ESSAYS ON DYNAMIC CAPABILITIES: THE ROLE OF INTELLECTUAL HUMAN CAPITAL IN FIRM INNOVATION

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ESSAYS ON DYNAMIC CAPABILITIES: THE ROLE OF INTELLECTUAL HUMAN CAPITAL IN FIRM INNOVATION

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SUMMARY

This dissertation attempts to contribute to our understanding of the antecedents to dynamic capability formation by exploring the interaction between the internal and external mechanisms firms employ to develop these capabilities. Each of the three chapters highlights the importance of not only considering the heterogeneity of a firm's intellectual capital but also the interaction between this resource and the other mechanisms firms can utilize; including spending on research and development, undertaking acquisitions, and forming strategic alliances.

Chapter 1 of the dissertation serves to introduce and synthesize the major themes and contributions of my dissertation. In Chapter 2, I develop a multi-level framework of dynamic capabilities formation. By analyzing the role individuals play in a firm's ongoing innovation efforts, I illustrate not only the process through which dynamic capabilities are formed but also how they relate to a firm's strategy-making process. In particular, I suggest that there are three stages in the process of dynamic capabilities formation, through which the firm identifies, acquires, codifies, and eventually commercializes new knowledge. My analysis highlights the role key employees play in moderating the effectiveness of the developed capabilities and the role average employees play in mediating their existence.

In Chapter 3 of my dissertation I turn to empirically examine, more generally, the importance of not only considering the heterogeneity of the intellectual human capital, developed in chapter 2, but also the other mechanisms firms employ to access and assimilate knowledge that resides outside of the firm. Following the dynamic capabilities perspective, I suggest that antecedents to innovation can be found at the individual, firm, and network level. Accordingly, I advance a set of hypotheses to assess the effect of

individual, firm, and network-level antecedents on innovation output. I then investigate whether a firm's antecedents to innovation lie across different levels. To accomplish this, I propose two competing hypotheses. I juxtapose the propositions that the individual, firm, and network-level antecedents to innovation are substitutes versus complements.

The forth chapter of my dissertation examines several of the interesting findings of Chapter 3 in more detail, through the lens of a specific dynamic capability, ambidexterity. To this end, I develop and empirically test a contingency framework of ambidexterity across exploration and exploitation activities. While an exploration-exploitation lens has been applied to strategic alliances based on their strategic motivation, I propose that it can also be applied to a firm's intellectual human capital based on a bifurcation of "star" versus "staff scientists." Following a dynamic capabilities perspective, I suggest that antecedents to building these capabilities *within* the same activity (either indented for exploration or exploitation) compensate for one another, and thus are *substitutes*. Conversely, I hypothesize that different dynamic capability antecedents *across* exploration or exploitation activities positively reinforcing one another, and thus are *complements*. To empirically investigate the relationship between different antecedents to dynamic capabilities, I focus on the pharmaceutical firms' adaptation to biotechnology over a 30-year time period, 1974-2003. In general, I find support for the notion that building capabilities within the same activity compensate for on another, while ambidexterity across exploration and exploitation enhances a firm's innovative performance. Finally, my dissertation concludes with Chapter 5, which again summarizes the major themes and contributions of my dissertation. In addition, I offer some limitations of the current study as well as areas of interest for future consideration.

The data utilized in the dissertation is an unusually comprehensive and detailed panel dataset that documents the innovation attempts of global pharmaceutical companies within the new biotechnology paradigm over a 23-year time period. In

general, my extensive data collection process has produced fine-grained, longitudinal data on over 3,100 alliances, 3,500 new drug introductions, 36,000 biotechnology patents that have been cited 80,000 times, 147,000 non-biotechnology patents, 171,000 publishing scientists, 672,000 journal publications, and 9.9 million journal citations.

CHAPTER 1

INTRODUCTION

The recent extension of the resource-based view into dynamic markets provides a new perspective for analyzing how firms develop new capabilities to cope with shifting markets (Teece, Pisano, & Sheun, 1997). This research reveals that a firm's ability to 'integrate, build, and reconfigure internal and external competencies to address rapidly changing environments' lies at the center of its ability to learn and innovate and thus realize potential competitive advantages (Teece et al., 1997: 516). Thus, these 'dynamic capabilities' facilitate not only the ability of an organization to recognize a potential technological paradigm shift but also to adapt to it through innovation (Cohen & Levinthal, 1990; Hill & Rothaermel, 2003; Teece et al., 1997). An important issue that has preoccupied researchers and practitioners is where the locus of such knowledge, or 'Shumpeterian' capital, resides. The purpose of this dissertation is to shed light on this issue, by investigating the nature of the mechanisms firms employ to develop dynamic capabilities.

The key aspect of this construct is that it extends the resource-based view ("RBV") of the firm beyond consideration of simple resource existence, to the more complex issues associated with resource emergence. Thus, while the RBV focuses on how organizations select between appropriate resources, dynamic capabilities emphasizes resource development and renewal. While this difference presents organizational researchers with unique opportunities to better understand resource emergence, it also presents significant theoretical and methodological challenges that have resulted in many questioning the efficacy of the construct. Although the construct of dynamic capabilities has its origins in the RBV, its focus on emergence requires that researchers move beyond the simple selection models associated with the RBV.

Research that utilizes this 'RBV lens', by investigating an organization's choice between appropriate dynamic capabilities, is inevitably plagued by endogeneity.

In this dissertation I suggest that while consideration of selection is important, of import is not the choice between capabilities, but rather the choice between the different mechanisms that organizations employ to develop and change these capabilities. This distinction is important because it allows for the analysis of the emergent properties of dynamic capabilities. By considering the relationship between these choices I hope to both refine as well as extend our understanding of the construct of dynamic capabilities.

Research investigating this issue has revealed that the relevant knowledge for innovation can be located either be developed internally or accessed from external network connections. The choice between internal and external technological sourcing is particularly relevant when the firm is attempting to adapt to a new technological paradigm, because of the significant investment required to develop or acquire knowledge that is new to the firm. Specifically, firms wishing to innovate in a new technological paradigm use their *internal* human capital asset base to develop key firm-level researching capabilities and thereby increase the efficiency of its *external* networking efforts. This five-chapter dissertation contributes to our understanding of the antecedents to dynamic capability formation by exploring this interaction between the internal and external mechanisms firms employ to develop these capabilities. Each of the chapters highlights the importance of not only considering the heterogeneity of a firm's intellectual capital but also the interaction between this resource and the other mechanisms firm's can utilize, including spending on research and development, undertaking acquisitions, and forming strategic alliances.

A major contribution of my dissertation is that it illustrates the need to incorporate the individual level of analysis when investigating the antecedents of dynamic capabilities. This need is best revealed by shifting the focus of analysis temporarily

away from the concrete investigation of firm activity to the abstract analysis of how the dynamic capabilities construct is positioned within the literature. As mentioned above, to date the construct of dynamic capabilities has been conceptualized as an extension of the resource-based view of the firm (RBV) (Eisenhardt & Martin, 2000; Teece et al., 1997). Central to RBV is the notion that resources are heterogeneously distributed among organizations (Barney, 1991). Additionally, researchers have theorized that the possession of certain valuable, rare, inimitable, and non-substitutable resources can allow a firm to achieve a competitive advantage. The theoretical focus of RBV researchers, therefore, has traditionally been at the resource level (Barney, 2001; Teece et al., 1997). In contrast, conceptual research on dynamic capabilities has primarily focused at the process or routine level of analysis. Of concern is that these firm processes and routines are themselves a collective action, representing combinations of firm resources (Nelson & Winter, 1982).

To specify a theory solely at the collective or group level, as it is been presented in the conceptual work on dynamic capabilities to date, researchers have implicitly assumed that the individual members of the group are sufficiently similar with respect to the construct in question. Such uni-level analysis makes two key assumptions: (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 more or less independent from other levels of analysis (Felin & Foss, 2005; Felin & Hesterly, 2007). As such, heterogeneity among individual group members is not taken into consideration, because a single value or characteristic is considered sufficient to describe the group (Klein, Dansereau, & Hall, 1994). By investigating routines such as R&D, alliance formation, or search processes *solely* at the process or collective level of analysis, dynamic capabilities researchers are inherently making the assumption that the resources that comprise these processes must be more or less homogeneous (Felin &

Foss, 2005). This assumption, however, contradicts the central premise of the resource-based view that valuable and rare resources are distributed heterogeneously across firms. Further, individual employees are often the very resources that contribute to a firm's competitive advantage (Coff, 1997; Tushman & Katz, 1980; Zucker, Darby, & Armstrong, 2002a).

Thus, it is problematic to ignore the specific role individuals play because firm innovative performance is at least partially a function of the value of its human capital (Hitt, Bierman, Shimizu, & Kochhar, 2001). My dissertation builds on the framework of Crossan, Lane, and White (1999) which describes the process through which organizations process knowledge and thus, learn. The authors suggest that individuals serve not only to facilitate the creation of tacit knowledge, but also aid in the process of intuiting the links between the sources of such knowledge. The creation and ownership of such tacit knowledge is especially crucial in high-velocity environments (Eisenhardt & Martin, 2000).

The premise that individuals are critical to the formation of dynamic capabilities has not gone unchallenged, however. For example, Levitt and March (1988: 320) claim that key routines are "independent of the individual actors who execute them." Similarly, Cohen and Levinthal (1990) claim that an organization's ability to acquire, assimilate, and apply external knowledge develops cumulatively, and thus tends to be path dependent. These abilities, referred to as a firm's absorptive capacity, tend to build on a firm's prior investments in its members' individual absorptive capacities (Lane, Koka, & Pathak, 2006). Therefore, while dynamic capabilities may not be vested in a single individual, a key component of their effectiveness, absorptive capacity, does depend upon the actions of individuals. Adding complexity to the issue, prior research has demonstrated that not all individuals are equally important in a firm's innovation efforts (Lacetera, Cockburn, and Henderson, 2004; Rothaermel and Hess, 2007; Zucker,

Darby, and Torero, 2002b). Explicating this heterogeneity is critical to the understanding of the roles individuals play in facilitating organizational innovation. Specifically, different individuals facilitate specific organizational capacities associated with the innovation process. Following Crossan et al. (1999), I suggest that these capacities are related to the organization's ability to intuit and interpret new knowledge, and in turn, allow organizations to identify and exploit new opportunities within their respective environments.

As previously indicated, the dissertation consists of three primary chapters, an introduction, and conclusion. Two of the primary chapters investigate the role of the individual within the firm empirically, while the other chapter conceptually builds a framework of organizational learning and adaptation. The data utilized in my dissertation is summarized within each chapter. In general, the database is an unusually comprehensive and detailed panel dataset that documents the innovation attempts of global pharmaceutical companies within the new biotechnology paradigm over a 23-year time period. In general, my extensive data collection process has produced fine-grained, longitudinal data on over 3,100 alliances, 3,500 new drug introductions, 36,000 biotechnology patents that have been cited 80,000 times, 147,000 non-biotechnology patents, 171,000 publishing scientists, 672,000 journal publications, and 9.9 million journal citations. I utilize the data to investigate the following model:

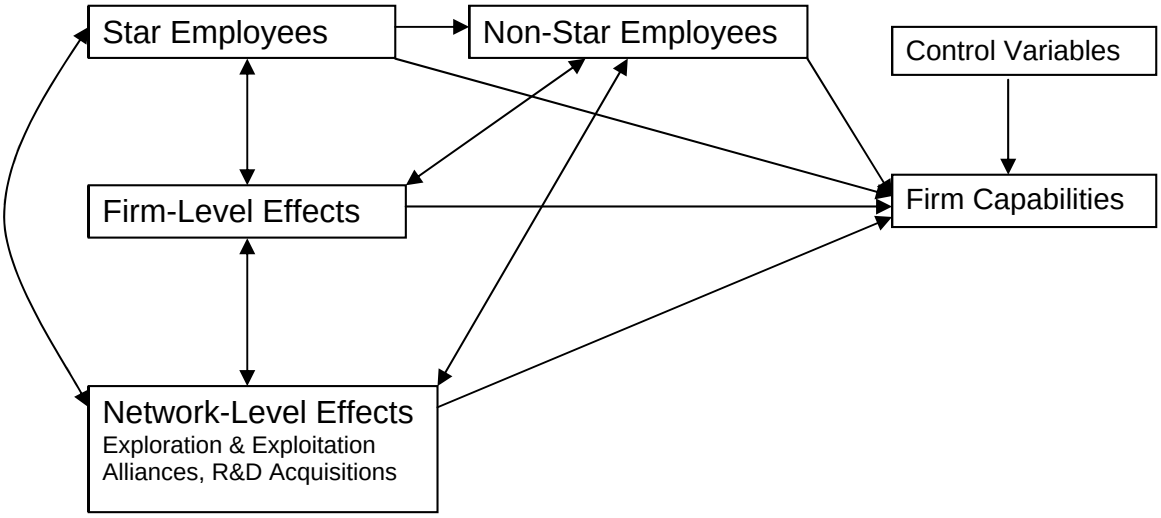

Figure 1.1: Model

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CHAPTER 2

A SYSTEM OF DYNAMIC CAPABILITY FORMATION

2.1 Introduction

As a matter of survival, organizations in rapidly changing environments need to possess the ability to identify and react to changes that originate outside their boundaries. This construct, known as dynamic capabilities, has recently emerged as a key topic for researchers interested in explaining how firms adapt to shifting knowledge environments. This research posits that a firm's dynamic capabilities enable it to integrate, build, and reconfigure internal and external competencies to address uncertain and changing environments (Teece, Pisano, & Shuen, 1997). It has been theorized that these capabilities can facilitate innovation and adaptation by allowing a firm the opportunity to derive economic rents from new and innovative processes, products, and services. Recent theoretical research suggests that these capabilities arise from an organization's ability to both explore for new information and exploit its current knowledge base (O'Reilly & Tushman, 2007). Indeed, a significant amount of research has examined the characteristics of such capabilities (Eisenhardt & Martin, 2000; Winter, 2003), their evolution and role in firm learning (Zollo & Winter, 2002), as well as the mechanisms that firms can employ to leverage their effectiveness (Rothaermel & Hess, 2007).

