

**BUILDING DYNAMIC CAPABILITIES:
INNOVATION DRIVEN BY INDIVIDUAL, FIRM, AND NETWORK LEVEL EFFECTS**

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Abstract

Following the dynamic capabilities perspective, we suggest that antecedents to innovation can be found at the individual, firm, and network level. Thus, we challenge two assumptions common in prior research: (1) that significant variance exists at the focal level of analysis, while 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 level 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 multi-level theoretical model using an unusually comprehensive and detailed panel dataset 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; multi-level 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, Pisano, and Shuen, 1997: 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: 1107) suggest that antecedents to dynamic capabilities, which they describe to be "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 under-explored 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 homogenous 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, competences, 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, Cockburn, and Henderson, 2004; Zucker and Darby, 1997a; Zucker, Darby, and Brewer, 1998; Zucker, Darby, and Armstrong, 2002), generally discount firm- and network-level effects.

Recent theoretical contributions (Felin and Foss, 2005; Felin and Hesterly, 2006; Klein, Dansereau, and Hall, 1994; Dansereau, Yammarino, and Kohles, 1999), however, have identified two serious problems with the dominant uni-level 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, while alternate levels of analysis are considered to be more or less homogenous. Studies of firm level heterogeneity assume, for example, that significant variation occurs at the firm level of analysis, while individuals are more or less homogenous 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 can potentially lead to spurious empirical findings.

To address the threats of homogeneity and independence, we develop a multi-level theoretical model that accounts for potential heterogeneity in and across three different and 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 herein 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, in order 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 herein 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 dataset 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. Uni-level research implicitly assumes not only that non-focal levels of analysis are homogenous, but also exhibits a lack in considering the importance of non-focal levels when predicting heterogeneity at the focal level of analysis (Felin and Foss, 2005; Felin and Hesterly, 2006). 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, Song, and Grant, 2002; Kogut and Zander, 1992). As an example, Henderson and Cockburn (1994) find that locally embedded knowledge and skills among a firm's intellectual human capital may be a unique innovation 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 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 anti-anxiety 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.

Firm innovative performance is at least partially a function of the value of its human capital (Hitt, Bierman, Shimizu, and Kochhar, 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, Henderson, and Stern, 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 notion 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, Leptien, and Vitt, 2000).

Therefore, we suggest that intellectual human capital can be conceptualized as consisting of two components: star scientists and non-star scientists. We understand a star scientist to be someone that is, by an order of magnitude, both more productive in and more influential on a specific research field than the average (non-star) 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 non-star 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, Darby, and Torero, 2002). 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, Higgins, and Thursby (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 non-star 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 a firm's R&D capability are necessary, because R&D effectiveness is path dependent, and thus, failure to invest in internal R&D at one point in time may foreclose future options in a particular technology (Cohen and Levinthal, 1989). In support of this notion, 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, a firm's R&D capability has the potential to be the kind of

valuable, rare, inimitable, and non-substitutable resource that can form the basis for superior innovation performance (Barney, 1991; Peteraf, 1993).

When confronted with a new technological paradigm, a firm's 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 multi-industry study, Rothaermel and Hill (2005) show that a firm's internal R&D capability has a positive effect on firm 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, a firm's R&D capability has become more critical to innovative performance as many industries have become more science-driven, and as such, firms are now even more compelled to leverage advances in the fundamental sciences (Cockburn, et al. 2000; Narin, Hamilton, and Olivastro, 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, Koput, and Smith-Doerr (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, Nohria, and Zaheer, 2000).

While 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, Duysters, and Noorderhaven, 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 notion 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, Walker, and Kogut, 1994) and predict innovation rates in the semiconductor as well as in the microcomputer industry (Rothaermel, Hitt, and Jobe, 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 had 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, since 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, in order 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 cardio-vascular 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 cardio-vascular exercise and pursuing a low-cholesterol diet are substitutes in achieving a lower risk of heart disease. Note that while cardio-vascular 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 cardio-vascular 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.

