for biotechnology start-ups (Deeds and Hill 1996, Shan et al. 1994) and predict innovation rates in the semiconductor as well as in the microcomputer industry (Rothaermel et al. 2006, Stuart 2000). Considering incumbent firms rather than start-ups, Ahuja (2000) examines the position of chemical firms within the industry's network and finds that direct network connections have a positive relationship with innovative output. Thus, we suggest that an incumbent firm's strategic alliances with the providers of new technology, like research universities and new technology

ventures, have a positive effect on the firm's innovative output.

HYPOTHESIS 3A. *A firm's innovative output is a positive function of its alliances with new technology providers.*

Acquisitions. Acquisitions are an increasingly important strategic tool for attaining the external technological know-how to supplement internal R&D efforts in a timely manner (Chesbrough 2003, Ranft and Lord 2002, Vanhaverbeke et al. 2002). We make the assumption that acquisitions are network-level mechanisms, primarily because the targets acquired by the pharmaceutical firms within our sample are, for the most part, similar to the firms with which they ally. That is, the majority of the acquired firms are small biotechnology firms focused predominantly on basic research, drug discovery, and early stage development. Acquisitions of small technology ventures are not idiosyncratic to biotechnology because they are commonplace in many other high-technology industries (Vanhaverbeke et al. 2002).

Within the biotechnology industry, large pharmaceutical firms often use acquisitions to facilitate innovation (Galambos and Sturchio 1998). Higgins and Rodriguez (2006) find that to overcome declining internal R&D productivity, many pharmaceutical firms have successfully innovated by acquiring biotechnology ventures. For example, Hoffman-La Roche, DuPont, and Schering-Plough all began to engage in serial acquisitions of small, specialized biotechnology firms in the mid-1980s instead of forming alliances (Galambos and Sturchio 1998).

HYPOTHESIS 3B. *A firm's innovative output is a positive function of its acquisitions of new technology firms.*

Interactions Across Levels—Complements or Substitutes?

To challenge the assumption of independence across levels of analysis, we shift our analysis to an investigation of interactions across levels and their effects on innovation. Specifically, we pursue the question of whether the interactions across levels are complementary or substitutive in nature. Two activities are said to be complements if the marginal benefit of each activity increases in the presence of the other activity. For example, one would suggest that cardiovascular exercise is more effective in reducing the risk of heart disease if combined with a low-cholesterol diet, and vice versa. On the other hand, two activities are said to interact as substitutes if the marginal benefit of each activity decreases in the presence of the other activity. Here, one would suggest that cardiovascular exercise and pursuing a low-cholesterol diet are substitutes in achieving a lower risk of heart disease. Note that although cardiovascular exercise can still have an absolute positive effect on lowering the risk of heart disease, over and above a low-cholesterol diet, the *marginal* effect of cardiovascular exercise is diminished in the substitution scenario, and vice versa.[1] Given the dearth of prior theoretical and empirical research pertaining to the locus of innovation antecedents across levels, we advance both a complementary and a substitutive hypothesis in a competing fashion.

Interactions Across Levels—Complements

Interaction Between Individual- and Firm-Level Effects. A positive interaction between individual- and firm-level effects is likely, considering that the level of R&D capability is a function of prior related knowledge (Cohen and Levinthal 1989, 1990). Relevant prior knowledge allows the firm to recognize the value of new information and to exploit it for commercial ends. In the pharmaceutical industry, the primary source of such knowledge is located upstream in the value chain, residing within research universities and new biotechnology ventures. Existing pharmaceutical companies must thus possess the requisite intellectual human capital to gain access to this research community, assimilate the new knowledge, and subsequently apply it to commercial ends.

We posit that an increase in the level of intellectual human capital results in a commensurate increase in R&D capability. Likewise, a firm that has significant R&D capability is more likely to experience an increase in the effectiveness of its intellectual human capital due to better research facilities, more knowledgeable colleagues, and cultural norms and processes that are more conducive to innovation (Hitt et al. 1991). As an example, Groysberg et al. (2004) find that when star financial analysts switched firms, both the worker and new employer saw a decrease in short-term performance. The effect was stronger when the star analyst switched from a higher-performing firm to a lower-performing one. This indicates that there are important firm-level complementary or supporting assets and processes that are required for an individual employee to realize a high level of performance. In a similar fashion, Lacetara et al. (2004) show that the hiring of star scientists positively interacts with firm-level policies, capabilities, routines, and people, thus indicating a potential complementarity between individual- and firm-level factors. Taken together, these observations lead us to suggest that the complex interactions between individual- and firm-level capabilities have the potential to transform resources obtained in strategic factor markets (e.g., the recruitment of scientists) into valuable, rare, inimitable, and nonsubstitutable resource combinations that can form the basis of a firm-level innovation advantage (Barney 1986, 1991; Lacetera et al. 2004).

Interaction Between Individual- and Network-Level Effects. We postulate that scientists positively moderate the effects of alliances and acquisitions on a firm's innovative output. Stuart et al. (2007) assert that within the realm of biotechnology firms, the breadth of the external networks of academic scientists employed by a firm facilitates the organization's ability to identify and incorporate pertinent university research. The presence of technological gatekeepers and boundary spanners can help offset different coding schemes between organizations, specifically between academic institutions and corporate R&D laboratories, thereby facilitating communication and knowledge transfer between organizations (Allen and Cohen 1969, Tushman and Katz 1980). The effect of this gatekeeping and boundary spanning is particularly important to firms attempting to innovate, because the tacit nature of many new discoveries often makes it necessary for the inventing scientist to assist in the firm's commercialization process (Stuart et al. 2007).

Due to their social and professional embeddedness in the scientific community, a pharmaceutical company's scientists are critical in evaluating the quality and potential fit of research that is conducted in universities and biotechnology ventures, and thus play a key role in directing the large pharmaceutical companies towards promising alliance partners (Liebeskind et al. 1996). This is an especially important task given the fact that across the world hundreds of universities and more than 2,000 biotechnology ventures are active in some area of biotechnology research (*BioScan,* diverse years).

The interaction between the level of intellectual human capital and the effect of R&D acquisitions on innovation is emphasized by research showing that if an acquiring firm has information relevant to the value of the target's research, which is often accurately evaluated by the firm's scientists, there is not only a greater likelihood of success, but also a greater probability that this knowledge may allow the firm to overcome some of the valuation difficulties that generally plague acquisitions (Higgins and Rodriguez 2006).

Interaction Between Firm- and Network-Level Effects. Without sufficient internal research capability developed at the firm level, firms are not likely to recognize important developments outside of their existing competencies, and this may limit their ability to innovate (Cohen and Levinthal 1990). Prior empirical research indicates that a level of commonality between the firm's internal research capability and external research may be necessary for successful knowledge transfer (Lane and Lubatkin 1998). Remember, alliances are dyadic exchanges between organizations searching for diverse sets of knowledge (Gulati et al. 2000). Moreover, it has been demonstrated that pharmaceutical firms possess an informational advantage over capital markets in assessing the research quality of biotechnology start-ups (Lerner et al. 2003), thus creating a synergistic effect between R&D capability and alliances and acquisitions.

HYPOTHESIS 4. *Antecedents to innovation located at the intersections between the individual and the firm level* (H4A)*, between the individual and the network level* (H4B)*, and between the firm and the network level* (H4C) complement *one another such that interactions across levels are* positive*, and thus* increase *a firm's innovative output.*

Interactions Across Levels—Substitutes

In juxtaposition to the prior hypothesis, we propose that the different mechanisms to advance innovation across individual, firm, and network levels are substitutes for one another. This implies that the simultaneous pursuit of innovation across multiple levels would actually reduce a firm's innovation output, at least at the margin. The theoretical foundation for this argument is based on the fact that investments in the various innovation antecedents tend to be path dependent, and as such, early decisions affect future outcomes (Dierickx and Cool 1989, Cohen and Levinthal 1990). Moreover, these investments are predominantly undertaken to attain the similar end of innovation, and thus the different innovation antecedents may exhibit some element of equifinality. In support of this idea, Cockburn et al. (2000) demonstrate that although initial conditions were an important factor influencing the adaptation of pharmaceutical firms to science-driven drug discovery, the firms also exhibited significant variance in their strategic choices and the subsequent speed of adaptation.

From a manager's perspective, firm innovation can be seen as a constrained optimization problem. In high-technology industries, which are often characterized by short time horizons, firms face not only limited financial resources, but perhaps more important, limited managerial resources. While all production decisions can be understood as constrained optimization, this problem is especially salient when different innovation mechanisms can be substitutes for one another. Using them in tandem might result in decreased innovative output at the margin. Therefore, a firm attempting to innovate might need to choose between different innovation antecedents at different levels in a discriminating fashion.

The different innovation antecedents across multiple levels can be seen as distinct, strategic alternatives, and thus as substitutes on the path to attaining firm-level innovation. As an example, Pennings and Harianto (1992) analyzed the U.S. banking industry's attempt to implement home banking, and found that the propensity of a firm to choose one innovation mechanism over others was history dependent in the sense that the choice was determined, to a large extent, by the firm's accumulated skills in a specific mechanism. The authors suggest that some computer, banking, and pharmaceutical

firms have chosen to innovate through internal corporate ventures, while other organizations have based their business model on innovation through either acquisitions or alliances. The pharmaceutical firm Merck has historically chosen to build its research capabilities internally, whereas Hoffman-La Roche and Eli Lilly have been more prolific in their use of acquisitions and alliances to innovate (Galambos and Sturchio 1998). Thus, firms make significant investments in their chosen mode of innovation because there are fundamental differences between the underlying innovation mechanisms.

It is important to emphasize that firms frequently discriminate between these strategic alternatives because of tension between these different modes of innovation (Pennings and Harianto 1992, Vanhaverbeke et al. 2002). The tension between these alternatives is born from the fundamentally different set of skills and capabilities that must be developed for a firm to effectively innovate along a particular path. By using one innovation mechanism repeatedly over time, firms learn by doing, and thus build up competencies in that specific innovation mechanism (Levitt and March 1988). Some firms have become proficient in recruiting and retaining star scientists because they have learned how to address the surrounding human resource issues (Galambos and Sturchio 1998, Zucker and Darby 1997b). By contrast, other firms have built firm-level R&D capabilities through an ongoing investment strategy (Helfat 1994a, b). Furthermore, some firms have developed alliance capabilities through learning by doing. This strategy often proves successful because it allows for the superior selection of alliance partners, as well as the contracting, monitoring, managing—and, if necessary—exiting of alliances (Anand and Khanna 2000, Kale et al. 2002, Rothaermel and Deeds 2006). However, other firms have learned superior acquisition and integration capabilities by engaging in multiple acquisitions over time (Haleblian and Finkelstein 1999, Hayward 2002). Taken together, these observations indicate that firms prefer to leverage the innovation mechanism in which they have built up some competence (Pennings and Harianto 1992). This idea implies that exploitation of the expertise in the preferred innovation antecedent drives out exploration of alternative innovation mechanisms (Levinthal and March 1993), and thus can lead to competency traps (see Levitt and March 1988).

By developing expertise in certain innovation mechanisms, switching costs between the different mechanisms can be substantial, and thus make the use of more than one mechanism cost prohibitive (Levinthal and March 1993). Switching costs are illustrated by the detrimental effects that substituting disparate modes of innovation can have on managerial perceptions and organizational culture. For example, managers may perceive that a significant investment in a network activity is intended to take the place of firm-level spending on R&D or intellectual human capital (Hitt et al. 1991). Additionally, a firm's acquisitions could not only interrupt the R&D process, but also alter an organizational culture focused on innovation, thus lowering an employee's incentive to follow through with the innovation process. Indeed, acquisitions were found to reduce both R&D expenditures and innovation outputs, thus pointing towards a substitution effect (Hitt et al. 1990).