Despite the insights offered in the extant literature, some researchers still question the validity and even the existence of dynamic capabilities. Such skepticism is warranted, as dynamic capabilities researchers have struggled to answer the fundamental question of how these capabilities are formed. This significant gap our understanding is a result of the fact that research has generally failed to consider the complex and multi-level nature of dynamic capability formation. We submit that to

deepen our understanding of how an organization forms dynamic capabilities, an approach that considers a system of capability formation is vital. Such a system-level analysis allows us to analyze the linkages between each distinct stage in the dynamic capability development process beginning with exploration for new knowledge and culminating in its exploitation. We submit that such an analysis requires a multi-level approach. The need for such an approach is illustrated by the fact that a dynamic capability itself represents change at the *routine* or *capability* level of analysis. This perspective resonates with Helfat, et al.'s (2007: 4) understanding of dynamic capabilities as "the capacity of an organization to purposefully create, extend, or modify its resource base." While a change in an organization's resource base is a direct result of the collective actions of *individuals*, the outcome of interest herein is the adaptation of the *organization* to an environmental knowledge shift. Therefore, we suggest that three levels of analysis are required to more fully understand both the inputs to and outputs of dynamic capabilities: the individual, routine, and organization level. Thus, a contribution of our research is to extend the current focus of dynamic capabilities researchers beyond the traditionally used capability level of analysis. While this focus is not surprising given that dynamic capabilities are often defined as higher-order capabilities or heuristics (Collis, 1994; Teece et al., 1997), viewing the construct through a broader lens will shed light on the system through which these capabilities emerge.

At the micro-level of analysis, we follow Felin and Hesterly (2007) and posit that consideration of the inputs to dynamic capabilities requires the analysis of a fundamental component of every firm: the individual. While this focus is not novel, the prior research that has considered the role of individuals has focused primarily on the role of middle and top managers (Burgelman, 1994; O'Reilly & Tushman, 2007). While an analysis of different management layers clearly improves our understanding of the organizational decision making process, it does not directly allow for consideration of how organizations explore for new information or exploit current knowledge bases, especially in high-tech

industries. A deeper understanding of these processes is vital, as both exploratory and exploitive activities are critical to an organization's innovative efforts (Eisenhardt & Martin, 2000; O'Reilly & Tushman, 2007; Tushman & O'Reilly, 1996; Tushman, Smith, Wood, Westerman, & O'Reilly, 2004). We suggest that to understand the process through which organizations sense and react to environmental knowledge shifts requires a deeper analysis of the organization's intellectual human capital. By considering the roles of both star and 'non-star' or average employees in the innovative activities of an organization we advance a framework that illustrates a system through which dynamic capabilities can be developed.

A systematic approach to the process of dynamic capability formation also requires the consideration of the outputs of the process as well. In the case of dynamic capabilities, these outputs need to be analyzed through the more aggregated, organizational level of analysis. The reason for this is because innovation at the process or capability level does not necessarily translate into adaptation at the organizational level. This relationship is similar to that described by Helfat et al. (2007) with regard to the technical and evolutionary fitness of a dynamic capability. The authors note that technical fitness is a measurement of the effectiveness of the individual capability (e.g., a count of the number of new products developed) without regard to its interaction with other organizational processes and capabilities. Technical fitness thus measures an organization's exploratory and exploitive innovative activities, but is only one component of the much broader evolutionary fitness, which assesses how well these activities enable an organization to integrate the needed modifications to its resource base to achieve superior performance in the market place. Through this lens we suggest that the existence of exploratory and exploitive activities within an organization represent a necessary but not sufficient condition for the formation of dynamic capabilities. Without activities focused on the integration of these innovative activities, modifications at the routine or capability level will not systematically lead to adaptation at the organizational

level. Based on this we suggest that three disparate activities are required if an organization is to build dynamic capabilities: *exploration*, *exploitation*, and *integration.*

To illuminate the roles that individuals play in facilitating these activities, we incorporate the construct of boundary spanning (Aldrich & Ruef, 2006; Allen, 1977; Allen & Cohen, 1969; Tushman & Katz, 1980) into Crossan, Lane, and White's (1999) multi-level framework of organizational learning. Crossan et al. (1999) offer a general theory of organizational learning that links the individual, group, and organizational levels of analysis. Of key interest is the authors' position that two key aspects of organizational learning, the ability to intuit and interpret new knowledge, occur at the individual level. As part of our theoretical framework, we develop a typology of individuals, which organizations employ to overcome stage-specific knowledge gaps. This synthesis allows us to provide an analysis of how incumbent firms in knowledge-intensive industries utilize different individuals to effectuate their continuous adaptation and thus innovation efforts. The boundary condition imposed by this setting is appropriate given that the purpose of dynamic capabilities is to allow existing firms to address rapidly changing or high velocity environments (Eisenhardt & Martin, 2000; Teece et al., 1997) through a continuous change in a firm's resource base (Helfat, et al. 2007).

In the spirit of Chen (1996), our theoretical analysis is buttressed by data and anecdotal evidence that detail the experiences of incumbent firms in knowledge-intensive industries that are attempting to build dynamic capabilities. We begin our framework development at the organizational level of analysis by investigating the different knowledge gaps an innovating firm faces. We then turn to a more micro-level of analysis to illustrate an important heterogeneity in an organization's intellectual human capital. It is through this analysis that we develop a typology of individuals based on the nature and level of connectivity. Finally, we explicate how effective dynamic capabilities, in terms of technical and evolutionary fitness result when firms use different individuals

to span different knowledge gaps. This analysis is exemplified through the description of a successful vaccine development at Merck.

2.2 Processes, Positions, and Paths

The purpose of this paper is not to offer another definition of dynamic capabilities. Rather, using the definition of dynamic capabilities by Teece et al. (1997),[1] we seek to illustrate the role individuals play in the formation these firm-level capabilities. We develop herein a framework emphasizing that dynamic capabilities are dependent on the individuals within the firm and on their respective roles in the innovation process. Theoretically, we conceptualize the construct of dynamic capabilities based on a synthesis between the knowledge-based view of the firm (Grant, 1996) and the absorptive capacity construct (Cohen & Levinthal, 1990). Support for conceptualizing dynamic capabilities as a synthesis between these well-established theoretical lenses is found by exploring the oft-ignored decomposition of dynamic capabilities presented by Teece et al. (1997). This decomposition serves as the foundation for our framework which illustrates the process through which knowledge is purposefully gathered by and processed within firms.

Teece et al. (1997) decompose dynamic capabilities into processes, positions, and paths. The authors posit that the *processes* refer to managerial and organizational routines or current practices, while the *positions* refer to the specific assets of the firm, including technological know-how, complementary, financial, and reputational assets. The final sub-category of dynamic capabilities, a firm's *paths*, represents the strategic alternatives or opportunities that face a firm. To better understand the relationship between these sub-categories, it is important to conceptualize the knowledge base of a

[1] Teece et al. (1997: 516) define dynamic capabilities "as the firm's ability to integrate, build, and reconfigure internal and external competences to address rapidly changing environments. Dynamic capabilities thus reflect an organization's ability to achieve new and innovative forms of competitive advantage given path dependencies and market positions (Leonard-Barton, 1992)."

firm as consisting of stocks and flows (Appleyard, 1996; DeCarolis & Deeds, 1999; Dierickx & Cool, 1989). Through this lens the processes and the positions of a firm can be considered to be its stocks of knowledge, while the paths represent changes to the flow of knowledge into the firm. Prior research, however, has focused primarily on the firm's processes and positions, as Teece et al. (1997) identified these as collectively making up a firm's competencies and capabilities.

This focus has resulted in a lack of understanding of how a firm's knowledge base changes over time, especially in the context of facilitating adaptation to a changing environment. Without consideration of the role and development of a firm's paths, a complete picture of dynamic capability formation cannot be developed, given that in high velocity industries the external environment is predominantly the locus of new knowledge (Powell, Koput, & Smith-Doerr, 1996). In changing environments the process of dynamic capability formation must be considered to be open in nature (Chesbrough, 2003). Such a case indicates that the firm needs a level of connectedness with external sources of technological change if it is to recognize environmental knowledge shifts and then develop the requisite processes and positions (Appleyard, 2003). In changing environments, the choice of a path determines both the direction and rate of change in the firm's stock of processes and positions. Thus, without consideration of the firm's strategic paths, the relationship between the sub-categories cannot be fully explored.

2.3 Obstacles to Dynamic Capability Formation

Each sub-category of a dynamic capability is unique in both its importance to the firm and the process through which it is formed. In addition to considering of the reciprocal relationship between these categories, the overall development of these sub-categories corresponds directly to sequential steps in the dynamic capability formation process. In particular, there are three significant obstacles that a firm must overcome to develop dynamic capabilities: 1) a cognitive gap; 2) an operational gap; and 3) an

engineering gap. Specifically, these obstacles correspond to the ability of a firm to develop each of the sub-categories (i.e., paths, processes, and positions) of dynamic capabilities, as well as consideration of the reciprocal, and thus learning, aspect of dynamic capability formation. More generally, we suggest that these three knowledge gaps are associated with the information conversion process through which an organization senses, seizes, and capitalizes on opportunities, and thus maintains competitiveness in dynamic environments (Teece, 2007).

Our analysis provides structure to the relationship between the sub-categories of dynamic capabilities, because the order of the gaps is critical to successful adaptation. When viewed through the lens of the real options perspective, each stage in the innovation process represents a decrease in the uncertainty surrounding the technological change. This notion is similar to Ashby's (1956) Law of Requisite Variety, which suggests that the variety in an internal control system must be equal to or larger than the variety of the perturbations in the environment to achieve control. When applied to organizations, Ashby's theory suggests that a flexible system with many options is better able to cope with change than one that is tightly optimized for an initial set of conditions (see also Weick, 1976). The optimized organization may be more efficient while the initial conditions hold, but is less likely to both identify and adapt to changes in its environment (McKelvey & Aldrich, 1983). Following this logic, organizations need to be sufficiently adaptable to cope with a changing knowledge environment. Individuals can, both directly and indirectly, provide the firm with this needed adaptability. Thus, the individual facilitates the firm's ability to monitor and cope with uncertainty, and by doing so aids the firm in developing dynamic capabilities.

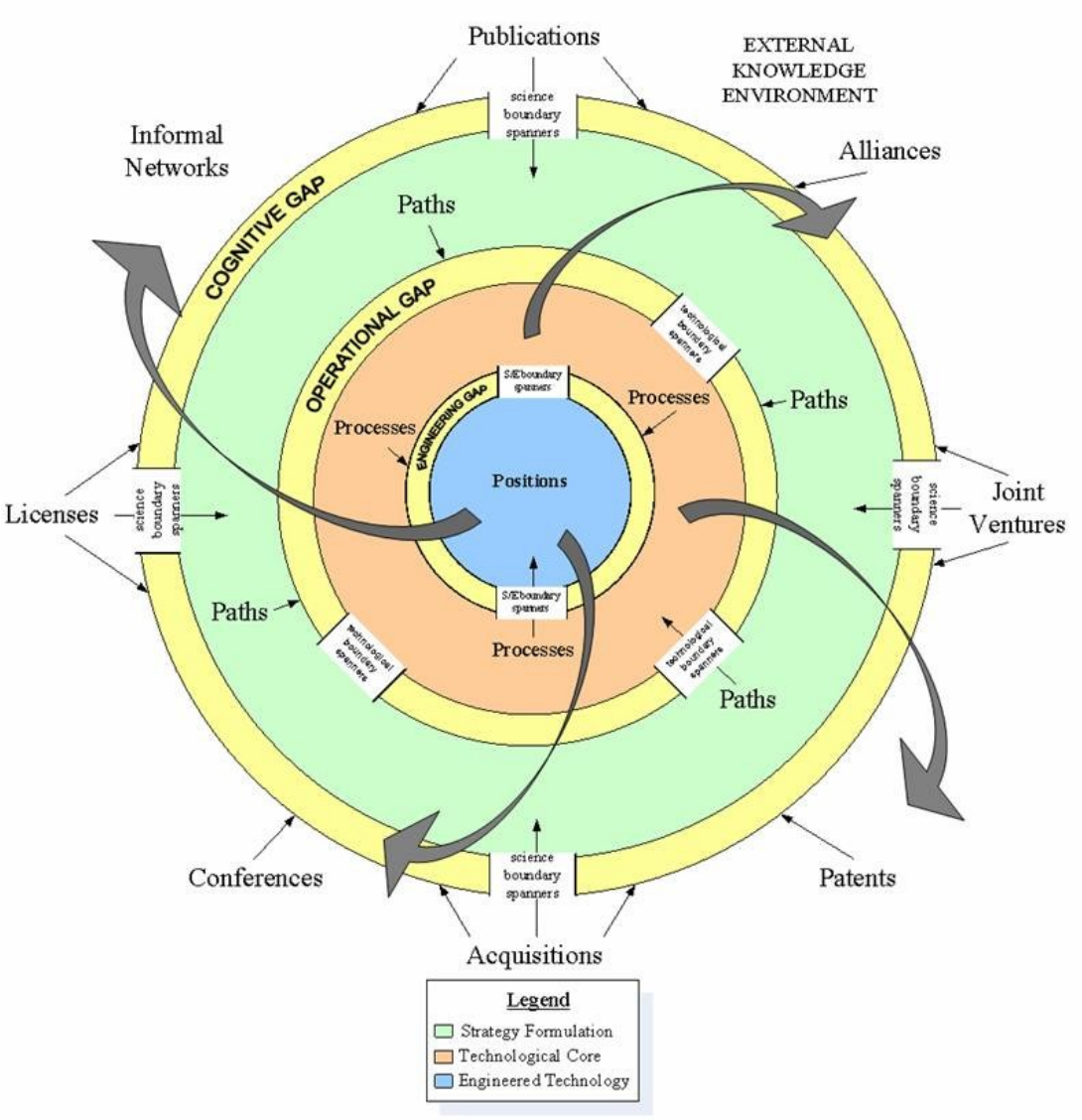

Figure 2.1: A System of Dynamic Capability Formation

Our model of dynamic capability formation depicted in Figure 2.1 illustrates some important but under-researched aspects of the firm innovation process. Central to this process is the notion that the locus of knowledge in many industries is external to the firm (Powell et al., 1996). The means through which this external knowledge is acquired and transformed is not a simple, linear process. Rather, as illustrated by the outward arrows in the figure, the process of dynamic capability formation is complex and iterative in nature. These feedback loops illustrate the significant managerial attention and

intention that is required if the firm is to build dynamic capabilities. This intentionality is required because the knowledge gaps in the innovation process are not perfectly aligned; that is, the flow of knowledge through an organization is not a linear or waterfall process. The imperfect alignment between the knowledge gaps occurs as a result of the different characteristics of both the gaps themselves, as well as the resources needed to effectively span them.