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 $\frac{\Delta x_i}{\Delta x_j} > 0$, and substitutes if $\frac{\Delta x_i}{\Delta x_j} < 0$.

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, Cohen, West, and Aiken, 2003: 255-260).

Interactions Across Levels – Complements

Interaction between Individual and Firm-Level Effects. A positive interaction between individual and firm-level effects is likely, when considering that a firm's level of R&D capability is a function of its 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 a firm's level of intellectual human capital results in a commensurate increase in a firm's 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, Hoskisson, Ireland, and Harrison, 1991). As an example, Groysberg, Nanda, and Nohria (2004) find that 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 non-substitutable resource combinations that can form the basis of a firm-level innovation advantage (Barney, 1986, 1991; Lacetara, et al. 2004).

Interaction between Individual and Network-Level Effects. We posit that a firm's scientists positively moderate the effects of its alliances and acquisitions on its innovative output. Stuart, Ozdemir, and Ding (2003) 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 gate-keeping and boundary-spanning is particularly important to firms attempting to innovate, because the tacit nature of many new discoveries often make it necessary for the inventing scientist to assist in the firm's commercialization process (Stuart et al., 2003).

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, Oliver, Zucker, and Brewer, 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 a firm's level of intellectual human capital and the effect of R&D acquisitions on innovation is emphasized by research revealing that if an acquiring firm possesses information relevant to the value of the target's research, which is often accurately evaluated by the acquiring firm's scientists, there is not only a greater likelihood of acquirer 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 competences, and thus limit their ability to innovate (Cohen and Levinthal, 1990). Prior empirical work 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), because 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, Tsai, and Shane, 2003), thus creating a synergistic effect between a firm's R&D capability and its 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 the 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 outcomes distant in time (Direckx 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 notion, Cockburn, et al. (2000) demonstrate that while 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 importantly, 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, because 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 located 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. Merck is an example of a pharmaceutical firm that 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 a tension often exists between these different modes of innovating (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 in order 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 competences 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, 1994b). 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, Dyer, and Singh, 2002; Rothaermel and Deeds, 2006). Yet 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 can potentially 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, Hoskisson, and Ireland, 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 their internal R&D productivity are more likely to engage in an acquisition strategy in order to augment their innovation efforts. In a similar fashion, firms may use one mode of innovation to compensate for a lack of experience using another mode (Bower, 2001). For example, the sharing of information and R&D personnel that often accompanies alliances can serve to reduce a firm's need to invest in internal R&D. Additionally, alliances with universities can provide a firm with ancillary research services that would otherwise need to be developed internally (George, Zahra, and Wood 2002). Indeed, the authors find that firms with ties to universities have lower R&D expenditures than those lacking 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 multi-level 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 has 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 been able to build 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, 1997b). 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). Additionally, 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 multi-level 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 (U.S.), 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

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 (details below).

We tracked annual data for each of the 81 sample firms, beginning in 1980 until the end of 2001 (81 x 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, Hoang, and Hybels, 1999: 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 non-exclusive 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, however, we proxied their innovative output by the number of *biotechnology patent applications granted* in each year during the 1980-2001

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 our 93 original firms were listed. This enhanced our confidence in the initial sample, where we tracked the firms forwardly rather than just sampling on surviving firms at the end of the study period. The remaining 32 firms were either smaller firms, which 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).

study period, while explicitly controlling for lagged biotechnology patents and for non-biotechnology 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, Jaffe, and Trajtenberg, 2000). Based on the population of biotechnology patents, a 3-year average time lag exists between the date 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 2-3 months (Darby and Zucker, 2003). Since 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 Cloudt, 2003; Stuart, 2000). The bivariate correlation between patent counts and citation-weighted patents has been shown to be above 0.77 ($p < .001$) in the pharmaceutical industry (Hagedoorn and Cloudt, 2003), which is especially relevant for this study, and above 0.80 ($p < .001$) in the semiconductor industry (Stuart, 2000), indicating some generalizability of this assertion. In sum, a pharmaceutical firm which 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 were able to obtain 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.