Prior research also indicates that different methods of innovating are often substituted for each other only when the current mode of innovation is determined to be ineffective. As an example, Higgins and Rodriguez (2006) find that firms that are experiencing deterioration in internal R&D productivity are more likely to engage in an acquisition strategy to augment innovation efforts. Similarly, firms may use one mode of innovation to compensate for a lack of experience in using another mode (Bower 2001). For example, the sharing of information and R&D personnel that often accompanies alliances can serve to reduce the need to invest in internal R&D. Alliances with universities can also provide a firm with ancillary research services that would otherwise need to be developed internally (George et al. 2002). Indeed, the authors find that firms with ties to universities have lower R&D expenditures than those without such ties. Taken together, these observations suggest that different innovation antecedents across multiple levels of analysis may substitute for one another.

HYPOTHESIS 5. *Antecedents to innovation located at the intersections between the individual and the firm level* (H5A)*, between the individual and the network level* (H5B)*, and between the firm and the network level* (H5C) substitute *for one another such that interactions across levels are* negative*, and thus* decrease *a firm's innovative output.*

Methods

Research Setting

We chose the global pharmaceutical industry to empirically test the proposed multilevel theoretical model for a number of reasons. The need for pharmaceutical firms to innovate is illustrated by the following trends, all in constant 1999 U.S. dollars (Higgins and Rodriguez 2006): Total R&D expenditures have grown from $6.8 billion in 1990 to $21.3 billion in 2000 (17% of sales); new drug development costs have increased from $231 million to $802 million between 1990 and 2000; and average sales per patented drug have fallen from $457 million in 1990 to $337 million in 2001. Moreover, emergence of biotechnology presented a new technological paradigm with respect to drug discovery and development for incumbent pharmaceutical companies (Pisano 1997).

The emergence of a new technological paradigm provides a natural laboratory for organizational researchers

because they can then observe when and how the existing firms have built innovation capabilities. Pharmaceutical drug discovery within the traditional chemical paradigm is based on random screening, whereas biotechnology is informed by a more science-driven approach that includes genetic engineering, genomics, and molecular biochemistry, among other disciplines. The scientific breakthroughs underlying biotechnology, such as recombinant DNA (rDNA) and hybridoma technology, were accomplished in the mid-1970s. The first new biotechnology drugs reached the market for pharmaceuticals in the 1980s.

In their attempts to build innovative capabilities in biotechnology, incumbent pharmaceutical firms made extensive use of all of the innovation mechanisms described earlier. Pharmaceutical incumbents have made a substantial investment in human capital, especially in the recruitment of star scientists (Zucker and Darby 1997a, b). The pharmaceutical industry also exhibits one of the highest R&D intensities because firm performance depends on continuous innovation through discovery and development of proprietary drugs, which creates patent races, temporary monopolies, and winner-take-all scenarios (Arthur 1989). In addition, the biotechnology industry has been identified as having one of the highest alliance frequencies (Hagedoorn 1993) and as an industry where firms outsource R&D through acquisitions (Higgins and Rodriguez 2006). Considering these factors, we submit that the global pharmaceutical industry is an appropriate setting to test the proposed multilevel theoretical model predicting innovation.

Sample

In an effort to limit a potential survivor bias when drawing our sample, we began our data collection process by compiling a list of all pharmaceutical firms alive as of 1980 based on standard industry classification (SIC) reports and a variety of industry publications.[2] Through this process, we identified 93 incumbent pharmaceutical firms worldwide. We defined an incumbent pharmaceutical firm as a firm that focuses on human therapeutics and was founded prior to the emergence of biotechnology in the mid-1970s. The pharmaceutical companies in the sample, like Fujisawa (Japan), Novartis (Switzerland), or Merck (United States), are generally large enterprises with an emphasis on proprietary drug discovery and development.

In a second step, we constructed a detailed "family tree" for each of these 93 firms for the 1980–2001 time period. We used multiple industry publications to construct the family tree from 1980 onwards, including Dun and Bradstreet's *"Who Owns Whom?"* and annual Standard & Poor's Industry Reports. Through this method, we identified 12 horizontal mergers among the pharmaceutical firms. When a horizontal merger took place, we combined the past data of the two merging firms, and tracked the combined entity forward.[3] Thus, the sample for final analysis consisted of 81 firms.[4]

We tracked annual data for each of the 81 sample firms, beginning in 1980 until the end of 2001 ($81 \times 22 = 1{,}782$ firm-year observations). We chose our study period to begin in 1980, which was the year when the commercialization of biotechnology began in earnest. This increase in commercialization activity can partly be explained by three important events that occurred in 1980 (Stuart et al. 1999, p. 323): (1) the phenomenal success of Genentech's IPO, the first public biotechnology firm, (2) the passage of the Bayh-Dole act, which sanctioned university patenting of inventions that resulted from federally funded research programs; and (3) the decision of the Supreme Court that life forms can be patented.[5] In addition, the Cohen-Boyer patent (U.S. Patent 4,237,224), disclosing recombinant DNA, was granted to Stanford University in 1980, thereafter allowing nonexclusive license to this breakthrough technology for a nominal fee.

It is important to note that the 81 sample firms accounted for the vast majority of the sales in the global pharmaceutical industry. Tracking detailed pharmaceutical sales is difficult because firms generally do not report sales differentiated by industrial sector. Nonetheless, we were able to track the detailed pharmaceutical sales of 35 sample firms that were not diversified outside pharmaceuticals. These 35 focused pharmaceutical companies represent only 38% of the initial sample, but accounted for 69% of the total sales for pharmaceuticals worldwide (*IMS Health* 2003). We are fairly confident that the remaining 46 firms account for a minimum 20% of pharmaceutical sales given the oligopolistic structure of this industry. These data suggest that the sample drawn for this study is indeed representative of the global pharmaceutical industry.

Dependent Variable

Innovative Output. The dependent variable for this study is the innovative output of pharmaceutical firms within biotechnology. We followed prior research that measured innovative output by a firm's patents (e.g., Ahuja 2000, Hagedoorn and Schakenraad 1994, Henderson and Cockburn 1994, Owen-Smith and Powell 2004, Shan et al. 1994, Stuart 2000). To specifically assess the pharmaceutical firm's innovative performance in biotechnology, we proxied their innovative output by the number of *biotechnology patent applications granted* in each year during the 1980–2001 study period, while explicitly controlling for lagged biotechnology patents and for nonbiotechnology patents.

Relying on patent applications granted is the preferred choice, because it provides a closer link between the timing of the invention and its recording (Hall et al. 2000). Based on the population of biotechnology

patents, a three-year average time lag exists between the date that patents are applied for by the inventing firm and the date when they are granted by the U.S. Patent and Trademark Office (U.S. PTO). In addition, the estimated time lag between the date of a completed invention and the patent application date is no more than two to three months (Darby and Zucker 2003). Because the U.S. PTO only records patent application dates when patents are granted, we obtained its most recent report including patent data until the end of 2004. The time series for this study ends in 2001 by design, thus attenuating any potential right truncation effect.

Research indicates that patents represent not only an important measure of innovative output, but also are an externally validated measure of technological novelty (Ahuja 2000, Griliches 1990, Henderson and Cockburn 1994). Additionally, patents have been shown to be critical to success in the pharmaceutical industry and are closely correlated with other performance measures, such as new product development, profitability, and market value (Comanor and Scherer 1969, Henderson and Cockburn 1994). The reliability of patent count data has been established empirically because prior research demonstrates that patent count data are highly correlated with citation-weighted patent measures, thus proxying the same underlying theoretical construct (Hagedoorn and Cloodt 2003, Stuart 2000). The bivariate correlation between patent counts and citation-weighted patents has been shown to be above 0.77 ($p < 0.001$) in the pharmaceutical industry (Hagedoorn and Cloodt 2003), which is especially relevant for this study, and above 0.80 ($p < 0.001$) in the semiconductor industry (Stuart 2000), indicating some generalizability of this assertion. In sum, a pharmaceutical firm that patents heavily in biotechnology can be seen as building innovation capabilities within a new technological paradigm.

The source for the patent data was the Technology Profile Report maintained by the U.S. PTO. Due to generous support from the U.S. PTO, we obtained detailed data on the complete population of all biotechnology patents awarded to the global pharmaceutical companies in this sample annually.[6] The average pharmaceutical firm in our sample was granted approximately seven biotechnology patents per year.

It may be argued that the patent data imply a bias in favor of U.S. companies; however, the patent literature, especially with respect to biotechnology patents, suggests otherwise. First, the United States represents the largest market worldwide for biotechnology, and thus it is almost compulsory for firms to first patent in the United States before patenting in any other country (Albert et al. 1991). Second, firms that are active in biotechnology have a strong incentive to patent in the United States, because intellectual property protection has been consistently supported by U.S. courts (Levin et al. 1987).

Independent Variables

Intellectual Human Capital and Star Scientists. Focusing on entrepreneurial biotechnology ventures, Zucker, Darby, and their colleagues were among the first to create a measure to proxy star scientists (Zucker and Darby 1997b; Zucker et al. 1998, 2002a). They identified a set of 327 star scientists based on their outstanding productivity up until April 1990. The primary selection criterion was the discovery of more than 40 genetic sequences as reported in GenBank (1990), a worldwide directory of all articles reporting newly discovered genetic sequences. Following this early time period, Zucker and colleagues identified stars as scientists that had published 20 or more articles, each reporting one or more genetic-sequence discoveries. These 327 stars constituted only 0.75% of the population of biotechnology scientists, but accounted for 17.3% of all the published articles. A star scientist, therefore, published more than 23 times as many articles as the average scientist. Recently, Lacetera et al. (2004) identified a star scientist as someone whose three-year moving average of annual publications was greater than five for at least one year.

To be conservative, we applied a more stringent definition of stardom than either Zucker et al. (1997b) or Lacetara et al. (2004). We constructed our star measure as follows. We searched the ISI Science Citation Index database to identify academic journal articles published between 1980 and 2004 that met the following criteria: (1) had a keyword related to science research (excluding social science research and nonhuman focused research, e.g., agricultural or veterinarian), and (2) could be unambiguously connected with one of the pharmaceutical firms in the sample, given the necessity of assuring that each of the authors was affiliated with a sample firm. From the population of over 480,000 academic journal articles, we collected the following information: author's name, author's affiliations, journal name, article title, keywords, publication year, number of times cited. Note that our time period to identify stars is three years longer than the study period. This allows us to account for a rising star effect to some extent, an issue that is particularly pertinent towards the end of the study period due to the necessary right censoring inherent in any study attempting to capture a dynamic phenomenon.

Once we completed the process of extracting the information for the 480,000 journal articles for each pharmaceutical firm, we compiled a list of total authors based on their publication record and aggregate times cited. This query yielded approximately 135,000 authors who published an average of 3.8 articles and were cited an average of 66.4 times. We then tied each author back to the pharmaceutical firms in our sample based on the authors' affiliations as indicated in the journal article(s). Thus, the total number of a firm's scientists who published in academic journals was our proxy for a firm's

intellectual human capital (*Scientists* [*total*]). The average firm in the sample employed 214 publishing research scientists per year.

Next, based on the distributions of citations and publications, we identified star scientists from the population of scientists using three different and increasingly more stringent approaches. The first method identified 2,392 "publication stars:" scientists who published, on average, more than 27 papers during the 25-year period, 1980–2004 (z-score > 3.0, or three standard deviations above the mean). The second approach yielded 1,570 "citation stars:" scientists whose publications had been cited at least 847 times (z-score > 3.0). Finally, our last approach was to identify researchers that were *both* publication *and* citation stars. In this intersection, we identified 851 star scientists. The 851 stars are less than 0.65% of the total population of scientists, but produced 15.2% of all publications and accrued 27.3% of all citations. This implies that the average star scientist from this data set published more than 25 times as many articles and is cited more than 45 times as often as the average scientist. Because applying both a publication and citation filter is a fairly stringent and thus conservative approach to identifying a star, we used it as our proxy for star scientists (*Star Scientists*).[7] This process also implies that the difference between *total scientists* and *star scientists* is our proxy for *nonstar scientists,* which we insert in the regression analysis to isolate the effect of star scientists on innovative output more fully. The average pharmaceutical firm employed about 17 star scientists and 197 nonstar scientists in a given year over the study period.