2.3.1 The Cognitive Gap

The first step for a firm developing dynamic capabilities is to gain access to the external knowledge environment. Knowledge held in the external environment can be accessed through a large number of different mechanisms, such as informal networks, conference attendance, publications in the open literature, patents assigned to other organizations, licenses, strategic alliances, joint ventures, and acquisitions (as depicted in Figure 1). Yet, an organizational boundary represents a cognitive gap between internal and external sources of knowledge and as such, represents a significant frontier for a firm attempting to adapt to a changing environment (Lavie, 2006). The learning that takes place through a connection that individuals have with the external environment bridges the cognitive gap, and thus allows for the selection of a path or strategic option for the future. Such a strategic option is similar to the identification process of a firm's emergent strategy (Mintzberg and McHugh, 1985). Thus, the obstacles to innovation are situated at the firm level, while the mechanisms to overcome these obstacles are located at the individual level.

The capability to access external knowledge is termed cognitive or potential absorptive capacity in prior conceptual work (Lavie, 2006; Zahra & George, 2002), as this capability relates to a firm's ability to identify changes within its environment through insight and awareness of technological change. Lavie (2006) indicates that this ability increases the efficiency with which a firm is able to search and evaluate new strategic

alternatives. A firm's cognitive absorptive capacity relates directly to the *path* selection explicated by Teece et al. (1997). Spanning the cognitive gap, therefore, requires not only connections to the external environment and the ability to assess the value of the new knowledge, but also deep connections within the company and to its top management team, because the selection of certain paths can have significant strategic ramifications.

Powell et al. (1996) posit that a firm's capability to access external knowledge is related to a firm's scope of collaborations. In contrast to Powell and colleagues, we suggest that these interorganizational relationships need to be investigated at the individual level, rather than at the alliance or collective level of analysis. The authors themselves seem to support this position by noting, for example, that the CEO of Centocor indicated that the number of formal alliances was simply the "tip of the iceberg – it excludes dozens of handshake deals and informal collaborations, as well as probably hundreds of collaborations by our company's scientists with colleagues elsewhere" (Powell, et al. 1996: 120).

It is worthwhile to note that within the setting of firm innovation, a firm's ability to identify not only key changes in the knowledge environment but also possible ways of addressing these changes has been taken as exogenous to the analysis of dynamic capabilities. The simple routines of Eisenhardt and Martin (2000) seem to arise from learning (Zollo & Winter, 2002), but consideration of both the sources of knowledge and the mechanisms through which this learning is accomplished are lacking. This represents a concern because if a firm fails to identify a key technological shift within a reasonable time window, its ability to effectuate the necessary transformation is reduced. The complexity and uncertainty facing the firm is accentuated by the fact that it is often the case that the relevant characteristics of the technological shift are unlikely to be known, even after their appearance (Anderson & Tushman, 1990; Tushman & Anderson, 1986). To address this issue, research on a firm's ability to identify a technological

change has highlighted the role of a firm's top management team, focusing on the connectivity of the key managers to external sources of knowledge (Kaplan, Murray, & Henderson, 2003).

Within pharmaceutical firms, for example, the decision of which path or technological alternative a firm selects has long-term financial performance implications (Gambardella, 1992; Thomke & Kuemmerle, 2002). The importance of strategic choice is due to the fact that a source of competitive advantage for pharmaceutical firms is its ability to develop competencies within a specific treatment area, such as Eli Lilly in the field of diabetic therapy or Hoffman-La Roche in the area of anti-anxiety drugs. The firm's ability to develop a blockbuster drug in a certain therapeutic category depends not only on its capability within that specific treatment area, but given the significant lead time associated with drug development, also in the firm's initial decision to follow the appropriate path.

While the selection of a strategic direction is a critical component of the innovation process, it acts as a determinant of the effectiveness of the innovation process, rather than its existence. The quality of the innovative process is directly related to the firm's ability to span this gap. Finally, the capability to span the cognitive gap requires not only external knowledge, but also deep firm-specific knowledge.

2.3.2 The Operational Gap

Knowledge requires other knowledge. This truism underscores the importance of a firm's ability to develop the internal competencies needed to effectuate the changes identified by spanning the cognitive gap. Similar to the underlying concept of absorptive capacity, this capability relates to the notion that a firm cannot internalize external knowledge without cost. Instead, the identification, assimilation, and exploitation of external knowledge requires effort, expertise, and purposeful action on the part of the firm (Cohen & Levinthal, 1989). The codification process entails transforming tacit

knowledge into repeatable and stable practices that can be used by the firm for diffusing the knowledge within the firm by means of a manual or tool (Nonaka, 1994; Zander & Kogut, 1995). Relating this to the discussion of the decomposition of dynamic capabilities, the routines and practices through which firms are able to do this are representative of its organizational *processes*. These processes represent the requisite resources needed to achieve an appropriate fit with a changing external knowledge environment (Lavie, 2006), and can include the development of the intellectual property associated with the firm's chosen direction.

Therefore, the second obstacle in the formation of dynamic capabilities is the *operational gap.* To span this gap, a firm is required to expand its requisite absorptive capacity to understand the knowledge associated with the chosen strategic path. It is through this exploitation of scientific knowledge that the company builds its technological core (Thompson, 1967). This technological core represents the competencies needed to 'crack the code' of scientific innovation. The successful accumulation of these needed competencies is often represented by the firm's stock of scientific patents. Based on this notion, the capability to span the operational gap *mediates* the overall innovation process. Of interest, however, is that possession of the requisite knowledge does not guarantee that the organization will be able to assimilate or apply this knowledge.

Nowhere is this notion more apparent than in the pharmaceutical industry, which has seen aggregate R&D expenditures since 1993 increase 250%, while the number of new drug submissions to the FDA has fallen by more than 70% (Raynor & Panetta, 2005). Given this trend, there has been a movement within the industry to reconfigure the R&D process. As an example, InnoCentive, a wholly owned subsidiary of Eli Lilly, offers firms a mechanism to facilitate the development of a technological core, and thus bridge its operational gap. Utilizing a global network of independent researchers, InnoCentive acts as a knowledge broker and facilitates the exchange of technological know-how, primarily associated with chemistry and biotechnology. Through this system

of open innovation, InnoCentive has realized a success-rate that is higher than traditional internal R&D approach, at approximately one-sixth the cost (Raynor & Panetta, 2005). As illustrated by the final gap in the innovation process, however, possession of these technological capabilities does not in itself guarantee adaptation or continued innovation.

2.3.3 The Engineering Gap

It is not necessarily the case that innovation follows directly from the successful crossing of the cognitive and operational gaps. The last step in the innovation process relates to the engineering of a firm's *positions* through the transformation of its collected and codified knowledge into commercially viable products and services. It is these innovations that are the end products of the innovation process and thus should be considered as the positions of the firm. This capability to transform knowledge has been ignored frequently, as the process of transforming science into technology has been viewed as a waterfall process, through which minimal effort is needed to transform knowledge obtained into technology underlying new processes, products, and services (Murray, 2002). In contrast, others argue that the process to span this gap is actually quite complex and highly nuanced (Dasgupta & David, 1994; Garud & Rappa, 1994).

Termed the *engineering gap,* the process requires that a firm be able to integrate disparate communities of practice associated with basic science and those of commercially applied technologies (Brown & Duguid, 2001; Murray, 2002). The engineering gap, therefore, separates a firm's "R," or internal research, from its "D," or development of technologies. The engineering gap remains a significant obstacle for firms attempting to innovate and thus a critical component of dynamic capability formation. More simply, the relevant question to consider is: can a firm integrate its exploratory and exploitive activities?

A comparison between the reward structure and knowledge distribution systems used in these two communities illustrates why some firms find themselves unable to span the gap between science and engineering. Specifically, the reward system in science is based mainly on dissemination of new knowledge through refereed journal publications, and exists primarily in research institutions and universities (Murray, 2002). This setting is focused on the community of learning and knowledge sharing. In contrast, the activities of the engineering world are focused on developing patentable and commercially viable products, processes, or services to generate economic returns. The importance of the community knowledge is replaced with concerns of appropriability and protection of intellectual property through patent protection, trade secrets, etc.

The importance of this difference between the science and engineering communities is illustrated by examining the characteristics of the knowledge exchange between a firm's departments focused on research and those on development. A firm's ability to learn from a partnership, for example, is *relative* to the characteristics of both partners involved in an exchange (Lane & Lubatkin, 1998). More specifically, when there is a sufficient level of commonality between the subject firm's internal research program and that of the external research source, knowledge transfer is often more successful. We extend this comparison to include the interaction between disparate communities of practice, which are dominated by different metrics of measuring performance (Dietz & Bozeman, 2005). Learning between two communities is posited to be greater if there exists a similarity between their dominant logics, knowledge-bases, as well as organizational structures and compensation policies (Prahalad & Bettis, 1986). Without a sufficient understanding of both the science and engineering communities, firms are hampered in attempting to commercialize their codified knowledge. The knowledge required to span the engineering gap usually involves an overlap of scientific knowledge and firm procedures and processes for manufacturing.

Within the semiconductor industry, the significance of the gap between science and engineering is illustrated by the fact that it is often the case that the inventors of a new technology are not the ones that profit from the invention (Chesbrough, 2003). Fairchild Camera and Instrument's experience in innovating in the semiconductor industry illustrates the potential impediment the engineering gap can pose to innovation. Fairchild was a pioneer in the industry and, although an aerial-survey company, through leveraging its 600 person research labs, had developed technology unique to the semiconductor industry. Despite this large investment in basic research, Fairchild failed to capitalize on its invention because of the tremendous disconnect that existed between these labs and the firm's engineering and production departments. The geographical separation of these departments was augmented by the lack of common design and production processes. Additionally, Chesbrough (2003: 115) notes that "this separation was exacerbated by an attitude of intellectual superiority on the part of the lab scientists toward the fab(rication) engineers."

The preceding section illustrated the knowledge gaps an organization must span if it is to develop a dynamic capability. We next turn to illustrate the activities and mechanisms that facilitate the spanning of these gaps. As a starting point, we consider the importance of individuals in the process of dynamic capability formation.

2.4 Individuals as Building Blocks of Dynamic Capabilities

It is problematic to ignore the specific role individuals play because a firm's innovative performance is at least partially a function of the value of its human capital (Hitt, Bierman, Shimizu, & Kochhar, 2001). Crossan, et al. (1999) present a multi-level framework of organizational learning that incorporates this notion. The authors argue that organizational learning is a multi-level process that begins with individual learning, which leads to group learning, and finally to organizational learning. They argue that learning across these levels is linked through bi-directional processes that involve both

the creation and application of knowledge. More specifically, they describe four processes that connect individual learning to organizational learning: intuiting, interpreting, integrating, and institutionalizing. Further, the authors suggest that individuals serve not only to facilitate the creation of tacit knowledge, but also aid in the process of intuiting the linkages between different sources of such knowledge. The creation and ownership of such tacit knowledge is especially crucial in high-velocity environments (Eisenhardt & Martin, 2000). This highlights the importance of considering the role individuals play in facilitating an organization's development of dynamic capabilities. Using an expanded theoretical lens, it allows researchers to analyze the complex interactions between individuals, firm processes, and the changing knowledge environment (Tripsas & Gavetti, 2000).

The premise that individuals are critical to the formation of dynamic capabilities has not gone unchallenged, however. For example, Levitt and March (1988: 320) claim that key routines are "independent of the individual actors who execute them." Similarly, Cohen and Levinthal (1990) argue that an organization's ability to acquire, assimilate, and apply external knowledge develops cumulatively, and thus tends to be path dependent. These abilities, referred to as a firm's absorptive capacity, tend to build on a firm's prior investments in its members' individual absorptive capacities (Lane, Koka, & Pathak, 2006). Therefore, while dynamic capabilities may not be vested in a single individual, a key component of their effectiveness, absorptive capacity, does depend upon the actions of individuals. Adding complexity to the issue, prior research has demonstrated that not all individuals are equally important in a firm's innovation efforts (Lacetera, Cockburn, and Henderson, 2004; Rothaermel and Hess, 2007; Zucker, Darby, and Torero, 2002). Explicating this heterogeneity is critical to the understanding of the roles individuals play in facilitating organizational innovation. Specifically, different individuals facilitate specific organizational capacities associated with the innovation process. Following Crossan et al. (1999), these capacities are related to the

organization's ability to intuit and interpret new knowledge; in turn, these abilities allow organizations to identify and exploit new opportunities within their respective knowledge environments.