⁶ The U.S. PTO compiled these data based on all biotechnology patents in the following patent classes: 424 [Drug, bio-affecting and body treating compositions (different sub-classes)], 435 [Chemistry: Molecular biology and microbiology], 436 [Chemistry: Analytical and immunological testing], 514 [Drug, bio-affecting and body treating

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 U.S. represents the largest market worldwide for biotechnology, and thus it is almost compulsory for firms to first patent in the U.S. before patenting in any other country (Albert, Avery, Narin, and McAllister, 1991). Second, firms that are active in biotechnology have a strong incentive to patent in the U.S., because intellectual property protection has been consistently supported by U.S. courts (Levin, Klevorick, Nelson, and Winter, 1987).

Independent Variables

Intellectual Human Capital and Star Scientists. Focusing on entrepreneurial biotechnology ventures, Zucker, Darby, and their colleagues were one of the first to create a measure to proxy star scientists (Zucker and Darby, 1997b; Zucker et al., 1998; Zucker et al., 2002). They identified a set of 327 star scientists based on their outstanding productivity up until April 1990. The primary criterion for selection was the discovery of more than 40 genetic sequences as reported in GenBank (1990), which is 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 Lacetera 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 biotechnology (excluding social science research and non-human 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

compositions (different sub-classes)], 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].

identify stars is by design somewhat longer than the study period (by three years), because 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 back each author 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 research pertaining to biotechnology 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 3 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 dataset 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 *non-star 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 non-star scientists in a given year over the study period.

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.

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 non-star 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 with 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

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, while 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) vs. 1995-2004 (mean of 105 days). While our selection included a number of different journals, there did not appear to be any significant difference between them.

research would be published under the imprimatur of his/her degree granting 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 s/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 accurateness 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.

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 co-founding Genentech in 1976, the first biotechnology company. 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 3 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 inter-source 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).

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.

Non-biotech Patents. To further reduce the threat of unobserved heterogeneity when using biotechnology patents as the dependent variable, it is critical to control for non-biotechnology 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 non-biotechnology patent applications granted per year as a control variable (*Non-Biotech Patents*). These data were obtained from the U.S. PTO. The average pharmaceutical firm was granted approximately 80 non-biotechnology 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 if 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 1 if the company is a specialized pharmaceutical firm (*Pharma*

Firm), and 0 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 in SIC 2890 (chemical products manufacturing), for example, it was coded 0, 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 1 if the firm is headquartered in the U.S. (*U.S. Firm*), the other indicator variable takes on the value of 1 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 U.S., while 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 to 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, Jaffe, and Trajtenberg, 2001).

Year Fixed Effects. Since 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 potentially 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 non-negative, integer count variable. Verified by a statistical test for overdispersion (Gourieroux, Montfort, and Trognon, 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, Hall, and Griliches, 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:

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

where n is a non-negative 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, in combination 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.

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.

RESULTS

Table 1 depicts the descriptive statistics and the bivariate correlation matrix, while 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 $p < .01$, or smaller.

Insert Tables 1 and 2 about here

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 ($p < .001$), which we proxied by a firm's total number of research scientists that (co-)authored at least one research article pertaining to biotechnology 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 non-star scientists. To highlight the importance of explicitly controlling for non-star 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 non-star 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 ($p < .01$). This finding would lead us to claim support for the hypothesis that a firm's innovative output is positive function of its star scientists. In Model 4, however, we inserted the number of non-star 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 non-star scientists that are a positive and statistically significant predictor of a firm's innovative output ($p < .05$). 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 non-star 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 the null hypothesis is true in reality. 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, given that inserting non-star scientists leads to a positive and statistically significant effect of non-star 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 non-star 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 ($p < .05$ 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 non-linear. 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 R&D expenditures and patenting is characterized by diminishing returns, because the linear term of R&D expenditures is positive and statistically significant ($p < .05$), while the squared term is negative and also statistically significant ($p < .001$). This result is not caused by multicollinearity, since the VIFs between linear and squared R&D terms reach only 2.45, well below the cut-off point of 10 (Cohen, et al. 2003).