To accurately connect scientists to pharmaceutical firms, it was important to establish a link between the point in time when a scientist was employed by a pharmaceutical firm and the resulting intellectual property (IP) disseminated in a journal publication. First, we further investigated the publication time lag between initial submission and appearance of a journal article in the natural sciences. In stark contrast to the social sciences, where the time lag between initial article submission and publication in a journal can take several years, the initial submission to publication lag in the natural sciences is rather short; it is estimated to range, on the average, from three to six months (Greene 1987, Murray and Stern 2004).[8]

Second, the issue of scientist mobility is critical to our analysis. Some further analysis reveals that scientists within the pharmaceutical industry, however, do not change employers frequently. Based on the propensity to switch employers for all of the over 135,000 scientists in the sample, we found that the average nonstar scientist has worked for only 1.3 pharmaceutical firms (standard deviation = 0.9) during the 22 years of our analysis, while the average star scientist has worked for 3.4 firms (standard deviation = 1.8). This roughly relates to a star scientist changing jobs every 6.5 years, or about three job changes during our study period.

The third and most critical issue concerns the accurate link between the locus of IP creation and the locus of IP appropriation. For example, in the social sciences it is the norm that researchers note their current employer as the organization of affiliation on a journal publication, even when the IP was created while employed by a different institution. The norms associated with publishing in the social sciences, however, differ significantly from those of the natural sciences. Here, based on interviews with natural scientists, we found that each author is required to put down the organization where the IP was generated as the affiliation on journal articles rather than his/her current employer. The question of who owns the IP is fairly straightforward in the natural sciences because each scientist is required to keep a detailed research log documenting his or her daily activities, research results, etc. For example, if Merck were to hire a newly minted PhD graduate, the first few publications that result from the person's dissertation research would be published under the imprimatur of his/her degree-graduating university, rather than under Merck's name. This process also implies that if a star moves, for example, from Lilly to Pfizer, all the work she or he has done at Lilly will be published under Lilly's name, even if the publication date of the article coincides with the star being on Pfizer's payroll. Here, the current employer would only be mentioned in a footnote, for example, as the current mailing address of the author. All subsequent research where the IP is generated at Pfizer's labs will be published under Pfizer's name. This publication norm in the natural sciences allows us to track articles and connect them to the locus of IP creation and IP appropriation with fairly good accuracy, because the two loci overlap significantly.[9] Taken together, neither publication time lags, mobility of scientists, nor concerns about IP appropriation are likely to introduce any significant error variance.

R&D Capability. Following prior research (Rothaermel and Hill 2005), we proxied a pharmaceutical firm's *R&D capability* by its R&D expenditures, while explicitly controlling for firm revenues. Proxying R&D capability by R&D expenditures is preferred over R&D intensity (R&D expenditures divided by revenues), because in the latter measure, significant uncertainty exists as to whether any observed effects on innovation are due to the numerator, as hoped for, or due to the denominator. We obtained the financial data used in this study from a number of sources, including Compustat, Datastream, and FIS Mergent. All financial variables are inflation adjusted in constant 2000 U.S. dollars.

Biotech Alliances. To document the alliances that the pharmaceutical firms entered with providers of biotechnology research, we tracked each firm's alliances

with universities, research institutions, and biotechnology firms. Moreover, we content analyzed each alliance description to ensure that the focal alliance indeed pertained to the new biotechnology paradigm. To ensure accuracy and completeness of the alliance data, we used various issues of the BioScan industry directory and the ReCap database provided by Recombinant Capital.[10] The average sample firm entered three alliances per year with providers of biotechnology knowledge.

Biotech Acquisitions. Following Higgins and Rodriguez (2006), among others, we used the SDC Platinum database, published by Thomson Financial, to identify the number of biotechnology acquisitions a pharmaceutical firm had consummated during the study period. Here, we studied each acquisition description in detail to ensure that the focal acquisitions were indeed targeted toward the sourcing of R&D. The average pharmaceutical firm in the sample acquired about one biotechnology firm every two years.

Control Variables

Lagged Biotech Patents. We lagged the dependent variable, biotechnology patents, by one time period, and included it as a right-hand side variable. Inserting a lagged dependent variable provides for a conservative estimation of the other regressors, and allows us to control for a potential specification bias that can arise from unobserved heterogeneity (Jacobson 1990). Moreover, lagged biotechnology patents can also be interpreted as a proxy for firm size in biotechnology.

Nonbiotech Patents. To further reduce the threat of unobserved heterogeneity when using biotechnology patents as the dependent variable, it is critical to control for nonbiotechnology patents to avoid spurious findings, because firms that patent heavily per se might also patent heavily in biotechnology and vice versa. Thus, we included the number of nonbiotechnology patent applications granted per year as a control variable (*Nonbiotech Patents*). These data were obtained from the U.S. PTO. The average pharmaceutical firm was granted approximately 80 nonbiotechnology patents per year during our study period.

Firm Merged. Over the last two decades, the pharmaceutical industry was characterized by increasing consolidation due to horizontal mergers. To account for this effect, we created, as described earlier, a comprehensive family tree to trace all firms in existence in 2002 back to their various ancestors alive in 1980. This approach allowed us to insert a dummy variable indicating whether a sample firm was the result of a horizontal merger or acquisition (1 = firm merged). About 13% of all sample firms engaged in at least one horizontal merger or acquisition during the study period.

Pharmaceutical Firm. The global pharmaceutical industry consists of specialized companies like GlaxoSmithKline, Schering-Plough, or Yamanouchi, which focus on proprietary drug discovery and development, as well as more diversified companies, most notably chemical companies like DuPont, Monsanto, or BASF. A firm's level of diversification, therefore, is likely to influence the extent to which it attempts to innovate within biotechnology. We controlled for the varying degree of diversification by coding the pharmaceutical companies as one if the company is a specialized pharmaceutical firm (*Pharma Firm*), and zero otherwise. Specialized pharmaceutical companies are firms that are active in SIC 2834 (pharmaceutical preparations manufacturing). However, if a company is active in both SIC 2834 and SIC 2890 (chemical products manufacturing), for example, it was coded zero, indicating a higher degree of diversification. More than half of the firms (54%) were fully specialized pharmaceutical companies.

Firm Nationality. We attempted to assess institutional and cultural differences by coding for the nationality of each pharmaceutical firm based on the location of its headquarters. Thus, one indicator variable takes on the value of one if the firm is headquartered in the United States (*U.S. Firm*), the other indicator variable takes on the value of one if the firm is headquartered in Europe (*European Firm*), with an Asian location as the reference category. The global nature of this sample is highlighted by the fact that only 34% of the firms are headquartered in the United States, whereas 42% are European, and the remaining 24% are Asian (mostly Japanese). Thus, we were able to overcome the U.S. centric bias prevalent in prior research.

Firm Performance and Firm Size. Firm performance and firm size have a direct bearing on a firm's innovative performance (Nohria and Gulati 1996, Schumpeter 1942). To control for these effects, we inserted a firm's *Net Income, Total Revenues,* and *Total Assets* into the regression equations. Inserting total revenues as a control variable is especially relevant to isolate the effect of R&D expenditures on patenting.

Time to First Cohen-Boyer Patent Citation. The Cohen-Boyer patent (U.S. Patent 4,237,224), disclosing recombinant DNA technology, represents a fundamental and industry-changing innovation that allowed firms to develop new drugs based on genetic engineering (Pisano 1997). The time to first citation of the Cohen-Boyer patent in a firm's own patents (backward patent citation) was found to be a significant predictor of firm innovation (Fabrizio 2005), and thus provides an indication of a firm's speed of innovation within the new technological paradigm. As such, we included it in our regression models as a control variable. To identify when a firm first cited the Cohen-Boyer patent, if at all, we searched both the U.S. PTO and the NBER patent databases (Hall et al. 2001).

Year Fixed Effects. Because we investigate a 22-year time period, it is prudent to control for time-varying factors that affect all firms, including macroeconomic conditions. We therefore inserted annual time dummies for each year, with 1980 being the omitted year and thus serving as the reference year. Such year fixed effects also capture secular movements in the dependent variable. Inserting year dummies is useful, because it addresses concerns that underlying secular trends could influence our inference by introducing a simultaneity bias in the relationship between the dependent variable, biotechnology patenting, and the main regressors of interest. In addition, year fixed effects also control for any right truncation effect that might remain in the time series.

Estimation Procedures

The dependent variable of this study, a pharmaceutical firm's patents in biotechnology, is a nonnegative, integer count variable. Verified by a statistical test for overdispersion (Gourieroux et al. 1984), the negative binomial estimation provides a significantly better fit for the data than the more restrictive Poisson model. Negative binomial regression accounts for an omitted variable bias, while simultaneously estimating heterogeneity (Cameron and Trivedi 1986, Hausman et al. 1984).

In theory, either fixed- or random-effects specification can be used to control for unobserved heterogeneity (Greene 2003). We applied a Hausman specification test (1978), and its result revealed that a random-effects estimation is appropriate.[11] Therefore, we applied the following random-effects negative binomial model:

$$P(n_{it}/\varepsilon) = e^{-\lambda_{it-1}\exp(\varepsilon)}\lambda_i^{n_{it-1}}/n_{it-1}! \qquad (1)$$

where n is a nonnegative integer count variable, representing each pharmaceutical firm's patents in biotechnology. Thus, $P(n_{it}/\varepsilon)$ indicates the probability that pharmaceutical firm i is granted n biotechnology patent applications in year t. The application of a random-effects negative binomial estimation addresses concerns of heterogeneity, and enables us to include covariates that tend to be time invariant, such as the firm's time to first citation of the Cohen-Boyer patent, national origin, or degree of diversification (Hsiao 2003). Moreover, we submit that through the application of the Hausman specification test and the resulting random-effects specification, combined with a rich set of detailed control variables, we have effectively addressed any potential endogeneity (Hamilton and Nickerson 2003).

Further, to interpret the results in a meaningful manner and to reduce potential collinearity, we standardized all independent variables before entering them into the various regression models. We standardized the independent variables prior to creating their cross products to test the moderating hypotheses (Cohen et al. 2003). To compensate for a potential simultaneity bias and to enhance any causality claims, we lagged the financial measures (net income, assets, revenues, and R&D expenditures), as well as biotechnology alliances and biotechnology acquisitions, by one year.

Results

Table 1 depicts the descriptive statistics and the bivariate correlation matrix, whereas Table 2 presents the regression results for the direct effect hypotheses (H1 through H3, Models 2, 3, and 4), and Table 3 provides the results for the interaction hypotheses (H4 and H5, Models 5 and 6). We first estimated a baseline model including the control variables only (Model 1). Each subsequent model represents a significant improvement over the baseline model at $p < 0.01$, or smaller.

Results—Direct Effect Hypotheses

The results shown in Model 2 provide support for Hypothesis 1A, indicating that a firm's innovative output is a positive function of its intellectual human capital ($p < 0.001$), which we proxied by a firm's total number of research scientists that (co-)authored at least one research article in a scientific journal.

In Hypothesis 1B, we postulate that a firm's innovative output is a positive function of its star scientists, above and beyond any effects of the firm's nonstar scientists. To highlight the importance of explicitly controlling for nonstar scientists, and thus to demonstrate the threat of unobserved heterogeneity, we first estimated the effect of a firm's star scientists on innovative output without controlling for nonstar scientists (Model 3). The results in Model 3 reveal that a firm's star scientists are a positive and statistically significant predictor of innovative output ($p < 0.01$). This finding would lead us to claim support for the hypothesis that a firm's innovative output is a positive function of its star scientists. In Model 4, however, we inserted the number of nonstar scientists to more fully isolate any star scientist effect. The results demonstrate that it is not the star scientists that are a significant predictor of innovative output, as hypothesized in H1B, but rather it is the firm's nonstar scientists that are a positive and statistically significant predictor of a firm's innovative output ($p < 0.05$). We thus reject Hypothesis 1B. This finding has two important implications.