2.4.1 Exploring the Heterogeneity of Individuals

Prior research relating individuals to firm outcomes has primarily focused on the role of key individuals or star employees (Tushman, 1977; Zucker, Darby, & Armstrong, 2002). The rationale behind this focus stems from the Lotka-Price Law of scientific knowledge distribution, in which Lotka (1926) and Price (1963) hypothesize that scientific progress follows an inverse square law. The Lotka-Price Law proposes that the number of scientists publishing n papers is proportional to $1/n^2$. This inverse square relationship suggests that for every 100 authors producing a single paper, 25 publish two papers, 11 publish three, and so forth. This law also indicates that approximately 50 percent of the papers published during a given period are produced by only 10 percent of the actively publishing scientists. Thus, a star scientist is by an order of magnitude, both, more productive and more influential than a non-star (or average) scientist in a specific field of research. As an empirical example of this relationship, Zucker and colleagues identified star scientists employed in biotechnology firms. While the 327 star scientists accounted for only 0.75 percent of the total scientific authors in the genomic sequence database GenBank, they accounted for 17.3 percent of the published articles, with nearly 22 times as many articles as the average scientist.

Even though elite or star employees are often more intelligent or creative than the average employee (Amabile, Conti, Coon, Lazenby, & Herron, 1996; Ernst, Leptien, & Vitt, 2000), within biotechnology, a star scientist's value is driven by his/her level of connectedness to external sources of knowledge (Zucker, Darby, & Armstrong, 1998). Within this context, star scientists have been shown to affect the location of firm entry into new technologies (both new and existing firms in the United States and Japan) (Zucker, Darby, & Brewer, 1998) and have a significant positive effect on a wide range of

firm-level measures, such as the number of products on the market, publishing propensity, and network connections (Audretsch & Stephan, 1996; Lacetera, Cockburn, & Henderson, 2004; Zucker, Darby, & Torero, 2002).

Our own analysis of innovation in the pharmaceutical industry, however, illustrates the need to look beyond the role of the elite employees. We identified a population of star scientists in the pharmaceutical industry using a unique dataset and measure of stardom. In particular, we investigated the importance of these star scientists by comparing their affect on firm performance with that of non-stars or average employees. For the time period between 1973 (which marks the discovery of recombinant DNA, and thus the beginning of the 'new biotechnology') and 2003, we collected data on nearly 150,000 scientists who published more than 480,000 journal articles related to biotechnology, and these articles were cited 9.2 million times. As a measure of stardom, we identified scientists whose publication and citation counts were three standard deviations above that of the average (staff) scientist. We found that the 851 stars identified in the pharmaceutical industry accounted for only 0.65 percent of the population of the publishing scientists but accounted for 15.2 percent of all publications and 27.3 percent of all citations.

It is interesting to note that the publication of research findings is only one aspect of the process through which scientific knowledge is codified. Through the lens of firm innovation, patents are frequently viewed as a more appropriate measure of a firm's technological capabilities than publications because they represent knowledge that tends to be more codified in nature (Stuart, 2000). Griliches (1990) suggests that patents and publications should not be considered as outputs of the same stage in the innovation process. In a science-driven industry, an organization's stock of publications are real options for future strategic directions (McGrath, 1997). Publications thus represent generally small and numerous investments in basic research, most of which do not directly result in commercially viable inventions. In our data, the average

pharmaceutical firm produced over 280 scientific journal publications per year, while producing just over 20 biotechnology patents per year. Thus, patents represent a more codified innovative output than publications, which in turn is associated with an organization's attempt to build its technological core.

As introduced above, Helfat et al. (2007) suggest two principle measurements, technical and evolutionary fitness, for evaluating the effectiveness of dynamic capabilities. The authors define technical fitness, as measuring how effectively a capability performs its function, regardless of how well the capability enables a firm to make a living. We suggest that the stock of publications within a given therapeutic area represents an appropriate measurement of the technical fitness of a pharmaceutical firm's drug discovery capability in that area. By contrast, evolutionary fitness relates to broader organizational issues, including survival, growth, and value creation. Based on this conceptualization, we suggest that patents represent an appropriate measurement of the evolutionary fitness of a pharmaceutical firm's drug development capability. In support of the differentiation between publications and patents, Murray and Stern (2004) found that the average lag between publication of a journal article and subsequent granting of a patent was a little over 3 years (37.5 months). This distinction is critical because it highlights the reason why the innovation process should not be considered linear in nature and emphasizes the different roles star and non-star scientists play in the innovation process. Analysis of data from the innovation process in the pharmaceutical industry sheds light on two interesting aspects of this non-linearity: first, the stars of publishing are not necessarily the stars of patenting. Second, the distribution of patents appears to be more egalitarian in nature than that of publications.

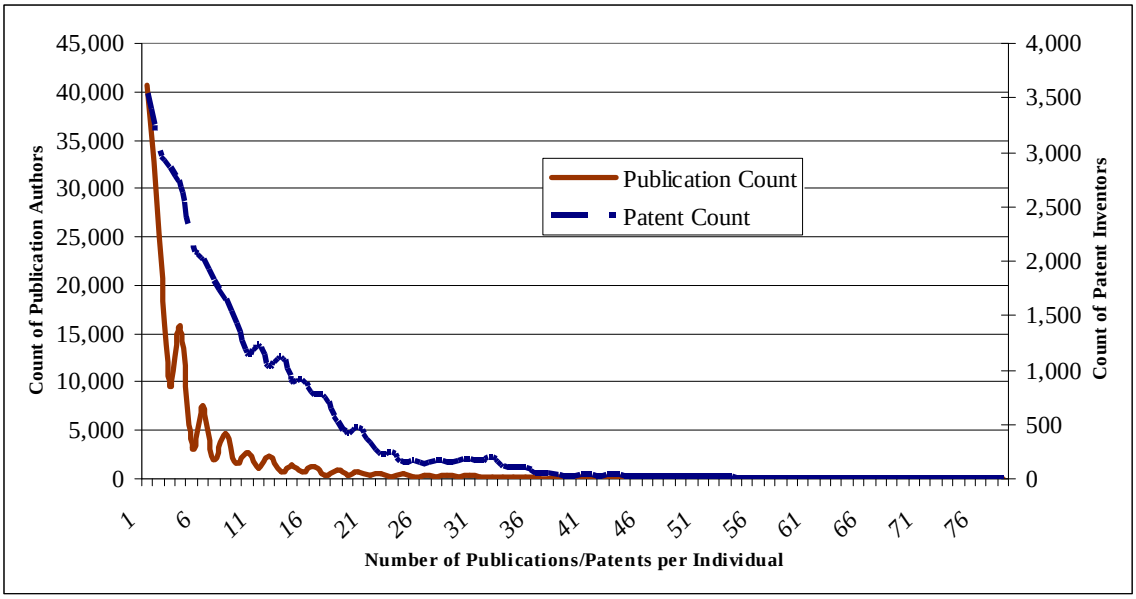

Figure 2.2: Distribution of Pharmaceutical Firms' Authors and Inventors by Scientific Publications and Patents in Biotechnology

Figure 2.2 illustrates that the distribution of inventors' names on a pharmaceutical firm's biotechnology patents is more egalitarian in nature than that of authors' names on firm publications. More specifically, we find that within the realm of a pharmaceutical firm's biotechnology patents, the top 1 percent of inventors account for 10.2 percent of all of the patents in the sample, while the top 1 percent of authors account for 50.8 percent of all publications ($p < 0.05$). This statistically significant difference, illustrated in Figure 2, appears to reflect the lower level of uncertainty associated with the more codified knowledge contained in a patent, when compared to the more the basic knowledge disseminated in a scientific publication. This finding is similar to Furukawa and Goto (2006) who illustrate that scientists with the highest publication performance scores did not apply for a considerably greater number of patents than other researchers in their companies. Instead, these star scientists had a positive effect on the number of patent applications filed by their non-star co-authors. Moreover, these star scientists served as channels through which external knowledge flows to the average researchers, thereby stimulating innovation by non-star scientists.

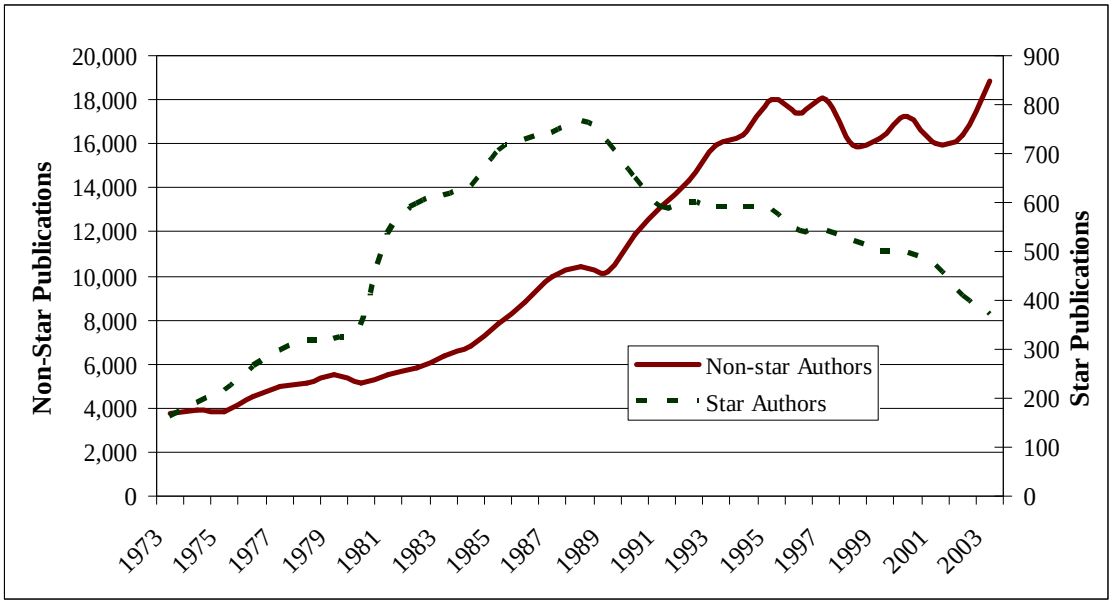

Figure 2.3: Scientific Journal Publications by Pharmaceutical Firms' Authors

Figure 2.3 illustrates the overall trend in star and non-star publication activity over time. The publication count of the stars began to increase in the early 1980's, shortly after the advent of biotechnology. This period represents a time when the knowledge related to using biotechnology for the purpose of drug discovery and development was not well dispersed (Gambardella, 1992). That is, in the early stages of biotechnology (mid 1970's-early 1980's) the knowledge associated with this nascent technology was held by a few key individuals who were critical to a firm's development of internal knowledge base. As such, the knowledge environment was highly changing as pharmaceutical firms struggled to secure the limited sources of knowledge (Zucker & Darby, 1997). The effect of the star scientists appears to peak in the late 1980's and subsequently declines, as this knowledge base became more widely dispersed.

As an example, the Cohen-Boyer patent disclosing the process recombinant DNA (genetic engineering), which was assigned to Stanford University in 1980 (U.S. Patent 4,237,224), represented a scientific breakthrough at the time but now is a common offering in graduate-level biotechnology courses (Galambos & Sturchio, 1998). In Figure 3, this dispersion is illustrated by the steadily increasing count of non-star

publications, as the total number of publications more than doubled, from 5,233 in 1980 to 10,740 in 1990. This trend points to an increasing need of a firm's average or non-star employees. We suggest that this dispersion often results in a shift in the role of individuals in the process of dynamic capability formation. As knowledge disperses throughout the environment, a firm's focus shifts from accessing external information to increasing the effectiveness with which such knowledge is codified and commercialized within the organization, thus moving dynamically from knowledge exploration to knowledge exploitation (March, 1991).

While extant research has focused on the importance of star employees, we posit that the overall process of dynamic capability formation cannot be understood in its entirety without explicit consideration of the average or non-star employees. As highlighted by our analysis, ignoring this potential source of unobserved heterogeneity can result in overestimating the importance of a firm's star employees. Below we develop a typology of research employees that illustrates the disparate, yet equally important roles that stars and staff scientists play in developing dynamic capabilities.

2.4.2 Typology of Research Employees as Boundary Spanners

The typology we present below is based on our examination of the differential roles that individuals play in incumbent firms in knowledge-intensive industries. In keeping with the empirical findings above, we consider *all* the employees involved in the innovation process to be a type of boundary spanner. We focus on all individuals, whether researchers, scientists, or engineers, who are directly involved in the innovation efforts of the firm. As each of these individuals plays a critical role in either facilitating the codification or flow of knowledge within a firm, we suggest that each of these employees should be considered a boundary spanner. The specific role the boundary spanner plays, however, depends on whether an individual is connected to either internal or external sources of knowledge. A significant interaction between the firm's

top management and its research and engineering departments, as developed further below, is needed to effectuate innovation.

The first type of boundary spanner we identify has above average connectivity with external sources of knowledge (Allen, 1977). These individuals are *inter*-organizational boundary spanners, given that their role in the organization is to select and filter the information entering the organization from external sources (Allen & Cohen, 1969; Tushman & Katz, 1980). Similar to the progression of science in society, both too much and too little information can stifle the process of scientific advancement. The filtering role played by these individuals is critical because of the breadth and depth of information available to an organization. Accordingly, these individuals function as gatekeepers and knowledge brokers by facilitating a firm's ability to identify promising areas of focus through connections to external sources of new knowledge within the greater scientific community. We term these individuals *science boundary spanners*.