Recall that our estimation technique is a negative binomial regression, and thus a non-linear, exponential 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: 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 herein 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 non-star scientists (10%), followed by biotechnology acquisitions (5%).

Insert Tables 4 about here

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

¹² It is important to note that this result cannot be attributed reasonably to collinearity, because the bivariate correlation between stars and non-stars is $r = .57$. While these two constructs are significantly correlated, and thus fulfill the requirement for potential mediation (Hair, Black, Babin, Anderson, and Tatham 2006), it also indicates discriminant validity because the bivariate correlation is well below the conventional ceiling of $r = .70$. Moreover, all variance inflation factors for stars and non-stars 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 1, while a positive beta value translates into an incidence rate ratio of greater than 1.

Hypothesis 3b, positing that a firm's innovative output is a positive function its acquisitions of new technology firms, because the coefficients for biotechnology acquisitions are positive and statistically significant ($p < .05$ 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, while 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 ($p < .01$ in Model 5). Star scientists and R&D capability also substitute for one another, because their interaction is negative and significant ($p < .05$ in Model 6). When evaluating the interactions between individual and network-level effects, we find that a firm's 1) intellectual human capital and its biotechnology alliances and 2) its non-star scientists and its biotechnology alliances are substitutes for one another, because the interaction effects are negative and significant ($p < .001$ in Models 5 and 6, respectively). 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 ($p < .01$ and $p < .001$, 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 non-star 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 notion that intellectual human capital is a substitute to 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 increase. 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

¹⁴ To further assess whether the results for the interaction effects could be driven by non-linearity 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 $r = 0.70$, while 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 non-star 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 non-star scientists and biotech alliances could lead to a level of collinearity where the significant interaction results are spurious due to non-linearity of the direct effects underlying the interaction effects, we followed Cortina's (1993) recommendation and tested the interaction between non-star scientists and biotech alliances after not only including all control variables and the linear direct effects for non-star scientists and biotech alliances, but also the squared terms of these two direct effects to control for potential non-linearity 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: 918). The results of this test indicate that the interaction between non-star scientists and biotech alliances remained negative and statistically significant ($p < .01$), despite the inclusion of linear and squared terms for non-star 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%.

Results of Control Variables

Some of the results of the control variables are also noteworthy. We assess them in the Model 1, the baseline estimation. The results indicate that firms that are heavily engaged in patenting overall, as proxied by their non-biotechnology patents, are also very active in biotechnology patenting ($p < .001$). In addition, past biotechnology patenting predicts future biotechnology patenting, because the lagged dependent variable is, as expected, positive and statistically significant ($p < .001$). Thus, the observed effects above are not spurious to due a firm size effect in biotechnology. Including a variable that captures a firm's overall inclination to engage in the focal activity (proxied by non-biotechnology 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 ($p < .001$). Larger firms, as proxied by their total assets, appear to be laggards in biotechnology patenting ($p < .001$). Firms with higher revenues are more active in biotechnology patenting ($p < .001$). 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, 1994b, 1997). As expected, firms that take longer to incorporate the breakthrough Cohen-Boyer patent into their knowledge base ($p < .001$) exhibit an overall lower innovation output. 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 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 be found at the individual, firm, and network level 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 uni-level research (Felin and Foss, 2005; Felin and Hesterly, 2006; 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.

With regard to 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 non-star scientists, we find that the positive direct effect of intellectual human capital on patenting can be attributed to a firm's non-star scientists, while 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, 1997b). This apparent tension, however, can be reconciled by the finding that non-star 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, Murray, and Henderson, 2003), rather than to facilitate its adaptation to the change itself.