First, it demonstrates the seriousness of the threat of unobserved heterogeneity. Had we not explicitly controlled for a firm's nonstar scientists, we would have accepted the hypothesis that stars are a significant predictor of innovative output, and thus committed a serious Type I error—accepting the research hypothesis when in reality the null hypothesis is true. Second, a closer look at the results presented in Models 3 and 4 reveals a fully mediated relationship between a firm's star scientists and its innovative output. This relationship is implied,

Table 1 Descriptive Statistics and Bivariate Correlation Matrix

	Mean	S.D.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1. Biotech patents	7.18	14.30																	
2. Year	1991	6.78	0.158																
3. Firm merged	0.07	0.26	0.081	0.261															
4. Pharma firm	0.54	0.50	0.081	−0.003	−0.150														
5. U.S. firm	0.34	0.47	0.109	−0.109	0.082	−0.069													
6. European firm	0.42	0.49	0.003	−0.114	0.020	0.149	−0.603												
7. Net income (MM$)*	842.17	2,235.08	0.269	0.184	0.185	−0.005	0.223	−0.007											
8. Total assets (MM$)*	12,264.81	15,608.86	0.105	0.083	0.105	−0.344	0.019	0.167	0.301										
9. Total revenues (MM$)*	12,190.34	20,195.48	0.055	−0.012	0.035	−0.366	−0.022	0.089	0.147	0.743									
10. Time to first Cohen-Boyer patent citation (years)	6.55	2.90	−0.196	0.059	−0.034	−0.028	−0.097	0.021	−0.024	0.033	0.036								
11. Nonbiotech patents	80.42	127.78	0.176	0.050	0.015	−0.374	0.089	0.049	0.179	0.519	0.624	0.029							
12. Lagged biotech patents	6.18	12.58	0.803	0.182	0.094	0.081	0.130	−0.016	0.277	0.107	0.049	−0.212	0.163						
13. Scientists (total)	214.01	288.46	0.474	0.247	0.336	0.118	0.207	0.035	0.346	0.146	0.055	−0.164	0.253	0.464					
14. Star scientists	16.89	43.29	0.407	0.070	0.176	0.124	0.233	−0.122	0.234	0.041	−0.009	−0.077	0.123	0.402	0.672				
15. Nonstar scientists	197.12	261.51	0.456	0.261	0.342	0.110	0.189	0.059	0.343	0.154	0.062	−0.169	0.258	0.446	0.992	0.575			
16. R&D expenditures (MM$)*	835.45	1,137.15	0.197	0.065	0.207	−0.228	−0.008	0.295	0.332	0.627	0.441	−0.024	0.500	0.192	0.386	0.122	0.406		
17. Biotech alliances	3.03	7.14	0.253	0.094	0.348	0.067	0.161	−0.022	0.170	0.084	0.020	−0.152	0.054	0.214	0.425	0.423	0.398	0.175	
18. Biotech acquisitions	0.68	1.94	0.172	0.178	0.436	0.085	0.133	0.021	0.194	0.123	0.020	−0.134	0.076	0.182	0.385	0.353	0.366	0.180	0.534

Notes. $N = 1{,}782$ firm-years. *Constant 2000 U.S. dollars.

Table 2 Regression Results of Random-Effects Negative Binomial Estimation Predicting Biotech Patenting

	Model 1		Model 2		Model 3		Model 4		Post-hoc analysis	
Direct effects models	Beta	Standard error	Beta	Standard error	Beta	Standard error	Beta	Standard error	Beta	Standard error
Constant	−0.8642	(0.7147)	−0.7957	(0.7353)	−0.4495	(0.7221)	−0.7138	(0.7392)	−0.8079	(0.7381)
Year is 1981	0.2655	(0.7429)	0.3590	(0.7643)	−0.0423	(0.7484)	0.2654	(0.7694)	0.5861	(0.7696)
Year is 1982	0.7668	(0.7353)	0.8162	(0.7569)	0.4277	(0.7424)	0.7223	(0.7621)	1.0335	(0.7620)
Year is 1983	0.5977	(0.7381)	0.6559	(0.7598)	0.2708	(0.7448)	0.5665	(0.7644)	0.8701	(0.7645)
Year is 1984	0.9750	(0.7306)	1.0380	(0.7515)	0.6511	(0.7365)	0.9472	(0.7563)	1.2339	(0.7557)
Year is 1985	0.7458	(0.7328)	0.7792	(0.7550)	0.3984	(0.7397)	0.6923	(0.7593)	0.9609	(0.7590)
Year is 1986	0.9618	(0.7301)	0.9688	(0.7516)	0.5849	(0.7370)	0.8782	(0.7564)	1.1340	(0.7555)
Year is 1987	1.1812	(0.7262)	1.2058	(0.7462)	0.8390	(0.7323)	1.1193	(0.7506)	1.3622*	(0.7498)
Year is 1988	1.1512	(0.7259)	1.1527	(0.7454)	0.7760	(0.7321)	1.0601	(0.7506)	1.2845*	(0.7487)
Year is 1989	1.0880	(0.7251)	1.1138	(0.7455)	0.7397	(0.7312)	1.0256	(0.7501)	1.2365*	(0.7487)
Year is 1990	1.4142*	(0.7198)	1.3710*	(0.7391)	1.0222	(0.7267)	1.2871*	(0.7434)	1.4764*	(0.7422)
Year is 1991	1.3977*	(0.7180)	1.3813*	(0.7356)	1.0318	(0.7238)	1.2931*	(0.7403)	1.4596*	(0.7384)
Year is 1992	1.5735*	(0.7172)	1.5306*	(0.7343)	1.1991*	(0.7229)	1.4485*	(0.7383)	1.6092*	(0.7371)
Year is 1993	1.7267**	(0.7173)	1.6621*	(0.7345)	1.3278*	(0.7238)	1.5773*	(0.7390)	1.7319**	(0.7375)
Year is 1994	1.9339**	(0.7162)	1.8833**	(0.7333)	1.5635*	(0.7224)	1.8044**	(0.7370)	1.9442**	(0.7363)
Year is 1995	2.1946***	(0.7158)	2.1913**	(0.7324)	1.8770**	(0.7218)	2.1136**	(0.7359)	2.2529***	(0.7354)
Year is 1996	1.5918*	(0.7153)	1.5049*	(0.7351)	1.1961*	(0.7229)	1.4373*	(0.7375)	1.5590*	(0.7381)
Year is 1997	1.9465**	(0.7146)	1.8674**	(0.7307)	1.5774*	(0.7204)	1.7999**	(0.7333)	1.9090**	(0.7336)
Year is 1998	1.6932**	(0.7163)	1.6461*	(0.7341)	1.3466*	(0.7221)	1.5809*	(0.7363)	1.6621*	(0.7370)
Year is 1999	1.7147**	(0.7163)	1.6917*	(0.7320)	1.3972*	(0.7211)	1.6232*	(0.7345)	1.6946*	(0.7345)
Year is 2000	1.4924*	(0.7168)	1.5234*	(0.7307)	1.2557*	(0.7208)	1.4641*	(0.7326)	1.5291*	(0.7327)
Year is 2001	1.3509*	(0.7171)	1.3429*	(0.7339)	1.0568	(0.7231)	1.2788*	(0.7360)	1.3321*	(0.7362)
Firm merged	0.1855***	(0.0312)	0.1473***	(0.0317)	0.1499***	(0.0315)	0.1460***	(0.0316)	0.1472***	(0.0314)
Pharma firm	−0.1404	(0.0866)	−0.2480**	(0.0910)	−0.2195**	(0.0896)	−0.2520**	(0.0911)	−0.2179**	(0.0904)
U.S. firm	0.1329	(0.0950)	−0.0164	(0.1008)	0.0094	(0.0999)	−0.0216	(0.1009)	−0.1050	(0.1035)
European firm	−0.0633	(0.0997)	−0.0788	(0.1077)	−0.0491	(0.1083)	−0.0672	(0.1084)	−0.1964*	(0.1132)
Net income	0.0613	(0.0577)	0.0433	(0.0596)	0.0566	(0.0585)	0.0468	(0.0596)	0.0241	(0.0604)
Total assets	−0.5691***	(0.0850)	−0.5189***	(0.0885)	−0.5353***	(0.0867)	−0.5220***	(0.0877)	−0.5758***	(0.0885)
Total revenues	0.1879***	(0.0433)	0.1849***	(0.0433)	0.1985***	(0.0425)	0.1889***	(0.0431)	0.1468***	(0.0444)
Time to first Cohen-Boyer patent citation	−0.6068***	(0.0831)	−0.6778***	(0.0900)	−0.6966***	(0.0925)	−0.6904***	(0.0916)	−0.6401***	(0.0889)
Nonbiotech patents	0.1608***	(0.0404)	0.1531***	(0.0399)	0.1546***	(0.0396)	0.1523***	(0.0398)	0.1547***	(0.0398)
Lagged biotech patents	0.1703***	(0.0164)	0.1509***	(0.0177)	0.1565***	(0.0178)	0.1493***	(0.0179)	0.1497***	(0.0174)
Scientists (total)			0.1296***	(0.0411)					0.0938*	(0.0418)
Star scientists					0.0775**	(0.0275)	0.0484	(0.0325)		
Nonstar scientists							0.0911*	(0.0478)		
R&D expenditures			−0.1080*	(0.0577)	−0.0768	(0.0548)	−0.1017*	(0.0575)	0.2784*	(0.1281)
R&D expenditures squared									−0.0872***	(0.0283)
Biotech alliances			0.0206	(0.0206)	0.0201	(0.0205)	0.0199	(0.0205)	0.0174	(0.0207)
Biotech acquisitions			0.0464*	(0.0246)	0.0556**	(0.0236)	0.0473*	(0.0243)	0.0480*	(0.0245)
Log likelihood	−2,587.22		−2,473.88		−2,475.23		−2,473.41		−2,467.94	
Chi square	807.24***		831.93***		831.53***		833.34***		822.03***	
Improvement over base ($\Delta\chi^2$)			24.69***		24.29***		26.10***		14.79**	

Notes. Standard errors are in parentheses; $^*p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

given that inserting nonstar scientists leads to a positive and statistically significant effect of nonstar scientists on innovative output, while the effect of star scientists switches from being statistically significant in Model 3 to not being statistically significant in Model 4.[12] This implies that the relationship between star scientists and innovative output is fully mediated by nonstar scientists.