The value of science boundary spanners to a firm stems less from the likelihood that these individuals create significant scientific breakthroughs themselves, and more from their ability to identify synergies between existing technologies (Schilling, 2005). Their ability to make novel connections between knowledge sources and to discern and leverage possibilities increases the organization's entrepreneurial intuition, which in turn generates new insights and supports exploration of new knowledge (Crossan et al., 1999). Science boundary spanners are most often highly talented individuals, employed within a specific department or laboratory of a firm. Given the time it takes to achieve visibility and gain reputation within scientific communities, these individuals tend to be senior employees. These individuals are frequently employed as directors of specific product innovations or areas of research and laboratory lead scientists.

By contrast, there are two types of *intra*-organizational boundary spanners who are able to increase the efficiency of a firm's communication, given their connectivity *within* an organization (Tushman, 1977). The need for first type of internal boundary

spanner, termed *technological boundary spanners,* is based on the notion that within an organization there exists a need for individuals who are strong researchers but whose primary connectivity is with other researchers within the firm. This type of intra-organizational boundary spanner differs from the typology discussed above, because the importance of these individuals is based on the scale or aggregate effort of the group, rather than on the superior effort of any particular individual. The value provided by technological boundary spanners is that they act to effectuate the change identified by the firm's externally-connected science boundary spanners. These individuals should be primarily responsible for the implementation of the strategic path selected by the science boundary spanners, in conjunction with top management, and are thus responsible for the development of the firm's intellectual property and technological capabilities. These individuals serve to increase an organization's expert intuition.

Whereas entrepreneurial intuition has to do with finding new possibilities for future growth, expert intuition provides insight into pattern recognition (Crossan et al., 1999). These patterns allow for the transformation of deliberate and planned action into tacit knowledge, thus forming expertise (Polanyi, 1967). Within society, and we suggest in an organization as well, this expertise develops more from collective efforts than it does from several key experts (Cole & Cole, 1972). Within this perspective, science progresses through the work of the many, rather than the few. Given that the nature of the connectivity of these boundary spanners is directly related to the scale or number of such individuals, these boundary spanners should be comprised of the firm's average (or laboratory bench) scientists. Whether it is from considerations of tenure or talent, a firm should structure a segment of its innovation efforts to maximize the efficiency of the communication between technological boundary spanners.

From a functional standpoint these non-stars serve a vital role within the organization (DeLong & Vijayaraghavan, 2003). Average performers can serve the important role of grounding and stabilizing the visionaries within the firm. Non-stars are

often more loyal to the organization and can make up for second-rate functional skills through an increased awareness of organizational processes and norms. These individuals often form networks within the firm with other non-star employees, and are thus able to increase the effectiveness of intra-firm communication. Recent empirical research illustrates that the role these non-stars play, as complementary resources, is so significant as to mediate the effect of star scientists on innovative output (Rothaermel & Hess, 2007). It is for this reason that an organization attempting to build effective dynamic capabilities should not be blinded by their star performers at the expense of their average employees.

A second type of *intra*-organizational boundary spanner, termed *science/engineering (S/E) boundary spanners*, is needed because different departments that are each critical to the innovation process often 'speak' different languages due to different mindsets. As such, certain key individuals are needed to 'translate' between different departments within the organization. For firms in high-velocity environments, this translation is most critical between the areas of the firm creating the *science* necessary for invention and those *engineering* the technology to innovate. Firms attempting to innovate require a resource that enables it to communicate between the disparate areas of basic scientific research, engineering, and manufacturing of the final innovative product. Based on this description, we suggest that S/E boundary spanners serve to increase the organization's interpretive ability by playing a key role in the firm's ability to actually create or manufacture the product based on the developed intellectual property. This ability requires the organization to develop an understanding of how to turn an invention into a commercializable innovation (Crossan et al., 1999). This capability to integrate disparate activities stems from the creation of a cognitive map, based on the experiences of the organization that creates a common language and shared meaning between disparate areas of the organization. It is through this

mechanism that S/E boundary spanners increase the efficiency of communication within the organization.

The requisite level of intra-organizational connectivity suggests that these individuals tend to be employed in a more general managerial role within the R&D or innovation process. These individuals might be employed as Chief Technology Officer, Chief Operating Officer, or Chief Executive Officer. Given the differences in their type of connectivity they possess, the same individual is not likely to occupy the role of both a science and S/E boundary spanner. Exceptions to this may be in limited resource conditions, such as small firms, or in extreme velocity environments, when key knowledge is held by only a few individuals, as was the case in the early years of biotechnology. The final step of our analysis is to illustrate how these types of research employees are utilized by incumbent firms to surpass the knowledge gaps that they encounter in the process of attempting to develop dynamic capabilities.

2.5 Building Dynamic Capabilities

2.5.1 Spanning the Cognitive Gap: Exploring for New Strategic Paths

Relating this discussion to March's (1991) development of the exploration-exploitation framework, surpassing the cognitive gap requires that firm undertakes exploratory activities. We suggest that the effectiveness of its exploratory activities is directly related to its *science* boundary spanners. This assertion is based on the notion that exploratory activities are focused on developing strategic opportunities for the organization. To assess the attributes of the strategic alternatives, information related to prior decisions made is combined with information attained from external sources of knowledge. To search out and assess new opportunities, organizations must be able to scan, create, learn, and interpret disparate sources of information (Teece, 2007). Thus, the selection of future strategic paths requires a resource that is connected to both the external and internal firm networks. A firm's science boundary spanners, in conjunction

with top management, facilitate a firm's ability to cross the cognitive gap by selecting between options representing future strategic paths. An organization focused on reducing the cognitive gap with the environment is interested in developing connections or channels with external sources through which information flows into the organization. Connectivity to external sources of knowledge in turn improves the positioning of a firm within its network (Powell et al., 1996).

The critical role that top management teams play in deciding firm strategy when it emerges from deep within the organization has been well-developed in the management literature (Burgelman, 1994; Kaplan et al., 2003; Tushman & Rosenkopf, 1996). This literature has illustrated that it is important for a firm's top management team to have both the focus and the technical ability to understand the strategic options presented to them (Kaplan et al., 2003). What remain unexamined are the mechanisms that top managers employ to gain both the knowledge of the alternatives as well as the ability to evaluate them. This research thus far has been limited to examining the managerial social networks, including job mobility and board interlocks (Rao, Davis, & Ward, 2000; Uzzi, 1997). Following the bottom-up perspective advanced by Rosenkopf, Metiu, and George (2001), analysis of managerial cognition requires the consideration of the interactions between top management teams and the firm's lower-level, but front-line researchers. Unlike Rosenkopf et al. (2001), however, we posit that these interactions should be formalized into organizational routines and structure, rather than be voluntary and non-contractual in nature. The formalization of such a consultancy role helps to shed light on how these individuals can increase the entrepreneurial intuition of the organization.

Support for the formalization of the role of science boundary spanners with top management is provided by Mintzberg and McHugh (1985), who note that a firm's emergent strategies are often formed through interactions between many people, including operating personnel, experts, and advisors. These experts and advisors not

only facilitate the process of selecting between strategic options but also the selection of the appropriate mechanisms (e.g., alliances, acquisitions, joint ventures, etc.) that should be employed to effectuate the selected strategic path (Ettlie and Pavlou, 2006; Rosenkopf et al., 2001). Given their position within the firm, the science boundary spanners, acting as knowledge brokers, should be used as consultants to the top management team for the firm to effectively develop the stock of real options representing areas of future growth (McGrath, 1997). This consultancy role allows the science boundary spanners to act as the champion of the new path or technology. Prior research has illustrated that the presence of such a technological champion increases the likelihood of buy-in from the top management team, which in turn results in greater financial and managerial support for the development of that technology (Hargadon & Sutton, 1997; Howell & Higgins, 1990). Additionally, this consultancy with science boundary spanners may quicken the process through which new technologies are identified, and thus lead to an earlier involvement of top managers in the process of new product development. This earlier involvement is key due to the observed inverse relationship over time between top managers' interest in the new product development process (which reaches its peak shortly before product introduction) and the ability to influence its direction based on strategic considerations (Schilling, 2005).

A firm's science boundary spanners represent a resource that both directly and indirectly helps the firm to increase its cognitive absorptive capacity. Science boundary spanners serve to not only select relevant information but also to limit irrelevant information from distracting the focus of the firm (Allen & Cohen, 1969). Their task is more often than not to decide which new knowledge *not* to pursue, rather than to identify new knowledge that should underlie a new strategic path. These boundary spanners have been shown to have to a significant positive effect on organizational subunit innovative output (Tushman & Katz, 1980). Well-connected individuals, acting as information gatherers and filters, are thus able to guide the organization down selected

pathways based on the characteristics of the information disseminated. Without such individuals, the innovation process of a firm would be 'headless,' and as such would be stifled by either too much or too little pertinent information coming into organizations. A key aspect of the boundary spanner role is creating knowledge conduits from the external environment into the firm through selection of alliance partners, acquisition targets, or choosing between alternative strategic directions.

Monsanto's early experience with university alliances illustrates the extent to which the presence of a science boundary spanner, in the form of a star scientist, can positively influence the quality of a firm's external technological sourcing. In Monsanto's attempt to transform their core business from a chemical to a life sciences company, it pursued a number of alliances with universities' research laboratories (Hill, 2004). The company found one of its first agreements, with Harvard Medical School, to be unsatisfying because the Monsanto scientists were unable to gain pre-publication access to the research findings and were unable to influence the direction of Harvard's research program. Subsequently, Monsanto hired star scientist Howard Schneiderman (dean of biological sciences at University of California, Irvine, and a leading expert in genetic engineering) to head the firm's research and development efforts. Schneiderman was able to influence not only whom Monsanto chose as partners, but also was able to negotiate subsequent agreements to give the firm greater access to and influence of the research process. As an example, under Schneiderman, Monsanto funded significant projects with key scientists at Washington University in St. Louis and Oxford University in the U.K., allowing the universities to hold any resulting patents while the company retained exclusive marketing rights. The decision to invest was made by a committee that included a combination of Monsanto and university scientists. Thus, key Monsanto scientists acting as boundary spanners, including Schneiderman, were able to guide the company toward research institutions where they felt the basic and applied research conducted could provide the most benefit to the firm.

Another important aspect of the science boundary spanner is the indirect effect these individuals often have on an organization, as they frequently adopt a training and socialization role within the organization (Tushman & Katz, 1980). Through this lens, boundary spanners facilitate the external communication skills of their colleagues through training and coaching on the job. The activity of science boundary spanners enhances the overall cognitive absorptive capacity of the organization by increasing the connectedness of other firm employees. It is through this process that the knowledge related to a new technology is disseminated.

2.5.2 Spanning the Operational Gap: Exploiting the Current Knowledge Base

By contrast, the spanning of the operation gap requires that the organization undertake activities that are focused on exploiting the current knowledge base. As suggested by our systems approach to dynamic capability formation, the firm's ability to identify promising paths is moot, if the firm is unable to effectuate the needed changes within the organization. The exploitive activities within the organization are effectuated by its *technological* boundary spanners. The importance of these individuals is illustrated by the notion that firms wishing to take advantage of research conducted outside their organizational boundaries need to invest in absorptive capacity by accumulating the knowledge, skills, and organizational routines necessary to identify and utilize externally generated knowledge (Cohen & Levinthal, 1990). These investments in a firm's absorptive capacity are particularly salient if firms are to take advantage of upstream advances in fundamental science (Cockburn & Henderson, 1998). If a firm is to be able to sense and react to shifts in the environment it must not only have sufficient connections to the external environment, but also the requisite knowledge assets and processes to effectuate the needed change. Relating this to the Crossan et al. (1999) framework, this knowledge represents the organization's expert intuition. In support of the notion that individuals matter to the development of such intuition, Cohen and

Levinthal (1990) note that absorptive capacity tends to develop cumulatively as a function of the scale of the organization's intellectual human capital.

For the firm to surpass the operational gap, therefore, a firm's investment in individuals should be focused on the scale or aggregate efforts of its individuals, rather than the few elite employees. Such scale is needed for the firm to develop the expertise to understand the knowledge associated with a chosen strategic path, which is the footprint of a strong absorptive capacity. As such, the firm's technological boundary spanners become critical for a firm to develop the requisite absorptive capacity. The processes developed during this stage serve to further reduce the uncertainties inherent to adapting to a shifting knowledge environment.

The notion that average employees matter represents a shift from the focus of prior research that has highlighted the importance of the elite employees. Support for the notion regarding the importance of non-star employees is provided in research demonstrating a positive effect of a firm's overall human and social capital on firm performance (Gardner, 2005; Hitt et al., 2001). Additionally, a firm's stock of intellectual human capital has been shown to be critical to its ability to adapt to a changing environment (Cockburn & Henderson, 1998; Rothaermel & Hess, 2007). As an example of this, Henderson and Cockburn (1994) find that locally embedded knowledge and skills are a specific competence for the firm and a source of enduring competitive advantage. More specifically, the disciplinary focus of groups of scientists within the firm can create deeply embedded knowledge that is not easily codified, and is thus difficult to transfer or imitate. In a similar fashion, Leonard-Barton (1992) indicates that the tacit knowledge developed by engineers with a specific production process over an extended period of time can develop into a source of competitive advantage for the firm. The specificity of the complex learning necessary for a firm to codify the knowledge associated with a new technology favors those firms that invest in significant levels of intellectual human capital, here conceptualized as the number of non-star employees within a firm.