The structure of Sanofi-Aventis' R&D process exemplifies the notion that the effects of star scientists on innovation are mediated by non-star 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, while non-star scientists are primarily responsible for drug development. Without the involvement of a large number of non-star 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, 2006). Since 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: 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: 121; italics added). We find that rank-and-file knowledge workers, here non-star scientists, have a direct bearing on the innovative performance of firms, while 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 while 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, while 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*, March 13, 2004).

We find support for the notion 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 notion 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. While 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.

In regards to 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 at developing and testing a multi-level 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 presented, 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 the confidence in the findings presented herein. 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 multi-level 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, non-obvious 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, while 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, inter-firm 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 multi-level effects associated with the various mechanisms firms can use to innovate contributes to the understanding of how firms build and refine dynamic capabilities in order 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, while 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. Our research indicates that it is those firms that are able to identify, with the help of star scientists, an exogenous paradigm shift and to assemble the requisite human assets in the form of rank-and-file scientists that are ultimately able of developing the innovation capabilities necessary to succeed.

Managers generally face the added burden of time constraints when attempting to innovate. It is tantamount, therefore, 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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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. US Firm	0.34	0.47	0.109	-0.109	0.082	-0.069													
6. EU 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. Non-Biotech 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. Non-Star 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

N = 1,782 firm-years.

* Constant 2000 U.S. dollars.

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

Direct Effects Models	Model 1		Model 2		Model 3		Model 4		Post-hoc Analysis	
	beta	s.e.	beta	s.e.	beta	s.e.	beta	s.e.	beta	s.e.
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)
US 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)
Non-Biotech 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)		
Non-Star 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	-2587.22		-2473.88		-2475.23		-2473.41		-2467.94	
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 **	

* $p < .05$; ** $p < .01$; *** $p < .001$; Standard errors are in parentheses

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

Interaction Effects Models	Model 5		Model 6	
	beta	s.e.	beta	s.e.
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)
US 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)
Non-Biotech 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)
Non-Star 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) x R&D Expenditures	-0.1141 **	(0.0450)		
Scientists (total) x Biotech Alliances	-0.0630 ***	(0.0174)		
Scientists (total) x Biotech Acquisitions	0.0171	(0.0149)		
Star Scientists x R&D Expenditures			-0.1037 *	(0.0613)
Star Scientists x Biotech Alliances			0.0132	(0.0114)
Star Scientists x Biotech Acquisitions			0.0028	(0.0107)
Non-Star Scientists x R&D Expenditures			-0.0604	(0.0484)
Non-Star Scientists x Biotech Alliances			-0.0873 ***	(0.0221)
Non-Star Scientists x Biotech Acquisitions			0.0212	(0.0225)
R&D Expenditures x Biotech Alliances	0.0802 **	(0.0320)	0.1036 ***	(0.0323)
R&D Expenditures x Biotech Acquisitions	0.0556	(0.0406)	0.0568	(0.0414)
Log likelihood	-2463.73		-2459.94	
Chi Square	891.99 ***		901.23 ***	
Improvement over Base ($\Delta\chi^2$)	84.75 ***		93.99 ***	

* $p < .05$; ** $p < .01$; *** $p < .001$; Standard errors are in parentheses

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
Non-Star 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) x R&D Expenditures	-0.1141 **	0.89	-0.11
Scientists (total) x Bio Alliances	-0.0630 ***	0.94	-0.06
Star Scientists x R&D Expenditures	-0.1037 *	0.90	-0.10
Non-Star Scientists x Biotech Alliances	-0.0873 ***	0.92	-0.08
R&D Expenditures x Biotech Alliances	0.0802 *	1.08	0.08
R&D Expenditures x Biotech Alliances	0.1036 ***	1.11	0.11

* $p < .05$; ** $p < .01$; *** $p < .001$.