We find that R&D expenditures, our proxy for R&D capability, are negative and statistically significant in predicting a firm's innovation output ($p < 0.05$ in Models 2 and 4). This does not imply, however, that R&D expenditures have an absolute negative effect on biotechnology patenting. Rather, it may indicate that the functional relationship between R&D expenditures and biotech patenting could be nonlinear. When we include the linear and squared term of R&D expenditures in a post hoc analysis (presented in the far right column of Table 2), we indeed see that the relationship between

Table 3 Regression Results of Random-Effects Negative Binomial Estimation Predicting Biotech Patenting

	Model 5		Model 6	
Interaction effects models	Beta	Standard error	Beta	Standard error
Constant	−0.3719	(0.7693)	−0.5968	(0.7849)
Year is 1981	0.0224	(0.7886)	0.2377	(0.8029)
Year is 1982	0.4840	(0.7809)	0.6928	(0.7955)
Year is 1983	0.3208	(0.7836)	0.5348	(0.7985)
Year is 1984	0.7219	(0.7775)	0.9308	(0.7921)
Year is 1985	0.4507	(0.7818)	0.6590	(0.7961)
Year is 1986	0.5527	(0.7816)	0.7447	(0.7960)
Year is 1987	0.8128	(0.7759)	1.0156	(0.7902)
Year is 1988	0.7934	(0.7756)	0.9702	(0.7897)
Year is 1989	0.7589	(0.7756)	0.9634	(0.7902)
Year is 1990	0.9956	(0.7709)	1.2135	(0.7857)
Year is 1991	0.9975	(0.7691)	1.2049	(0.7844)
Year is 1992	1.1299	(0.7682)	1.3459*	(0.7834)
Year is 1993	1.2646*	(0.7679)	1.4863*	(0.7837)
Year is 1994	1.4659*	(0.7670)	1.7010*	(0.7830)
Year is 1995	1.7952**	(0.7697)	2.0355**	(0.7860)
Year is 1996	1.0784	(0.7717)	1.3228*	(0.7879)
Year is 1997	1.4904*	(0.7643)	1.7347*	(0.7806)
Year is 1998	1.2525	(0.7689)	1.5117*	(0.7862)
Year is 1999	1.2695*	(0.7625)	1.5063*	(0.7787)
Year is 2000	1.1655	(0.7596)	1.4036*	(0.7738)
Year is 2001	1.0027	(0.7631)	1.2502	(0.7780)
Firm merged	0.1337***	(0.0322)	0.1284***	(0.0329)
Pharma firm	−0.2416**	(0.0903)	−0.2302**	(0.0910)
U.S. firm	−0.0565	(0.1037)	−0.0469	(0.1044)
European firm	−0.1026	(0.1089)	−0.0996	(0.1102)
Net income	0.0602	(0.0593)	0.0685	(0.0602)
Total assets	−0.5627***	(0.0899)	−0.5269***	(0.0910)
Total revenues	0.1745***	(0.0438)	0.1725***	(0.0443)
Time to first Cohen-Boyer patent citation	−0.6838***	(0.0920)	−0.6896***	(0.0944)
Nonbiotech patents	0.1666***	(0.0399)	0.1662***	(0.0398)
Lagged biotech patents	0.1713***	(0.0200)	0.1719***	(0.0211)
Scientists (total)	0.2186***	(0.0532)		
Star scientists			0.0613	(0.0460)
Nonstar scientists			0.1766**	(0.0656)
R&D expenditures	−0.0297	(0.0615)	−0.0583	(0.0653)
Biotech alliances	0.0443	(0.0347)	0.0387	(0.0355)
Biotech acquisitions	−0.0265	(0.0453)	−0.0376	(0.0465)
Scientists (total) × R&D expenditures	−0.1141**	(0.0450)		
Scientists (total) × biotech alliances	−0.0630***	(0.0174)		
Scientists (total) × biotech acquisitions	0.0171	(0.0149)		
Star scientists × R&D expenditures			−0.1037*	(0.0613)
Star scientists × biotech alliances			0.0132	(0.0114)
Star scientists × biotech acquisitions			0.0028	(0.0107)
Nonstar scientists × R&D expenditures			−0.0604	(0.0484)
Nonstar scientists × biotech alliances			−0.0873***	(0.0221)
Nonstar scientists × biotech acquisitions			0.0212	(0.0225)
R&D expenditures × biotech alliances	0.0802**	(0.0320)	0.1036***	(0.0323)
R&D expenditures × biotech acquistions	0.0556	(0.0406)	0.0568	(0.0414)
Log likelihood	−2,463.73		−2,459.94	
Chi square	891.99***		901.23***	
Improvement over base ($\Delta\chi^2$)	84.75***		93.99***	

Notes. Standard errors are in parentheses; $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

R&D expenditures and patenting is characterized by diminishing returns, because the linear term of R&D expenditures is positive and statistically significant ($p < 0.05$), whereas the squared term is negative and also statistically significant ($p < 0.001$). This result is not caused by multicollinearity, because the VIFs between linear and squared R&D terms reach only 2.45, well below the cutoff point of 10 (Cohen et al. 2003).

Recall that our estimation technique is a negative binomial regression, and thus a nonlinear, exponential

Table 4 Interpretation of Negative Binomial Regression Results

	Beta	Incidence rate ratio = exp(beta)	Factor change = IRR-1
Direct effects			
Scientists (total)	0.1296***	1.14	0.14
Star scientists	0.0775**	1.08	0.08
Nonstar scientists	0.0911*	1.10	0.10
R&D expenditures	0.2784*	1.32	0.32
R&D expenditures squared	−0.0872***	0.92	−0.08
Biotech acquisitions	0.0464*	1.05	0.05
Biotech acquisitions	0.0473*	1.05	0.05
Interaction effects			
Scientists (total) × R&D expenditures	−0.1141*	0.89	−0.11
Scientists (total) × bio alliances	−0.0630***	0.94	−0.06
Star scientists × R&D expenditures	−0.1037*	0.90	−0.10
Nonstar scientists × biotech alliances	−0.0873***	0.92	−0.08
R&D expenditures × biotech alliances	0.0802*	1.08	0.08
R&D expenditures × biotech alliances	0.1036***	1.11	0.11

$*p < 0.05$; $**p < 0.01$; $***p < 0.001$.

estimation technique as explicated in Equation (1) above. Therefore, to interpret the reported beta coefficients in a meaningful manner, one needs to exponentiate the respective beta value [$\exp(\beta)$ or e^{β}] to obtain the incidence rate ratio, holding all other variables constant (see Long 1997, pp. 228–229; for a recent application see Ichino and Maggi 2000).[13] Table 4 provides an interpretation of the direct effects and interaction effects on biotechnology patenting. We translate beta values into incidence rate ratios and factor changes. When comparing the factor changes obtained for the statistically significant linear direct effects, we find that intellectual human capital (14%) had the strongest effect on biotechnology patenting, divided into star scientists (8%) and nonstar scientists (10%), followed by biotechnology acquisitions (5%).

We do not find support for Hypothesis 3A, suggesting that a firm's innovative output is a positive function of its alliances with new technology providers. The results, however, do reveal support for Hypothesis 3B, positing that a firm's innovative output is a positive function of its acquisitions of new technology firms, because the coefficients for biotechnology acquisitions are positive and statistically significant ($p < 0.05$ or smaller in Models 2–4).

Results—Interaction Hypotheses

We propose two competing interaction hypotheses, which we evaluate in Models 5 and 6 presented in Table 3. In Hypothesis 4 we posit that the different innovation antecedents across levels complement one another, whereas in Hypothesis 5 we suggest that they substitute for one another.

We find support for the hypothesis that a firm's intellectual human capital (proxied by its total scientists) and a firm's R&D capability are substitutes for one another because the interaction between these two variables is negative and statistically significant ($p < 0.01$ in Model 5). Star scientists and R&D capability also substitute for one another because their interaction is negative and significant ($p < 0.05$ in Model 6). When evaluating the interactions between individual- and network-level effects, we find that a firm's nonstar scientists and its biotechnology alliances substitute for one another because the interaction effect is negative and significant ($p < 0.001$ in Model 6). Taken together, this implies that individual- and firm-level effects as well as individual- and network-level effects compensate for one another when pursued in parallel, at least at the margin. For example, for pharmaceutical firms with a high level of intellectual human capital, alliances are less important to achieve biotech patenting. Thus, new knowledge generated through research efforts by scientists may compensate for new knowledge that could be gained from external sources. This points to some level of equifinality based on the different internal and external knowledge sources.

When focusing on the interactions between firm- and network-level factors, we find that a firm's R&D capability and its biotechnology alliances complement one another, because the interaction effects are positive and significant in both Models 5 and 6 ($p < 0.01$ and $p < 0.001$, respectively). Here, firm- and network-level effects reinforce one another when pursued in parallel, at least at the margin. For pharmaceutical companies with a high level of R&D capability, the incremental benefit of pursuing alliances increases biotech patenting over and above simple additive effects. This finding points to positive knowledge spillovers between an internal R&D capability and external knowledge sources, at least for alliances.

In sum, the pattern for the interaction effect results suggests that individual-level antecedents to innovation (intellectual human capital, star scientists, and nonstar scientists) appear to be substitutes for firm-level antecedents to innovation (R&D capability) as well as for network-level antecedents (biotechnology alliances) to innovation, thus lending support to Hypotheses (5A) and (5B). On the other hand, firm- and network-level antecedents (biotechnology alliances) to innovation appear to complement one another, thus providing support for Hypothesis (4C).[14]

The net effects of the interactions are depicted in Table 4, which further substantiates our claims pertaining to substitutive and complementarity effects. The idea that intellectual human capital is a substitute for firm-

and network-level antecedents to innovation is highlighted by the fact that the positive direct effect of intellectual human capital on biotechnology patenting declines as R&D expenditures or the number of biotechnology alliances are increased. In particular, an innovation strategy that jointly emphasizes intellectual human capital and R&D expenditures or intellectual human capital and biotechnology alliances reduces the expected number of biotechnology patents between 6% and 11%, when any of the respective interaction variables is increased by one standard deviation. On the other hand, the joint effects of R&D expenditures and biotechnology alliances on innovative output reinforce one another, thus highlighting their complementary natures. In particular, the effect of R&D capability on innovative output increases between 8% and 11% above and beyond the direct effects when the number of biotechnology alliances is increased by one standard deviation, and vice versa.[15]

Results of Control Variables

Some of the results of the control variables are also noteworthy. We assess them in Model 1, the baseline estimation. The results indicate that firms that are heavily engaged in patenting overall, as proxied by their nonbiotechnology patents, are also very active in biotechnology patenting ($p < 0.001$). In addition, past biotechnology patenting predicts future biotechnology patenting, because the lagged dependent variable is, as expected, positive and statistically significant ($p < 0.001$). Thus, the observed effects above are not spurious due to a firm-size effect in biotechnology. Including a variable that captures a firm's overall inclination to engage in the focal activity (proxied by nonbiotechnology patents) and including a lagged dependent variable follow the recommendations of how to control for unobserved heterogeneity (Heckman and Borjas 1980). The results obtained are reassuring not only because they reduce the threat of unobserved heterogeneity, but also because they rule out the alternative explanation that the key independent variable findings might be caused by a firm's innovation strategy, which is unobservable.

With regard to the annual indicator variables, we see that the year dummies capture a trend acceleration and eventual deceleration in biotechnology patenting over time. Patenting activity significantly accelerates in the early 1990s, peaks in the mid-1990s, and slows down somewhat towards the end of the study period. This pattern suggests that inserting year dummies effectively controls for any remaining right truncation effect. Pharmaceutical companies that underwent a horizontal merger or acquisition during the lengthy study period exhibit a significantly greater number of biotechnology patents ($p < 0.001$). Larger firms, as proxied by their total assets, appear to be laggards in biotechnology patenting ($p < 0.001$). Firms with higher revenues are more active in biotechnology patenting ($p < 0.001$). This result is important, because it isolates the effect of R&D expenditures on biotechnology patenting more fully, and because R&D expenditures and revenues are the two components of the frequently used R&D intensity measure (Cohen and Levinthal 1989, 1990; Helfat 1994a, b, 1997). As expected, firms that take longer to incorporate the breakthrough Cohen-Boyer patent into their knowledge base exhibit an overall lower innovation output ($p < 0.001$). Noteworthy is the strong negative effect of being late in citing the breakthrough Cohen-Boyer rDNA patent: Every 2.9 years of delay lowers the expected number of biotechnology patents by 45%. This finding clearly highlights the imperative of being a fast mover in this dynamic industry, where competition is characterized by winner-take-all scenarios (Arthur 1989).

Discussion

Following recent theoretical developments emphasizing that antecedents to dynamic capabilities can either be found at the individual, firm, and/or network levels of analysis (Eisenhardt and Martin 2000, Teece et al. 1997, Zollo and Winter 2002), we set out to challenge the assumptions of homogeneity across, and independence from, different levels of analysis commonly found in extant unilevel research (Felin and Foss 2005, Felin and Hesterly 2007, Klein et al. 1994, Dansereau et al. 1999). First, we scrutinized the assumption of homogeneity across levels of analysis by simultaneously testing the effects of different innovation antecedents across levels, thus explicitly controlling for alternate levels of analysis. Second, we examined the assumption of independence from different levels of analysis by testing two competing interaction hypotheses concerning the potential complementary and substitutive nature of innovation antecedents in the intersections across different levels of analysis.

Taken together, the results not only demonstrate heterogeneity across levels of analysis, but also interdependence with alternate levels of analysis. We therefore reject both the assumption of homogeneity across levels and the assumption of independence from alternate levels of analysis. These overarching findings resulted from attempting to answer questions pertaining to the locus of dynamic capabilities.