InnoCentive, an initiative matching scientists to R&D challenges posed by organizations seeking assistance, supports our contention that successful spanning of the operational gap requires a critical mass of non-star employees. As this example illustrates, scale does not necessarily represent the development of an internal competency, but rather can be the product of ample connectivity with the external scientific environment. Specifically, by using InnoCentive, an organization attempts to build an expertise by opening its R&D process to any scientist, not just researchers within the organizational boundaries. As individuals, the scientists of the InnoCentive network are not necessarily stars. Any researcher, or group of researchers, can submit a solution and potentially win a pre-specified reward for solving the problem. In return, these individuals sign over the related intellectual property rights. The effectiveness of this approach is illustrated by the fact that many companies including Boeing, Ciba, Dow, DuPont, Novartis, and Procter & Gamble have all joined the InnoCentive network exchange.

The InnoCentive example helps to illustrate the distinction between expert and entrepreneurial intuition (Crossan et al., 1999). More specifically, organizations seeking the support of the InnoCentive network are attempting to build their expert intuition. It is important to note that the utilization of this approach cannot directly facilitate the development of entrepreneurial intuition. Such intuition is a pre-requisite for the seeking organization, however, as it must have ex-ante knowledge relating to the potential solutions. In addition, if the seeking organization is to derive value from its participation in the InnoCentive network, it must be able to clearly define the problem of interest. Thus, it remains up to the individual firms or clients of InnoCentive to determine what question *should* be asked or how the knowledge gained *should* be transformed into manufacturing.

The sequence of how new knowledge enters an organization and is subsequently transformed into innovation matters. More specifically, the cognitive gap

must be spanned prior to the firm attempting to cross the operational gap. In a similar notion, Zollo and Winter (2002) indicate that codification by itself does not necessarily yield benefits to the firm. They posit that the codification process must not only be done correctly for it to benefit the firm, but that the codification process itself can lead to the early identification of potential mistakes. In contrast, it is not the codification process that helps to identify mistakes but instead, the final obstacle in the dynamic capability formation process, the spanning of the engineering gap.

2.5.3 Spanning the Engineering Gap: Turning Invention into Innovation

While exploration and exploitation activities are critical for innovation at the process or capability level, additional activities focused on the integration of these activities is necessary for organizational adaptation to occur. As previously discussed, activities focused on integration are very difficult for organizations because of the significant mismatch between the communities of practice focused on science and those on engineering activities. The mismatch between these different communities can be potentially alleviated by the use of boundary spanners. Compared to the science boundary spanners, the value of science/engineering boundary spanners in spanning this gap stems from their connectivity *within* the firm (Tushman & Katz, 1980). Specifically, in industries where the locus of knowledge is upstream, S/E boundary spanners are critical because they serve to connect the disparate departments relating to the discovery of an invention and those relating to engineering the manufacturing of the innovation. As previously mentioned, these individuals increase the efficiency of communication within the organization by increasing the organization's ability to 'speak' a common language across disparate sources of knowledge. S/E boundary spanners take on an active training and socialization role within the organization (Tushman & Katz, 1980).

S/E boundary spanners are employed to answer such critical questions as: how does this invention fit our current business? Can this invention be effectively and efficiently manufactured, and thus turned into innovation? Can the underlying technology be protected? What will the market reaction to the product be? It is important to note that the S/E boundary spanning role can be filled by specific individuals within the firm, or by a process through which the opinions of key individuals in disparate departments are compiled together to form a single opinion.

An example from Intel illustrates how key individuals can fill the S/E boundary spanner role as well as instill a culture that fosters the needed level of connectivity between business practices. The founders of Intel, Gordon Moore and Robert Noyce, had worked at Fairchild and designed the R&D process at Intel specifically to minimize the engineering gap. Intel fostered the S/E boundary spanning nature of its employees by assigning each of its new researchers to work for six months in the manufacturing department (Chesbrough, 2003). By contrast, Procter & Gamble (P&G) filled the S/E boundary spanning role by developing a process, called the 'eureka catalog,' that was distributed to key managers in marketing, manufacturing, R&D and others (Huston & Sakkab, 2006). P&G laboratory heads solicit comments from each of these managers and formulate general opinions as to whether or not a project should be recommended for manufacturing. Both of these approaches appear to be effective in filling the S/E boundary spanning role.

2.5.4 The Feedback Loop: Learning from the Dynamic Capability Formation Process

The final step in the dynamic capability formation process involves the learning or reciprocal nature of the relationship between the sub-categories of dynamic capabilities. During this process the firm must transmit the results of the entire formation process back to be used for the selection of future firm paths. This importance stems from the notion that for a firm to adapt to a continuously changing knowledge environment, it must

be a member of the larger scientific community. Within the scientific community, a member must give, if it is to get. To gain access to and membership in these communities, a firm must be actively involved in the disclosure of new knowledge through presentations at conferences and publications in academic journals. Thus, biotechnology or pharmaceutical firms whose members are actively participating in this community are more efficient learners and, therefore, have a higher absorptive capacity than firms not included in this network (Deeds, 2001). Depending on whether the knowledge created is proprietary (e.g., trade secrets) or open (e.g., publications or patents), the knowledge may or may not extend outside the organization. Successful management of the learning or feedback loop requires a resource that not only has strong intra-organizational connections, but also a fundamental understanding of the larger scientific community. Based on this, the S/E boundary spanners should play a significant role in the circulation of information within the firm, while the science boundary spanners, in conjunction with top management, should ultimately make the decisions as to which information gets released outside of the firm.

2.6 The Model in Action at Merck

While the analysis of the individual components of our framework offer interesting insights into the formation of dynamic capabilities, the true complexities of the innovation process can only be examined when the entire model is analyzed in action. Merck's successful vaccine research development program in the 1970's and 1980's illustrates the various important, yet disparate roles played by individuals in an effective dynamic capability formation process.

Merck, one of the most successful pharmaceutical firms in the U.S., can attribute its high performance to its superior in-house research capability and drug discovery and development processes (Gambardella, 1992). Head scientists, acting as science boundary spanners, have been successful in the recruitment and retention of strong

research personnel, in part because they maintain an academic-like atmosphere within the company's research laboratories. Additionally, by promoting scientists to managerial roles within the company, Merck has been able to foster effective S/E boundary spanners. This combination of visionary scientists and strong internal communication mechanisms allowed Merck to out-innovate its competitors and develop an effective and affordable vaccine for hepatitis B. As reflected in our framework, the process was not linear, but rather iterative as Merck learned from its prior mistakes.

The hepatitis B vaccine, unlike the vaccines for polio, measles, mumps, and rubella, could not be cultivated in cell culture (Galambos & Sewell, 1995). The development of a successful vaccine would require human blood, where only subunits of the human virus would be used. Maurice Hilleman, working as a 'star' biologist at the Merck Institute for Therapeutic Research, recognized the need to develop an effective vaccine for hepatitis B as well as the importance of the possibility of developing a vaccine from subunits of the virus. Hilleman was not the head of the Merck's Virus and Cell Biology Research Department, but was well-connected in the science community, and ultimately played a central role in developing the company's scientific capabilities. Based on his positioning and tenure, we suggest that Hilleman was acting in the role of science boundary spanner. Following Hilleman's chosen path, Merck developed the capabilities and knowledge base that was new to both the firm and the industry. After many years of extensive research and testing, Merck developed a subunit hepatitis B vaccine made from purified human blood. By 1981, the serum-based vaccine was made available for general use (Patlack, 2000).

The initial vaccine developed was expensive and had a lead time that was longer than any other vaccine at the time. Production of the hepatitis B subunit vaccine in large quantities was hampered by the need for the blood of hepatitis B carriers and the realization that the plasma form of the vaccine raised concerns with the public regarding its safety in light of the newly discovered AIDS virus (Galambos & Sewell, 1995).

Working with the former scientist turned CEO, Roy Valegos, Hilleman realized that the current vaccine production would not be practical in meeting demand. Changing the vaccine required that Merck create new connections both within Merck and between its research partners. As CEO and a former research scientist, Valegos was an effective S/E boundary spanner and thus was well-aware of many of the other research initiatives both at Merck and within the scientific community. Through this connectivity, he recognized the new developments in DNA technology and molecular biology and the unique opportunities they offered researchers producing antigens.

While Hilleman encouraged Merck to spend more than $8 million (roughly $26 million in 2005 dollars) on upgrading its production facilities, Valegos recognized that Merck did not have the necessary capabilities in-house to make large-scale vaccine production possible. Instead, he hired microbiologists and refocused the firm's labs on using this new technology for vaccine research. Valegos used this new knowledge base to establish collaborative research programs with renowned scientist William Rutter at the University of California, San Francisco. This partnership eventually lead to the novel technique used to insert genetic information into DNA, termed genetic splicing (Galambos & Sewell, 1995). This new process would both ensure that the vaccine contained no contamination from other sources and allowed production of large quantities of the vaccine (Patlack, 2000). Merck spent considerable time and effort to develop the internal capability to produce a recombinant yeast-derived antigen, rather than the previously developed blood plasma-derived antigen.

Hilleman, acting as a science boundary spanner, identified the appropriate *path* for Merck to pursue. Following his advice, Merck devoted significant time and money to hire the technological boundary spanners needed to build the new technical capabilities and *processes* necessary to develop this vaccine. Lastly, acting as the S/E boundary spanner, Valegos recognized the need for changes and redirection of the processes if effective and efficient manufacturing and development was to take place. Altogether,

these interactions led to Merck's new innovative *position*, an improved version of a hepatitis B vaccine. This recombinant vaccine was the first of its kind for use in humans and was approved by the U.S. Food and Drug Administration for general use in 1986, after nine years of research (Patlack, 2000). Merck's Recombivax HB has been identified as the sixth largest blockbuster drug to license the Cohen-Boyer recombinant DNA patent (Feldman, 2005).

2.7 Discussion

We advanced herein a framework that explicates a system of dynamic capability formation. Our point of departure is the contention that the process of continuous firm-level innovation is hampered by three distinct knowledge gaps relating to the development of the sub-categories of dynamic capabilities identified by Teece et al. (1997): a cognitive gap, an operational gap, and an engineering gap. By analyzing how individuals can help span these gaps, we shed light on the relationship between elite and average employees in the context of firm innovation. While this relationship has primarily been considered to be substitutive or competitive in nature, our analysis illustrates that the roles of elite and average employees are actually complementary in nature. Viewed through a sociological lens, this paper offers an extension of the Kuhnian paradigm (Kuhn, 1962). Whereas Kuhn describes a world in which some key scientists perform a paradigm-breaking function and a much larger group performs the "normal science" that follows, we argue that this perspective also applies to the framework of dynamic capability formation within an organization.

To accomplish this we leverage the construct of boundary spanning within an organization, which treats the individual's level of connectivity as the value-driving characteristic. By positioning this construct within our framework of innovation, we highlight that, in addition to the elite employees playing the role of boundary spanners, the average employees should also be considered boundary spanners. To effectively

build dynamic capabilities, a firm should construct its innovative efforts to recognize not only the existence of these disparate roles, but also leverage their path-dependent nature.

Within the setting of incumbent firms in knowledge-intensive industry, this path-dependence illustrates that dynamic capabilities can only be built if the knowledge gaps are spanned in sequential order. This order is critical because the first step of the process requires the firm to identify the environmental shift of concern, as well as discern the appropriate strategies in response. The activities associated with surpassing this gap are exploratory in nature. The effectiveness of these activities directly relate to the technical fitness of the dynamic capability being developed. We demonstrate that the firm's science boundary spanners are critical to the success of these activities. Here, we suggest that there is an inverse relationship between the velocity of an industry and the number of individuals with whom the new knowledge resides. In high-velocity environments the new knowledge is initially held only by a few key individuals that can leverage a significant connectivity with the external environment. The initial period after the emergence of biotechnology serves as a good illustrator of this relationship (Zucker and Darby, 1997b; Zucker, et al. 1998b).

During the second stage of our framework, technological boundary spanners codify the knowledge gained in the first stage to develop the ordinary capabilities necessary to effectuate the identified change. A firm's technological boundary spanners, comprised largely of the firm's average scientists, serve to develop the technological capabilities needed to accomplish this goal. Given that the focus of these activities is often on improving technological and operating efficiencies, these activities are exploitive in nature.

The third stage in the process of dynamic capability formation requires that a firm to integrate its new and existing capabilities and processes it has developed in prior stages in our framework. Again, this is accomplished by highly connected individuals or

boundary spanners. These individuals, termed science/engineering boundary spanners, are well connected internally within the firm (rather than externally, as in the case with science boundary spanners). These individuals facilitate communication between the disparate organizational departments or divisions associated with basic science and engineering. Taken together, the effectiveness of the organization in surpassing these two knowledge gaps directly relates to its evolutionary fitness. Incorporating this notion into our system of dynamic capability development illustrates that technical fitness is a necessary but not sufficient condition for the organizational growth, survival, and competitiveness associated with evolutionary fitness (Helfat, et al. 2007). Following this logic, while star scientists may allow an organization to sense and react to opportunities, it is the balance between stars and staff scientists that gives organizations the ability to exploit these opportunities.

In the final stage of the process, the science and S/E boundary spanners of the firm transmit knowledge related to the overall process of innovation outwards to accomplish knowledge diffusion within the organization, and, where advantageous, beyond the organization's boundaries to participate in the open science community. The amount and destination of this knowledge is determined by the nature of both the intellectual property produced as well as the nature of the knowledge environment facing the firm. The information contained in these feedback loops is of critical importance to the firm's ability to evaluate and integrate emergent strategies (Mintzberg & McHugh, 1985).

Top management plays two critical roles in the innovation process. The first role comes about through interactions with the firm's boundary spanners, who serve as knowledge brokers for these top managers and thus are central to the decision-making process. The second role played by top managers is in determining how the firm allocates its resources between stages of the dynamic capability formation process. Given that our typologies of boundary spanners are formalized, their direction and

implementation requires managerial attention. To illustrate this point, we suggest that while the process of dynamic capability formation is cyclical, it does not follow that each stage is equally important to every firm. In assessing which of the three disparate stages is the most critical in determining the effectiveness of the developed capability, it is important to once again investigate the knowledge structure of the underlying knowledge environment as well as the strategic direction of the firm.