Regarding heterogeneity across levels of analysis, we find that a significant amount of variance in innovation was explained by individual-level factors. When splitting a firm's intellectual human capital into its two components, star and nonstar scientists, we find that the positive direct effect of intellectual human capital on patenting can be primarily attributed to a firm's nonstar scientists, whereas its star scientists did not exert a significant direct effect on patenting. At first glance, this result is somewhat surprising given that it highlights the importance of scale in intellectual human capital,

accomplished through a large number of rank-and-file knowledge workers (Ashworth and Carley 2006) rather than the primacy of elite scientists, which is emphasized in the few prior studies in this area (Lacetera et al. 2004; Zucker and Darby 1997a, b). This apparent tension, however, can be reconciled by the finding that nonstar scientists fully mediate the effect of star scientists on innovative output. It appears, therefore, that the primary role of the star scientist is to help cue the firm to potential shifts in the environment and direct it towards promising new research areas (Kaplan et al. 2003), rather than to facilitate its adaptation to the change itself.

The structure of Sanofi-Aventis' R&D process exemplifies the idea that the effects of star scientists on innovation are mediated by nonstar scientists. Sanofi-Aventis has two distinct research groups. The Discovery Research Group is comprised of a few key scientists and is responsible for identifying important treatment areas. Every year this group recommends 15–20 promising areas for treatment. These recommendations are followed up by the International Development Group, which is responsible for seeing the potential drug treatments through to development (Sanofi-Aventis 2004 Annual Report). This structure seems to indicate that Sanofi-Aventis employs star scientists as visionaries in the Discovery Group, whereas nonstar scientists are primarily responsible for drug development. Without the involvement of a large number of nonstar scientists in the development process, any innovative effect stars have would be attenuated.

In contrast to prior work emphasizing networks as the locus of innovation (Powell et al. 1996, Owen-Smith and Powell 2004), our findings highlight the importance of individual-level factors in explaining firm-level heterogeneity in innovation, and thus validate recent theoretical calls for a stronger micro foundation in strategic management research (Felin and Foss 2005, Felin and Hesterly 2007). Because innovation is, by its nature, a knowledge-intensive activity, the question turns to the issue of how firms learn. Simon (1991) suggests that intellectual human capital, especially the recruitment of scientists, can be an effective way to learn and innovate. He emphasizes that "all organizational learning takes place inside human heads; an organization learns in only two ways: (a) by the learning of its members, or (b) by ingesting new members who have knowledge the organization didn't previously have" (Simon 1991, p. 125). The role of individuals in knowledge creation is also highlighted by Grant, who argues that "the emphasis upon the role of the individual as the *primary* actor in knowledge creation and the principle repository of knowledge . . . is essential to piercing the veil of organizational knowledge and clarifying the role of organizations in the creation and application of knowledge" (Grant 1996, p. 121; italics added). We find that rank-and-file knowledge workers, here nonstar scientists, have a direct bearing on the innovative performance of firms, although controlling for alternative explanations across different levels. We submit that future research needs to consider the role of individuals when studying antecedents to a firm's dynamic capabilities in particular, and firm performance in general.

Rather than finding a linearly positive relationship between R&D expenditures and biotech patenting, as hypothesized, we find that this relationship is characterized by diminishing marginal returns. This implies that although additional R&D expenditures may translate into a higher number of expected biotechnology patents, their positive effect, however, decreases as R&D expenditures increase. A recent analysis of R&D expenditures and innovative output in the global pharmaceutical industry between 1980 and 2003 details the phenomenon of ever-increasing R&D expenditures, although the number of new drug registrations declines, and concludes that "despite its outward strength, the [pharmaceutical] industry is ailing. The pipelines of forthcoming drugs on which its future health depends have been drying up for some time" (*The Economist* 2004).

We find support for the idea that acquisitions increase innovative output, but no support for our hypothesis that alliances do the same. This interesting result may be the product of our richly specified model, which allows us to uncover the effects of these disparate innovation mechanisms in greater detail. More specifically, our findings point to the idea that acquisitions can be a "stand-alone" mechanism to innovation. In an acquisition, a pharmaceutical firm often acquires not only the drug pipeline of the target firm, but also the firm's internal research capability (Galambos and Sturchio 1998, Higgins and Rodriguez 2006). In contrast, alliances between large pharmaceutical firms and biotechnology ventures often entail the sharing of explicit knowledge only in the later stages of drug development and subsequent commercialization (Rothaermel and Deeds 2004). The successful transformation and implementation of codified knowledge obtained in an alliance still requires that the firm has the ability to assimilate and apply this knowledge (Cohen and Levinthal 1989). Thus, by controlling for this internal ability, encompassing both intellectual human capital and R&D capability, we see that alliances, as a stand-alone mechanism, appear to be of little value to firm innovation. Although a firm can acquire the requisite dynamic capabilities to innovate through acquisitions, we find, in contrast, that the firm must already possess prior R&D capability for alliances to be a viable mechanism for innovation, as is highlighted in the significant interaction effects across levels of analysis.

Regarding the demonstrated interdependence of alternate levels across analysis, we found, in general terms, that individual-level antecedents to innovation are substitutes for firm- and network-level antecedents to innovation, and that firm- and network-level antecedents to innovation are complements. The results obtained here are

interesting in the sense that we find support for both substitutability and complementarity hypotheses, depending on which levels of analysis and intersections across levels are considered. Thus, choosing between different innovation mechanisms in a discriminating fashion appears to be critical to firm innovation. Taken together, the antecedents to innovation capabilities clearly lie *across* different levels of analysis.

Limitations and Future Research

This research represents an initial attempt to develop and test a multilevel model, incorporating individual-, firm-, and network-level effects, for use in investigating firm innovation. As such, it is prone to several limitations that, in turn, open pathways to future research. For example, it is possible that some of the results, specifically those related to R&D capability and alliances, could be attributable to our choice of measurement rather than to the underlying effect of the mechanism. By using more fine-grained data, future research could increase confidence in our finding. For example, prior research illustrates that when focusing exclusively on alliances, different types of alliances and different types of alliance experiences have differential effects on firm innovation (Hoang and Rothaermel 2005, Rothaermel and Deeds 2006). Future research could incorporate detailed alliance distinctions into the multilevel theoretical model presented, while controlling for alternative innovation mechanisms, and thus expand our understanding of the mechanisms that drive firm innovation in a more in-depth manner.

An additional limitation of this study is that we proxy firm R&D capability in biotechnology with an aggregate measure of R&D expenses. This issue is especially troublesome for the more diversified pharmaceutical firms in this sample, such as Johnson & Johnson, because we are unable to segregate the portion of R&D expenses that are directed towards biotechnology. Future research may increase the validity of the findings presented by parsing out the amount of firm-level R&D capability that is associated only with a firm's biotechnology efforts.

We also acknowledge that future research may be able to develop and implement a better measure of firm innovation than patent counts. We emphasize, however, that patents are useful for measuring technological innovation, because they are only awarded to novel, nonobvious inventions that represent advancements over existing technology. Moreover, we caution that alternative innovation measures, including new products developed, frequently exhibit too little variance to be feasible as a dependent variable and are difficult to track in the scale and detail necessary for a comprehensive longitudinal analysis.

Finally, although the results presented offer fresh insights into firm innovation, the study's focus on biotechnology innovation by large pharmaceutical firms raises questions about the generalizability of the findings. This industry segment is unique in its significant reliance upon basic scientific research as well as its protracted and arcane product development and approval cycle. Despite these unique characteristics, we submit that our results could be generalizable to other industries, because prior work details the increasing importance of research in basic science, interfirm cooperation, and acquisitions in determining the innovation success or failure of individual firms across a diverse set of industries (Chesbrough 2003, Cockburn et al. 2000, Hagedoorn 1993).

Conclusion

Our initial attempt to disentangle the multilevel effects associated with the various mechanisms firms can use to innovate contributes to the understanding of how firms build and refine dynamic capabilities to adapt to radical technological change. This research demonstrates that individuals matter and that it is inappropriate to investigate firm adaptation and innovation without the consideration of its intellectual human capital. Further, the various interactions between the levels of analysis indicate that the antecedents to dynamic capabilities lie across different levels. Firm- and collective-level mechanisms appear to be complementary in nature, whereas intellectual human capital appears to substitute for firm- and network-level mechanisms. The development of a strong intellectual capital base requires time and the commitment of resources that are often not available to a firm faced with the demands of adapting to a new technological paradigm. Therefore, firms should, with the help of star scientists, identify an exogenous paradigm shift, and then assemble the requisite human assets in the form of rank-and-file scientists. Our research indicates that these firms will develop the innovation capabilities necessary to succeed.

Managers generally face the added burden of time constraints when attempting to innovate. Therefore, it is paramount to firm success that a manager be able to not only weigh the strengths and weaknesses of the available innovation mechanisms, but also to understand and predict how these mechanisms will interact when used in tandem. Faced with the daunting task of adapting to a new technological paradigm, however, managers often choose the "grab bag" approach to innovating, employing a variety of available mechanisms simultaneously without knowledge of the possible deleterious interaction effects. Our research demonstrates that, due to path dependency and constraints imposed on a firm's financial-, managerial-, and research-related resources, a tandem approach may actually lead to decreases in innovative output. In other words, when investigating the number of innovation mechanisms a manager should employ, more is not always better. Instead, the managers who take a discerning and discriminating approach towards selecting innovation mechanisms will be most

successful in building the dynamic capabilities necessary to continuously innovate.

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Endnotes

[1]Formally: Let x_i denote one activity (e.g., recruitment of intellectual human capital) and x_j denote a second activity (e.g., forming strategic alliances); then, these two activities are said to be complements if $\Delta x_i/\Delta x_j > 0$, and substitutes if $\Delta x_i/\Delta x_j < 0$. 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, pp. 255–260).

[2]Including: *BioScan* (*annual volumes*), *Burrill & Company Life Sciences Annual Industry Reports, Compustat, Datastream* (*Thomson Financial*), *Ernst & Young's Annual Biotech Industry Reports, FIS Mergent*, and *Scrip's Yearbooks on the Global Pharmaceutical Industry,* among other sources.

[3]We explicitly controlled for horizontal mergers in the regression analysis through the inclusion of an indicator variable.

[4]To assess the validity of the initial sample obtained, we independently sampled the databases maintained by Recombinant Capital, a research firm specializing in biotechnology. We tracked 125 pharmaceutical companies, among which all of our 93 original firms were listed. This enhanced our confidence in the initial sample, in which we tracked the firms forward rather than just sampling on surviving firms at the end of the study period. The remaining 32 firms were either smaller firms that did not receive sufficient coverage to merit inclusion in any of the industry publications that we consulted, or were more recent entries into the industry, and thus did not qualify under our definition of an "incumbent pharmaceutical firm."

[5]*Diamond v. Chakrabarty* 447 U.S. 303 (1980).

[6]The U.S. PTO compiled these data based on all biotechnology patents in the following patent classes: 424 [Drug, bioaffecting and body-treating compositions (different subclasses)], 435 [Chemistry: Molecular biology and microbiology], 436 [Chemistry: Analytical and immunological testing], 514 [Drug, bioaffecting, and body-treating compositions (different subclasses)], 530 [Chemistry: Natural resins or derivatives; peptides or proteins; lignins or reaction products thereof], 536 [Organic compounds], 800 [Multicellular living organisms and unmodified parts thereof and related processes], 930 [Peptide or protein sequence], PLT [plants].

[7]Alternatively, we proxied stars by whether a researcher had received a Nobel Prize in either chemistry or medicine, the two fields relevant to our study. We cross-referenced the list of all Nobel Laureates with our author database to assess whether any of the Nobel Laureates had published research articles where they listed a pharmaceutical company as their affiliation. This process yielded 23 Nobel Laureates who published 148 papers. The variance among firms, however, was too small for any meaningful econometric analysis.

[8]Notwithstanding this evidence, we further investigated this issue empirically. We took a random sample of 40 articles from our database and collected the information from these publications pertaining to date of submission and date of publication. Based on the input received from industry experts, we collected 20 articles from the period between 1984 and 1994, whereas the remaining 20 articles were from the period between 1995 and 2004. The analysis of the data was in line with what we learned from our qualitative data. The mean time for all 40 papers, from submission to acceptance, was 115 days (a minimum of 22 days and a maximum of 263 days). The submission to publication time lag appears to shorten, however, as there was a statistically significant difference for the time to publication for papers published between 1984–1994 (mean of 134 days) versus 1995–2004 (mean of 105 days). Although our selection included a number of different journals, there did not appear to be any significant difference between them.

[9]The same holds true for patents. For example, when the Cohen-Boyer patent (U.S. Patent 4,237,224) was granted in 1980, it was assigned to Stanford University, the locus of IP creation, even though Boyer had left academia to commercialize the breakthrough in rDNA when cofounding Genentech, the first biotechnology company, in 1976. In general, journal

publications precede patents in time. Murray and Stern (2004) found that the average lag between publication of a journal article and subsequent granting of the patent was a little over three years (37.5 months) for their sample of 169 patent-paper pairs.

[10]BioScan and Recombinant Capital are fairly consistent in their reporting. We found the intersource reliability to be greater than 0.90 when documenting alliances. BioScan and Recombinant Capital appear to be the two most comprehensive publicly available data sources documenting the global biopharmaceutical industry, and have been used frequently in prior research focusing on different questions and generally relying on only one of these two sources (e.g., Shan et al. 1994, Lane and Lubatkin 1998, Lerner et al. 2003, Powell et al. 1996).

[11]To assess how sensitive our results are to the reported random-effects specification, we additionally applied a fixed-effects estimation. The results remained robust.

[12]It is important to note that this result cannot be attributed reasonably to collinearity, because the bivariate correlation between stars and nonstars is $r = 0.57$. Although these two constructs are significantly correlated, and thus fulfill the requirement for potential mediation (Hair et al. 2006), it also indicates discriminant validity because the bivariate correlation is well below the conventional ceiling of $r = 0.70$. Moreover, all variance inflation factors for stars and nonstars were below 1.5, thus well below the traditional cut-off ceiling of 10 (Cohen et al. 2003).

[13]A negative beta value translates into an incidence rate ratio of less than one, whereas a positive beta value translates into an incidence rate ratio of greater than one.

[14]To further assess whether the results for the interaction effects could be driven by nonlinearity of the direct effects composing the interaction effects or by collinearity between these direct effects (Cortina 1993), we determined the bivariate correlations and shared variances of each of the direct-effect combinations constituting the interactions as well as all variance inflation factors. The bivariate correlations for the direct effects underlying the interaction effects are in the range between $0.122 \leq r \leq 0.423$, and the shared variances are between $1.49\% \leq r^2 \leq 17.89\%$. Thus, the bivariate correlations are well below the traditional cut-off of $r = 0.70$, whereas the shared variances are well below the recommended ceiling of 50% shared variance (Cohen et al. 2003). Estimating all variance inflation factors (VIFs) reveals that in the fully specified direct-effects model, the average VIF is 1.90 and the maximum VIF is 3.20. In the interaction models the average VIF in Model 5 is 2.71, with a maximum VIF of 6.19. The average VIF in Model 6 is 3.85, with a maximum VIF of 10.91. Therefore, all VIFs, except for the interaction between nonstar scientists and biotech alliances, are below the recommended ceiling of 10 (Cohen et al. 2003). To investigate in more detail whether the slightly elevated VIF between nonstar scientists and biotech alliances could lead to a level of collinearity where the significant interaction results are spurious due to nonlinearity of the direct effects underlying the interaction effects, we followed Cortina's (1993) recommendation and tested the interaction between nonstar scientists and biotech alliances after not only including all control variables and the linear direct effects for nonstar scientists and biotech alliances, but also the squared terms of these two direct effects to control for potential nonlinearity in the relationship between the direct effects and biotech patenting. This approach allows the researcher to "control for possible non-linear effects and thus to rule out alternative explanations," and as such "this solution is conservative [because] it involves the addition of [squared] terms to the equation that must be partialled out before the assessment of the interaction term" (Cortina 1993, p. 918). The results of this test indicate that the interaction between nonstar scientists and biotech alliances remained negative and statistically significant ($p < 0.01$), despite the inclusion of linear and squared terms for nonstar scientists and biotech alliances. These findings enhance our confidence in the results reported.

[15]The betas for Biotech Alliances in Table 2 are 0.0206 (Model 2) and 0.0199 (Model 4). This translates into an incident rate ratio of 1.02[exp(beta)] and a factor change of 2%.

References

Ahuja, G. 2000. Collaboration networks, structural holes, and innovation: A longitudinal study. *Admin. Sci. Quart.* **45** 425–455.

Albert, M. B., D. Avery, F. Narin, P. McAllister. 1991. Direct validation of citation counts as indicators of industrially important patents. *Res. Policy* **20** 251–259.

Allen, T. 1977. *Managing the Flow of Technology*. MIT Press, Boston, MA.

Allen, T., S. I. Cohen. 1969. Information flow in R&D laboratories. *Admin. Sci. Quart.* **14** 12–19.

Almeida, P., J. Song, R. Grant. 2002. Are firms superior to alliances and markets? An empirical test of cross-border knowledge building. *Organ. Sci.* **13** 147–161.

Anand, B., T. Khanna. 2000. Do firms learn to create value? The case of alliances. *Strategic Management J.* **21** 295–316.

Anderson, P., M. L. Tushman. 1990. Technological discontinuities and dominant designs: A cyclical model of technological change. *Admin. Sci. Quart.* **35** 604–633.

Arthur, W. B. 1989. Competing technologies, increasing returns, and lock-in by historical events. *Econom. J.* **99** 116–131.

Ashworth, J. W., K. M. Carley. 2006. Who you know vs. what you know: The impact of social position and knowledge of team performance. *J. Math. Soc.* **30** 43–75.

Audretsch, D. B., P. E. Stephan. 1996. Company-scientist locational links: The case of biotechnology. *Amer. Econom. Rev.* **86** 641–652.

Barney, J. 1986. Strategic factor markets. *Management Sci.* **32** 1231–1241.

Barney, J. 1991. Firm resources and sustained competitive advantage. *J. Management* **17** 99–120.

BioScan. Diverse years. *The Worldwide Biotechnology Industry Reporting Service*. Thomson, American Health Consultants, Atlanta, GA.

Bower, J. L. 2001. Not all M&As are alike—And that matters. *Harvard Bus. Rev.* **79**(3) 92–101.

Cameron, A., P. Trivedi. 1986. Econometric models based on count data: Comparisons and applications of some estimators and tests. *J. Appl. Econometrics* **1** 29–53.

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

Christensen, C. M. 1997. *The Innovator's Dilemma. When New Technologies Cause Great Firms to Fail*. Harvard Business School Press, Boston, MA.

Cockburn, I. M., R. M. Henderson, S. Stern. 2000. Untangling the origins of competitive advantage. *Strategic Management J.* **21** 1123–1145.

Cohen, P., J. Cohen, S. G. West, L. S. Aiken. 2003. *Applied Multiple Regression/Correlation Analysis for the Behavioral Sciences*, 3rd ed. Erlbaum, Hillsdale, NJ.

Cohen, W. M., D. A. Levinthal. 1989. Innovation and learning: The two faces of R&D. *Econom. J.* **99** 569–596.

Cohen, W. M., D. A. Levinthal. 1990. Absorptive capacity: A new perspective on learning and innovation. *Admin. Sci. Quart.* **35** 128–152.

Comanor, W. S., F. M. Scherer. 1969. Patent statistics as a measure of technical change. *J. Political Econom.* **77** 392–398.

Cortina, J. M. 1993. Interaction, nonlinearity, and multicollinearity: Implications for multiple regression. *J. Management* **19** 915–922.

Dansereau, F., F. J. Yammarino, J. C. Kohles. 1999. Multiple levels of analysis from a longitudinal perspective: Some implications for theory building. *Acad. Management Rev.* **24** 346–357.

Darby, M. R., L. G. Zucker. 2001. Change or die: The adoption of biotechnology in the Japanese and U.S. pharmaceutical industries. *Res. Tech. Innovation, Management, Policy* **7** 85–125.

Darby, M. R., L. G. Zucker. 2003. Grilichesian breakthroughs: Inventions of methods of inventing and firm entry in nanotechnology. NBER Working Paper 9825, Cambridge, MA.

Deeds, D. L., C. W. L. Hill. 1996. Strategic alliances and the rate of new product development: An empirical study of entrepreneurial biotechnology firms. *J. Bus. Venturing* **11** 41–55.

Dierickx, I., K. Cool. 1989. Asset stock accumulation and sustainability of competitive advantage. *Management Sci.* **35** 1504–1511.

Dyer, J. H., H. Singh. 1998. The relational view: Cooperative strategy and sources of interorganizational competitive advantage. *Acad. Management Rev.* **23** 660–679.

Economist, The. 2004. Fixing the drugs pipeline. **370**(8366, March 13) 37–38.

Eisenhardt, K. M., J. A. Martin. 2000. Dynamic capabilities: What are they? *Strategic Management J.* **21** 1105–1121.

Ernst, H., C. Leptien, J. Vitt. 2000. Inventors are not alike: The distribution of patenting output among industrial R&D personnel. *IEEE Trans. Engrg. Management* **47** 184–199.

Fabrizio, K. R. 2005. Absorptive capacity and innovation: Evidence from pharmaceutical and biotechnology firms. *Annual Atlanta Competitive Advantage Conf., Atlanta, GA.*

Felin, T., W. S. Hesterly. 2007. The knowledge-based view, heterogeneity, and new value creation: Philosophical considerations on the locus of knowledge. *Acad. Management Rev.* **32** 195–218.

Felin, T., N. J. Foss. 2005. Strategic organization: A field in search of micro-foundations. *Strategic Organ.* **3** 441–455.

Foster, R. N. 1986. *Innovation. The Attacker's Advantage*. Summit Books, New York.

Galambos, L., J. Sturchio. 1998. Pharmaceutical firms and the transition to biotechnology: A study in strategic innovation. *Bus. Hist. Rev.* **72**(Summer) 250–278.

Gardner, T. 2005. Interfirm competition for human resources: Evidence from the software industry. *Acad. Management J.* **48** 237–256.

GenBank, Release 65.0. 1990. Machine readable database. IntelliGenetics, Inc., Palo Alto, CA.

George, G., S. A. Zahra, D. R. Wood. 2002. The effects of business-university alliances on innovative output and financial performance: A study of publicly traded biotechnology companies. *J. Bus. Venturing* **17** 577–609.

Gourieroux, C., A. Monfort, A. Trognon. 1984. Pseudo maximum likelihood methods: Applications to Poisson models. *Econometrica* **52** 701–720.

Grant, R. 1996. Toward a knowledge-based theory of the firm. *Strategic Management J.* **17**(Winter, Special Issue) 109–122.

Greene, S. 1987. Is quality a casualty in the race to publish? *The Scientist* **1**(20) 1.

Greene, W. H. 2003. *Econometric Analysis*, 5th ed. Prentice Hall, Upper Saddle River, NJ.

Griliches, Z. 1990. Patent statistics as economic indicators: A survey. *J. Econom. Lit.* **28** 1661–1707.

Groysberg, B., A. Nanda, N. Nohria. 2004. The risky business of hiring stars. *Harvard Bus. Rev.* **82**(5) 92–100.

Gulati, R. 1998. Alliances and networks. *Strategic Management J.* **19** 293–317.

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

Gulati, R., N. Nohria, A. Zaheer. 2000. Strategic networks. *Strategic Management J.* **21** 203–215.

Hagedoorn, J. 1993. Understanding the rationale of strategic technology partnering: Interorganizational modes of cooperation and sectoral differences. *Strategic Management J.* **14** 371–385.

Hagedoorn, J., M. Cloodt. 2003. Measuring innovative performance: Is there an advantage in using multiple indicators? *Res. Policy* **32** 1365–1379.