For example, in industries where the majority of the velocity comes from accessing upstream information for the purposes of differentiating the firm's product offering (e.g., biotechnology and pharmaceuticals) the first step in the process is the most critical. By contrast, when cost is the primary driver of innovation (e.g., wholesale retailing), it may be the second step that is critical to the effectiveness of the developed capabilities. Finally, if uncertainty of an industry stems from the ability of a firm to successfully and efficiently manufacture the end technology (e.g., semiconductors) the final stage in the model is the most critical. In this case, S/E and technological boundary spanners play important roles in dynamic capability formation.

2.71 Conclusion

The construct of dynamic capabilities has been met with skepticism. The tautological conceptualization of dynamic capabilities is the primary reason that, in more than a decade since its inception, researchers have struggled to use the construct in the prescriptive fashion called for by Teece and colleagues (Teece & Pisano, 1994; Teece et al., 1997). This conceptualization results from neglecting the inherent multi-level nature of the construct. Recent research has attempted to overcome this shortcoming by investigating the micro-foundations of such capabilities—the skills, processes, procedures, and organizational structures that comprise dynamic capabilities (Teece, 2007). Of interest, however, is that these processes and procedures themselves represent collective actions. As such, we suggest that the actual micro-foundations of

dynamic capabilities are the individuals within the firm (Felin and Hesterly, 2007). Thus, we suggest that the foundations of long run enterprise success may rest in the organization's ability to understand the different roles individuals play in the formation of dynamic capabilities. It is important to note that identification and implementation of these roles represents a necessary but not sufficient condition to effective dynamic capability formation. Rather, the formation of effective dynamic capabilities requires that the right individuals be inserted into the appropriate roles in the system of capability formation. Therefore, understanding the heterogeneity inherent in the organizational intellectual human capital is critical to both the technical and evolutionary fitness of the developed capabilities.

In the spirit of prior conceptual work on dynamic capabilities (Eisenhardt and Martin, 2000; Teece, et al. 1997), application of the framework we have developed here should allow a firm to adapt or even create continuously changing environments, and thereby gain competitive advantage through earning a continuous string of Schumpeterian rents based on the introductions of innovative products or services. The systematic nature of capability formation is illustrated by the fact that this evolutionary fitness is a function of the technical fitness of its existing capabilities (Helfat et al., 2007). Further, technical fitness is itself a function of the organization's ability to develop formalized roles for individuals within the organization's decision-making process. To this end, we introduce a typology of these different roles that helps explicate how firms can identify, modify, and implement emergent strategies. By developing the inputs and outputs of the construct independently, we have moved past the tautological conceptualization of dynamic capabilities, thus opening the door for empirical researchers to attempt the needed falsification of the dynamic capability formation model developed herein.

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CHAPTER 3

INNOVATING WITHIN A NEW TECHNOLOGICAL PARADIGM: THE ROLE OF INDIVIDUAL, FIRM, AND NETWORK-LEVEL EFFECTS IN BUILDING CAPABILITIES

3.1 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 learn and innovate and thus to realize potential competitive advantages (Teece, Pisano, and Shuen, 1997: 516). 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 Teece, et al. 1997).

Assuming that firms 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?*

In attempting to answer the question pertaining to the locus of the antecedents to dynamic capabilities, extant research has generally focused on only one level of

analysis, while neglecting other levels of analysis, thus opening the door for spurious findings due to unobserved heterogeneity. In their insightful theoretical treatment of the locus of knowledge in value creation, Felin and Hesterly (2005) identify two serious problems with the uni-level research approach. 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 the 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 threats of homogeneity to and independence from alternate levels of analysis are serious concerns that can potentially lead to spurious empirical findings.

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 highlighting 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.

To address the threats of homogeneity and independence common in prior research, we develop a multi-level theoretical model that accounts for potential heterogeneity at and across three different and distinct levels when predicting innovation within a new technological paradigm. In particular, we integrate potential heterogeneity at the individual, the firm, and the network-level of analysis by developing direct- as well as moderating-effect hypotheses. Thus, the three levels of analysis revealed in this process of building capabilities are: the *individual-level*, representing internal investments such as employee hiring (Allen and Cohen, 1969; Cockburn and Henderson, 1998; Lacetera, et al. 2004; Stuart, Ozdemir, and Ding, 2003; Zucker and Darby, 1997), the *firm-level*, representing internal investments such as research and development (R&D) (Almeida, Song, and Grant, 2002; Cockburn and Henderson, 1998; Cohen and Levinthal, 1989; Deeds, 2001; Henderson and Cockburn, 1994; Zahra and George, 2000), and the *network-level*, representing external investments such as alliances (George, Zahra, and Wood, 2002; Gulati, 1999; Hagedoorn and Schankenraad, 1994; Owen-Smith and Powell, 2004; Rothaermel, 2001; Shan, Walker, and Kogut, 1994)

While prior work clearly demonstrates that each of these three distinct levels of capability development affect a firm's ability to innovate through the acquisition of new knowledge, each of the three research streams has neglected to consider the challenges of homogeneity and independence across levels. Therefore, their results may be spurious due to misattribution (Felin and Hesterly, 2005). Moreover, such an isolated research approach does not help us answer questions pertaining to the relative importance of each level, nor does it allow us to address questions concerning interactions across different levels.

In contrast, the integrative theoretical approach advanced herein enables us to not only assess the effect of each level of analysis on innovation in isolation, while controlling for potentially confounding lower- or higher-order levels of analysis, but also to assess how the three different levels of analysis moderate one another. Indeed, we hope to make our most significant theoretical contribution by analyzing different interaction effects across different levels. This approach enables us to test the hypotheses that the different individual, firm, and network mechanisms that build dynamic capabilities in the face of radical technological change can be considered as complements or substitutes.

The research setting selected to empirically test such an integrative theoretical model across multiple levels of analysis is the global pharmaceutical industry, which experienced a radical transformation during the 23-year period between 1980 and 2002. Here, we document the attempts of incumbent pharmaceutical companies to build the capabilities necessary to innovate within the new biotechnology paradigm. Methodologically, we make a contribution in developing and analyzing a novel panel dataset that approaches the population of observations across different levels of analysis and categories. Due to exhaustive data collection efforts on our part, in combination with the generous support of the U.S. Patent and Trademark office, we are fortunate to leverage fine-grained data on over 900 acquisitions, 4,000 alliances, 13,200 biotechnology patents, 110,000 non-biotechnology patents, 130,000 scientists, 480,000 publications, and 2.2 million journal citations.

3.2 Theory and Hypotheses Development

In the subsequent section, we develop hypotheses pertaining to the role of individual, firm, and network-level effects when predicting innovation within a new technological paradigm. We move from a micro-level to a macro-level of analysis by

beginning with an examination of individual-level effects before analyzing firm- and network-level effects. The development of direct effects hypotheses is necessary to assess the effect of each level of analysis on firm innovation, while explicitly controlling for confounding levels of analysis. This approach allows us to challenge the assumption of homogeneity across levels that is implicit in most extant research explaining and predicting innovation. After developing the direct effects hypotheses, we concentrate on the interactions across levels, where we advance hypotheses highlighting complementarity and substitutability across the three different levels under investigation. This allows us to assess the validity of the assumption of independence across levels that is commonly found in prior research.

3.1.1 Individual-level Effects

3.1.1.1 Intellectual Human Capital. Most of the empirical research investigating the locus of innovation focuses primarily on the networks of inter-organizational relationships (e.g., Ahuja, 2000; DeCarolis and Deeds, 1999; Hagedoorn, 1993; Shan et al., 1994; Powell, Koput, and Smith-Doerr, 1996; Rothaermel, 2001; Stuart, 2000). Thus, it is not surprising that both Teece et al. (1997: 518-520) and Eisenhardt and Martin (2000: 1108, 1112) explicitly highlight 'allying' as a dynamic capability. Uni-level research focuses on alliances and networks, and implicitly assumes not only that lower levels (i.e., firm and individual levels) are homogenous, but also a lack of primacy in the consideration of the import of the individuals to firm-level heterogeneity (Felin and Hesterly, 2005).

By investigating individual-level effects as a critical antecedent to firm-level innovation, we attempt to question the legitimacy of the conjecture of homogeneity across levels. In contrast to the assumption of perfectly competitive factor markets (Hirshleifer, 1980), we posit that intellectual human capital can be heterogeneously distributed across firms, and thus must be accounted for when investigating firm-level

innovation (Barney, 1986; Felin and Hesterly, 2005). With intellectual human capital, we refer to 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 when we focus on research scientists that publish in academic journals.

We posit that intellectual human capital facilitates a firm's innovative output within a new technological paradigm. We build on prior research that has investigated the role that intellectual human capital plays in helping a firm process and utilize external information (Cockburn and Henderson, 1998; Lacetera et al., 2004; Stuart et al., 2003; Zucker and Darby, 1997). This research reveals that while alliances and acquisitions can be necessary to a firm's ability to innovate and adapt, they are often of little value if the firm is not able to codify and integrate the external information (Allen, 1977; Allen and Cohen, 1969; Levinthal and Cohen, 1990; Tushman, 1977; Tushman and Katz, 1980). The importance of highly-skilled human capital was demonstrated by Allen and Cohen (1969), who produced convincing evidence for the existence of different coding schemes between organizations, specifically between academic institutions and corporate R&D facilities. These different coding schemes create the possibility of communication difficulties in knowledge transfer. This mismatch can be potentially alleviated by the use of a few key individuals "who are capable of translating between two coding schemes either through personal contact or knowledge of the literature, and who can act as bridges linking the organization to other organizations and workers in the field" (Allen and Cohen, 1969: 13). Thus, intellectual human capital can link organizations effectively to external information, while enhancing the internal efficiency of communication.

Accordingly, prior research highlights 'gate keeping' and 'boundary-spanning' as possible mechanisms to overcome the difficulties of communicating simultaneously

across and within organizations (Allen, 1977; Allen and Cohen, 1969; Tushman, 1977; Tushman and Katz, 1980). Gatekeepers are thus defined as key individuals within a firm who are capable of understanding and translating contrasting coding schemes. Additionally, individuals acting as gatekeepers are able to span organizational/environmental boundaries to act as an information filter by evaluating, streamlining, and organizing knowledge flows from external sources (Tushman and Katz, 1980). 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 to translate and disseminate this information into terms that are meaningful and useful to other organization members.

Research also indicates that firm innovative performance is at least partially a function of the value of its human capital, which, in turn, is critical to an organization's ability to adapt to a changing environment (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 pharmaceutical biotechnology 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).

To understand intellectual human capital, researchers have investigated the role that the development of tacit knowledge plays in a firm's ability to adapt to new technological paradigms. As an example, Henderson and Cockburn (1994) find that locally embedded knowledge and skills among a firm's intellectual human capital may be a competence for the firm and a source of enduring competitive advantage. More

specifically, it is the disciplinary focus of groups of scientists within the firm that can create 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 in the field of diabetic therapy or Hoffman-La Roche in the area of anti-anxiety drugs (Henderson and Cockburn, 1994). 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 and thus competitive advantage for the firm. Taken together, the specificity of the complex external and internal learning necessary for a firm to generate innovation within a new technological paradigm favors those firms that invest in and maintain significant levels of intellectual human capital.

Hypothesis 1a:A firm's innovative output within a new technological paradigm is a positive function of its intellectual human capital.

3.1.1.2 Star Scientists. Numerous empirical and qualitative studies provide convincing evidence, however, that not all intellectual human capital is created equally. Thus, significant heterogeneity exists even 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. Such a skewed distribution in research output across scientists is also reflected in recent data on patenting activity in U.S. and Japanese semiconductor firms (Narin and Breitzman, 1995) as well as patenting output in German companies in the chemical, mechanical, and electric industries (Ernst, Leptien, and Vitt, 2000). Thus, we suggest that intellectual human capital can be conceptualized as consisting of two components: star scientists and non-star scientists. Here, we

hypothesize that there exists a positive and significant relationship between a firm's star scientists and its innovative output, while explicitly controlling for non-star scientists.

While the analysis of nearly any performance metric will yield high performers, the magnitude of the 'stardom' of the scientists identified by Zucker and colleagues, for example, can be illustrated by the following statistics. Zucker et al. identified, based on publication measures, 327 star scientists in biotechnology (Zucker and Darby, 1997; Zucker et al., 2002). These 327 stars constituted only 0.75% of the population of biotechnology scientists, but accounted for 17.3% of all the published articles. These stars published more than 23 times as many articles as the average scientist.

Within the context of entrepreneurial biotechnology ventures, star scientists have been shown to affect the 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 heterogeneity inherent in most firm-level and alliance research is even more questionable when focusing on elite scientists as part of a firm's intellectual human capital.

A firm's star scientists not only function as technological boundary-spanners and gatekeepers, but also as the organization's information and knowledge center, and thus are critical to firm innovation. Other important pathways through which star scientists can improve the innovative output of firms include positive spillovers to other researchers through the changing of behavioral and cultural norms, such as legitimizing a stronger focus on basic research, changing the strategic direction of the firm's

research and human resource policies, recruiting other like-minded scientists, and so forth (Lacetera, et al. 2004).

Individual-level heterogeneity in the form of star scientists can provide a plausible alternative explanation for many firm-level performance variables highlighted in prior research. This assertion is an important one, because it challenges the hypothesis of perfectly competitive factor markets (Hirshleifer, 1980). Assuming perfectly competitive markets, rent-generating resources cannot be bought in strategic factor markets, because the price of the resource should anticipate its rent-generating potential, and thus the rents will be captured by the resource owner (i.e., star scientists) and not by the firms who hire the stars. Therefore, the simple act of hiring additional employees, regardless of talent level, cannot in itself result in a significant source of competitive advantage. For example, the mobility of a Nobel prize-winning chemist is likely to result in a wage that is reflective of their value-generating capability, thus any rent-generating potential is captured by the star scientist and not by the firm employing the star.