Hagedoorn, J., J. Schakenraad. 1994. The effect of strategic technology alliances on company performance. *Strategic Management J.* **15** 291–309.

Hair, J. F., W. S. Black, B. J. Babin, R. E. Anderson, R. L. Tatham. 2006. *Multivariate Data Analysis*, 6th ed. Prentice Hall, Upper Saddle River, NJ.

Haleblian, J., S. Finkelstein. 1999. The influence of organizational acquisition experience on acquisition performance: A behavioral learning perspective. *Admin. Sci. Quart.* **44** 29–56.

Hall, B. H., A. Jaffe, M. Trajtenberg. 2000. Patent citations and market value: A first look. NBER Working Paper 7741, Cambridge, MA.

Hall, B. H., A. Jaffe, M. Trajtenberg. 2001. The NBER patent citations data file: Lessons, insights and methodological tools. NBER Working Paper 8498, Cambridge, MA.

Hamilton, B. H., J. A. Nickerson. 2003. Correcting for endogeneity in strategic management research. *Strategic Organ.* **1** 51–78.

Hausman, J. 1978. Specification tests in econometrics. *Econometrica* **46** 1251–1271.

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

Hayward, M. L. A. 2002. When do firms learn from their acquisition experience? Evidence from 1990–1995. *Strategic Management J.* **23** 21–39.

Heckman, J. J., G. J. Borjas. 1980. Does unemployment cause future unemployment: Definitions, questions, and answers for a continuous time model of heterogeneity and state dependence. *Econometrica* **48** 247–283.

Helfat, C. E. 1994a. Firm-specificity in corporate R&D. *Organ. Sci.* **5** 173–184.

Helfat, C. E. 1994b. Evolutionary trajectories in petroleum firm R&D. *Management Sci.* **40** 1720–1747.

Helfat, C. E. 1997. Know-how and asset complementarity and dynamic capability accumulation: The case of R&D. *Strategic Management J.* **18** 339–360.

Henderson, R. M., K. B. Clark. 1990. Architectural innovation the reconfiguration of existing product technologies and the failure of established firms. *Admin. Sci. Quart.* **35** 9–30.

Henderson, R. M., I. Cockburn. 1994. Measuring competence? Exploring firm effects in pharmaceutical research. *Strategic Management J.* **15** 63–84.

Higgins, M., D. Rodriguez. 2006. The outsourcing of R&D through acquisition in the pharmaceutical industry. *J. Financial Econom.* **80** 351–383.

Hill, C. W. L., F. T. Rothaermel. 2003. The performance of incumbent firms in the face of radical technological innovation. *Acad. Management Rev.* **28** 257–274.

Hitt, M. A., R. E. Hoskisson, R. D. Ireland. 1990. Mergers and acquisitions and managerial commitment to innovation in M-form firms. *Strategic Management J.* **11** 29–47.

Hitt, M. A., L. Bierman, K. Shimizu, R. Kochhar. 2001. Direct and moderating effects of human capital on strategy and performance in professional service firms: A resource-based perspective. *Acad. Management J.* **44** 13–28.

Hitt, M. A., R. E. Hoskisson, R. D. Ireland, J. S. Harrison. 1991. Effects of acquisitions on R&D inputs and outputs. *Acad. Management J.* **34** 693–706.

Hoang, H., F. T. Rothaermel. 2005. The effect of general and partner-specific alliance experience on joint R&D project performance. *Acad. Management J.* **48** 332–345.

Hsiao, C. 2003. *Analysis of Panel Data*, 2nd ed. Cambridge University Press, Cambridge, UK.

Ichino, A., G. Maggi. 2000. Work environment and individual background: Explaining regional shirking differentials in a large Italian firm. *Quart. J. Econom.* **115** 1057–1090.

IMS Health. 2003. Global pharmaceutical sales by region, 2002. March 12.

Jacobson, R. 1990. Unobservable effects and business performance. *Marketing Sci.* **9** 74–85.

Kale, P., J. H. Dyer, H. Singh. 2002. Alliance capability, stock market response, and long-term alliance success: The role of the alliance function. *Strategic Management J.* **23** 747–767.

Kaplan, S., F. Murray, R. M. Henderson. 2003. Discontinuities and senior management: Assessing the role of recognition in pharmaceutical firm response to biotechnology. *Indust. Corporate Change* **12** 203–233.

Klein, K. J., F. Dansereau, R. J. Hall. 1994. Levels issues in theory development, data collection, and analysis. *Acad. Management Rev.* **19** 195–229.

Kogut, B., U. Zander. 1992. Knowledge of the firm, combinative capabilities, and the replication of technology. *Organ. Sci.* **3** 383–397.

Lacetera, N., I. Cockburn, R. M. Henderson. 2004. Do firms change capabilities by hiring new people? A study of the adoption of science-based drug discovery. J. A. C. Baum, A. M. McGahan, eds. *Business Strategy over the Industry Lifecycle: Advances in Strategic Management*, Vol. 21. Elsevier, Boston, MA, 133–159.

Lane, P. J., M. Lubatkin. 1998. Relative absorptive capacity and interorganizational learning. *Strategic Management J.* **19** 461–477.

Leonard-Barton, D. 1992. Core capabilities and core rigidities: A paradox in managing new product development. *Strategic Management J.* **13** 111–126.

Lerner, J., H. Shane, A. Tsai. 2003. Do equity financing cycles matter? Evidence from biotechnology alliances. *J. Financial Econom.* **67** 411–446.

Levin, R. C., A. K. Klevorick, R. R. Nelson, S. G. Winter. 1987. Appropriating the returns from industrial R&D. *Brookings Papers Econom. Activity* **3** 783–820.

Levinthal, D. A., J. G. March. 1993. The myopia of learning. *Strategic Management J.* **14** 95–112.

Levitt, B., J. G. March. 1988. Organizational learning. *Ann. Rev. Soc.* **14** 319–340.

Liebeskind, J. P., A. L. Oliver, L. Zucker, M. Brewer. 1996. Social networks, learning, and flexibility: Sourcing scientific knowledge in new biotechnology firms. *Organ. Sci.* **7** 428–443.

Long, J. S. 1997. *Regression Models for Categorical and Limited Dependent Variables*. Sage Publications, Thousand Oaks, CA.

Lotka, A. 1926. The frequency distribution of scientific productivity. *J. Washington Acad. Sci.* **11** 317–323.

Murray, F., S. Stern. 2004. Do formal intellectual property rights hinder the free flow of scientific knowledge? An empirical test of the anti-commons hypothesis. NBER Working Paper 11465, Cambridge, MA.

Narin, F., A. Breitzman. 1995. Inventive productivity. *Res. Policy* **24** 507–519.

Narin, F., K. S. Hamilton, D. Olivastro. 1997. The increasing linkage between U.S. technology and public science. *Res. Policy* **26** 317–330.

Nelson, R. R., S. G. Winter. 1982. *An Evolutionary Theory of Economic Change*. Harvard University Press, Cambridge, MA.

Nohria, N., R. Gulati. 1996. Is slack good or bad for innovation? *Acad. Management J.* **39** 1245–1264.

Owen-Smith, J., W. W. Powell. 2004. Knowledge networks as channels and conduits: The effects of spillovers in the Boston biotechnology community. *Organ. Sci.* **15** 5–21.

Pennings, J. M., F. Harianto. 1992. Technological networking and innovation implementation. *Organ. Sci.* **3** 356–382.

Peteraf, M. A. 1993. The cornerstones of competitive advantage: A resource-based view. *Strategic Management J.* **14** 179–191.

Pisano, G. P. 1997. *The Development Factory. Unlocking the Potential of Process Innovation*. Harvard Business School Press, Boston, MA.

Powell, W. W., K. W. Koput, L. Smith-Doerr. 1996. Interorganizational collaboration and the locus of innovation: Networks of learning in biotechnology. *Admin. Sci. Quart.* **41** 116–145.

Ranft, A. L., M. D. Lord. 2002. Acquiring new technologies and capabilities: A grounded model of acquisition implementation. *Organ. Sci.* **13** 420–441.

Rosenberg, N. 1990. Why do firms do basic research (with their own money)? *Res. Policy* **19** 165–174.

Rothaermel, F. T. 2001. Incumbent's advantage through exploiting complementary assets via interfirm cooperation. *Strategic Management J.* **22** 687–699.

Rothaermel, F. T., D. L. Deeds. 2004. Exploration and exploitation alliances in biotechnology: A system of new product development. *Strategic Management J.* **25** 201–221.

Rothaermel, F. T., D. L. Deeds. 2006. Alliance type, alliance experience, and alliance management capability in high-technology ventures. *J. Bus. Venturing* **21** 429–460.

Rothaermel, F. T., C. W. L. Hill. 2005. Technological discontinuities and complementary assets: A longitudinal study of industry and firm performance. *Organ. Sci.* **16** 52–70.

Rothaermel, F. T., M. A. Hitt, L. A. Jobe. 2006. Balancing vertical integration and strategic outsourcing: Effects on product portfolio, product success, and firm performance. *Strategic Management J.* **27** 1033–1056.

Schumpeter, J. A. 1942. *Capitalism, Socialism and Democracy*. Harper & Row, New York.

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

Simon, H. 1991. Bounded rationality and organizational learning. *Organ. Sci.* **2** 125-134.

Stephan, P. E., M. Higgins, J. Thursby. 2004. Capitalizing the human capital of university scientists: The case of biotechnology IPOs. *Roundtable for Engineering Entrepreneurship Research* (*REER*). Georgia Institute of Technology, Atlanta, GA.

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

Stuart, T. E., H. Hoang, R. C. Hybels. 1999. Interorganizational endorsements and the performance of entrepreneurial ventures. *Admin. Sci. Quart.* **44** 315–349.

Stuart, T. E., S. Ozdemir, W. Ding. 2007. Brokerage in a vertical alliance network. *Res. Policy* **36** 477–498.

Teece, D. J. 1992. Competition, cooperation, and innovation: Organizational arrangements for regimes of rapid technological progress. *J. Econom. Behav. Organ.* **18** 1–25.

Teece, D. J., G. Pisano, A. Shuen. 1997. Dynamic capabilities and strategic management. *Strategic Management J.* **18** 509–533.

Tilton, J. H. 1971. *International Diffusion of Technology: The Case of Semiconductors*. Brookings Institution, Washington, D.C.

Tushman, M. L. 1977. Special boundary roles in the innovation process. *Admin. Sci. Quart.* **22** 587–605.

Tushman, M. L., P. Anderson. 1986. Technological discontinuities and organizational environments. *Admin. Sci. Quart.* **31** 439–465.

Tushman, M. L., R. Katz. 1980. External communication and project performance: An investigation into the role of gatekeepers. *Management Sci.* **26** 1071–1085.

Vanhaverbeke, W., G. Duysters, N. Noorderhaven. 2002. External technology sourcing through alliances or acquisitions: An analysis of the application-specific integrated circuits industry. *Organ. Sci.* **13** 714–734.

Zollo, M., S. G. Winter. 2002. Deliberate learning and the evolution of dynamic capabilities. *Organ. Sci.* **13** 339–351.

Zucker, L. G., M. R. Darby. 1997a. Present at the biotechnological revolution: Transformation of technological identity for a large incumbent pharmaceutical firm. *Res. Policy* **26** 429–446.

Zucker, L. G., M. R. Darby. 1997b. Individual action and the demand for institutions: Star scientists and institutional transformation. *Amer. Behav. Scientist* **40** 502–513.

Zucker, L. G., M. R. Darby, J. S. Armstrong. 2002a. Commercializing knowledge: University science, knowledge capture, and firm performance in biotechnology. *Management Sci.* **48** 138–153.

Zucker, L. G., M. R. Darby, M. B. Brewer. 1998. Intellectual human capital and the birth of U.S. biotechnology enterprises. *Amer. Econom. Rev.* **88** 290–306.

Zucker, L. G., M. R. Darby, M. Torero. 2002b. Labor mobility from academe to commerce. *J. Labor Econom.* **20** 629–660.