Contrary to the arguments put forth in the treatment of perfectly competitive factor markets in neo-classical economics (Hirshleifer, 1980), we propose that star scientists can be recruited from the labor market, and that they can be the source of firm-level heterogeneity, especially as it pertains to innovative output. This assertion is especially true if firms have different ex-ante expectations of the rent-generating potential of a star scientist (Barney, 1986). 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 imperfections. 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. Thus, the assumption of imperfectly competitive strategic factor markets would enable incumbent firms to recruit star scientists, which may then be an antecedent to firm-level competitive advantage. Herein, the effect of stars on firm performance is hypothesized to be particularly pronounced when incumbents need to innovate within a new technological paradigm.

Hypothesis 1b:A firm's innovative output within a new technological paradigm is a positive function of its star scientists, controlling for non-star scientists.

3.1.2 Firm-level Effects

Following Cohen and Levinthal (1989, 1990), we posit that organizations are heterogeneous in their capability to recognize, assimilate, and process external new information (see also Zahra and George, 2002). Thus, we suggest that heterogeneity in absorptive capacity across firms partly explains innovative performance differentials, especially within a new technological paradigm. Here, a focus on competences, processes, and routines is deliberate in order to highlight the effect of absorptive capacity on innovative performance, above and beyond the effects of intellectual human capital, especially those of the star scientists discussed above.

Cohen and Levinthal (1990: 129) emphasize that "absorptive capacity may be created as a byproduct of a firm's R&D investments." One important byproduct of internal R&D, therefore, is the creation of firm-specific knowledge that enables a firm to take advantage of knowledge generated externally (Mowery, 1983). Tilton (1971: 71), for example, observed this phenomenon in the semiconductor industry, and concluded that internal R&D "provided an in-house technical capability that could keep these firms abreast of the latest semiconductor developments and facilitate the assimilation of new technology developed elsewhere." Moreover, Rosenberg (1990: 171) underscores the importance of internal R&D by stressing that a firm needs "a substantial research

capability to understand, interpret and to appraise knowledge that has been placed upon the shelf." Cohen and Levinthal (1990: 128) consider this capability to generate firm-specific knowledge under the construct of absorptive capacity, defined as "the ability of a firm to recognize the value of new, external information, assimilate it, and apply it to commercial ends." More recently, Zahra and George (2002: 185) suggest that a firm's overall absorptive capacity is based on two subsets, potential and realized absorptive capacity: "Potential capacity comprises knowledge acquisition and assimilation, and realized capacity centers on knowledge transformation and exploitation."

Underlying the concept of absorptive capacity, therefore, is the notion that a firm cannot internalize external knowledge without cost. Instead, the identification, assimilation, and exploitation of external knowledge requires effort, expertise, and purposeful action on the part of the firm. Firms wishing to take advantage of knowledge outside their organizational boundaries need to invest in absorptive capacity by accumulating the skills, competences, and routines necessary to identify and utilize such externally generated knowledge (Cohen and Levinthal, 1989, 1990; Zahra and George, 2002). Continuing investments in a firm's absorptive capacity are necessary, because its effectiveness is path dependent, which implies that failure to invest in internal R&D at one point in time may foreclose future options in a particular technology (Cohen and Levinthal, 1990). 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). Thus, a firm's absorptive capacity has the potential to be the kind of valuable, rare, inimitable, and non-substitutable resource that can form the basis a firm's superior innovation performance (Barney, 1991; Peteraf, 1993). Further, a firm's absorptive capacity has become more critical to innovative performance, as many industries have become more science-driven; as such, firms are now more compelled to leverage advances in the

fundamental sciences (Cockburn, et al. 2000; Narin, Hamilton, and Olivastro, 1997). Thus, we suggest that a positive association exists between a firm's competences, processes, and routines to identify and absorb external sources of knowledge and its ability to generate innovative output.

Hypothesis 2: A firm's innovative output within a new technological paradigm is a positive function of its absorptive capacity.

3.1.3 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. Indeed, Powell, Koput, and Smith-Doerr (1996) provide support for the hypothesis that the locus of innovation in industries characterized by complex and rapidly expanding knowledge bases is found in 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 of alliances and acquisitions. 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 of the firm 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. It is not surprising, therefore, that the ability to leverage external networks to adapt to a rapidly changing environment is highlighted by Teece et al. (1997: 518-520) and Eisenhardt and Martin (2000: 1108, 1112) 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 capabilities by incumbent firms (Hill and Rothaermel, 2003; Higgins and Rodriguez, 2005; Vanhaverbeke, Duysters, and Noorderhaven, 2002). As such, we investigate how each type of external sourcing strategy affects an existing firm's innovative output within a new technological paradigm.

3.131 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: 293). It is not surprising that strategic alliances are often highlighted as a prime mechanism used by firms in order to access external technology, and that 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 has provided evidence for the notion that strategic alliances enhance innovative output. With regard to new technology ventures, prior studies produce evidence that strategic alliances not only increase patent and new product development rates for biotechnology start-ups (Deeds and Hill, 1996; Shan et al., 1994), but also predict innovation rates in the semiconductor industry (Stuart, 2000). Considering existing incumbent firms rather then start-ups, Ahuja (2000) examined the position of chemical firms within a network and found 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 affect on the firm's innovative output within the new technological paradigm.

Hypothesis 3a: A firm's innovative output within a new technological paradigm is a positive function of its alliances with new technology providers.

3.132 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 within our sample, the targets acquired by the pharmaceutical firms 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 (Hayward, 2002). Anecdotal evidence for the significance of sourcing R&D through acquisitions is provided by John Chambers, president and CEO of Cisco, who states "If you don't have the resources to develop a component or product within six months, you must buy what you need or miss the opportunity" (quoted in Bower, 2001: 99).

Our hypothesis, that acquisitions positively affect firm innovation, is of interest because empirical investigations of the issue have been mixed (Gupta and Cao, 2005; Hitt, Hoskisson, and Ireland, 1990; Hitt, Hoskisson, Ireland, and Harrison, 1991; Higgins and Rodriguez, 2005; Vanhaverbeke et al., 2002). Research has postulated several reasons why R&D acquisitions may actually hinder an organization's attempt to innovate and adapt. Hitt et al. (1991) indicate, for example, that an acquisition may disrupt an organizational culture focused on innovation, and thus reduce overall innovation output.

While some research has indicated that acquisitions may actually hinder a firm's attempts at innovation, within the biotechnology industry, large pharmaceutical firms often use this mechanism to facilitate innovation (Galambos and Sturchio, 1998). Higgins and Rodriguez (2005) find that in order to overcome declining R&D productivity, many pharmaceutical firms have successfully innovated by acquiring biotechnology ventures. As an example of how firms consummate acquisitions in an attempt to innovate within a new technological paradigm, Hoffman-La Roche in the mid-1980s, similar to DuPont and Schering-Plough, began to make acquisitions of small, specialized biotechnology firms instead of forming alliances (Galambos and Sturchio, 1998).

Hypothesis 3b: A firm's innovative output within a new technological paradigm is a positive function of its acquisitions of new technology providers.

3.1.4 Interactions Across Levels – Complements or Substitutes?

To address the question whether the locus of innovation lies across multiple levels of analysis, we now turn to an investigation of interactions across levels and their effects on innovation. Specifically, we pursue the question of whether the interactions across levels complement one another or substitute for each other. 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. Please 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.[2] Given the dearth of prior theoretical and empirical research pertaining to the locus of innovation across levels, we advance a complementarity and a substitutability hypothesis in a competing fashion. This approach enables us to expose the competing hypotheses to empirical falsification (Popper, 1959).

3.1.5 Interactions Across Levels – Complements

3.1.5.1 Interaction between Individual and Firm-Level Effects. A positive bi-directional nature of the interaction between individual and firm-level effects is evident considering that a firm's level of absorptive capacity 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, thereby translating potential absorptive capacity into realized absorptive capacity (Zahra and George, 2002).

We posit that an increase in a firm's level of intellectual human capital results in a commensurate increase in a firm's absorptive capacity, and thus synergistically

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[2] 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).

enhances the effectiveness of a firm's R&D expenditures. Likewise, a firm that has significant R&D expenditures is more likely to experience an increase in the effectiveness of its intellectual human capital due to better research facilities, more knowledgeable colleagues, and cultural norms and processes that are more conducive to innovation (Hitt et al., 1991). As an example, Groysberg, Nanda, and Nohria (2004) found that that when 'star' financial analysts switched firms, both the worker and new employer saw a decrease in short term performance. This effect was shown to be stronger when the star analyst switched from a higher performing firm to a lower one, indicating that there are important firm-level complementary or supporting assets and/or 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 already in place, thus pointing towards potential complementarity between individual and firm-level factors. Song, Almeida, and Wu (2003) investigated the conditions under which the mobility of R&D engineers is most likely to facilitate inter-firm knowledge transfer. The authors conclude that 'learning-by-hiring' is more likely to occur when the hiring firm's strategy is more focused on exploring technologically distant knowledge rather than exploiting its accumulated knowledge, again providing some evidence for 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; Lacetera, et al. 2004).

3.152 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 et al. (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 R&D facilities, thereby facilitating communication and knowledge transfer between organizations (Allen and Cohen, 1969; Tushman and Katz, 1980). The effect of such gate keeping and boundary spanning is particularly important to firms attempting to innovate within a new technological paradigm, 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).

The interaction between a firm's level of intellectual human capital and the effect of acquisitions on innovation is emphasized by research revealing that if an acquiring firm possesses information relevant to the value of the target's assets, 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 frequently plague acquisitions (Higgins and Rodriguez, 2005). Research also indicates that the success of an acquisition is, in part, a function of continuity in top management and key researchers before and after an acquisition (Granstrand and Sjölander, 1990). The acquiring firm is often interested in getting specialized, technical knowledge that is often tacit and thus difficult to transfer. Thus, the success of technologically motivated acquisitions has been shown to depend significantly on whether or not the key innovators, employees, or managers stayed with the firm post acquisition (Ernst and Vitt, 2000). This finding points to a positive interaction between a firm's star scientists and its use of acquisitions as a means of innovation.

3.1.5.3 Interaction between Firm and Network-Level Effects. Without a sufficient internal research capacity developed at the firm-level, firms are not likely to recognize important developments outside of their existing competences, and thus the ability to innovate is limited (Cohen and Levinthal, 1990). This notion is supported by research indicating that a level of commonality between the firm's internal research orientation and the 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, a firm's relevant absorptive capacity also allows the firm to identify promising alliance partners and acquisitions targets among the many new entrants attempting to commercialize a new technology, and thus increases the focal firm's chances to innovate (George, et al. 2002).

This latter aspect of absorptive capacity is especially pertinent when adapting to a new technology, because multiple new technologies or different versions of the same underlying technology frequently vie for supremacy until a new dominant design emerges (Anderson and Tushman, 1990). While the global pharmaceutical industry has a fairly oligopolistic structure, with only a few dozen firms engaged in proprietary drug discovery and development, about 2,000 new organizations emerged to commercialize the new biotechnology since its beginnings in mid-1970s (*BioScan,* diverse years). Thus, not only are incumbents with relevant absorptive capacity more attractive as partners for biotechnology start-ups, but they are also better positioned to assess the quality of the research conducted in new technology ventures. Some scholars provide support for the hypothesis that the 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 absorptive capacity and its alliances and acquisitions.

Hypothesis 4: The interactions between individual and firm-level effects (H4a), between individual and network-level effects (H4b), and between firm and network-level effects (H4c) are positive such that the interactions across levels complement one another, and thus increase a firm's innovative output within a new technological paradigm.

3.1.6 Interactions Across Levels – Substitutes

A competing hypothesis posits that the different mechanisms to advance innovation across the individual, firm, and network levels are substitutes for one another. This hypothesis 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 are path-dependent, and as such, require significant expenditures on the part of the firm, frequently over an extended period of time (Direckx and Cool, 1989; Levinthal and Cohen, 1990). Moreover, these investments are predominantly undertaken to attain the similar end of innovation, and thus the different innovation levers may exhibit some element of equifinality. In support of this notion, Cockburn, et al. (2000) demonstrates 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. Thus, from a manager's perspective, firm innovation can be seen as a constraint optimization problem, because firms face limited financial, and perhaps more importantly, limited managerial resources combined with short time horizons in high-technology industries. Therefore, a firm attempting to innovate might

choose between different innovation antecedents located at different levels, since using them in tandem might result in decreased innovative output.

Therefore, the different innovation levers 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 firms to chose one mechanism over the others was history dependent, in the sense that the choice was partly determined by the accumulated skills in a specific innovation mechanism. For example, firms that tended to use internal venturing in the past were more likely to use internal venturing in the future, while firms that used cooperative arrangements in the past were more likely to use them in the future. In more generalizable terms, 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 (Pennings and Harianto, 1992). Merck is an example of a pharmaceutical firm that has historically chosen to build its research capabilities internally, while others, including Hoffman-La Roche and Eli Lilly, have been more prolific in terms of using 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 mechanisms of each.

It is important to emphasize that firms must choose between these strategic alternatives, because there often exists a tension between these alternative modes of innovation (Pennings and Harianto, 1992; Vanhaverbeke, et al. 2002). The tension between these alternatives is born from the fundamentally different set of skills and capabilities that must be developed in order for a firm to effectively innovate. By using

one innovation mechanism repeatedly over time, firms learn by doing, and thus build up competences in a specific innovation mechanism (Levitt and March, 1988). Some firms have become proficient in recruiting and retaining star scientists, since they have learned how to address the surrounding human resource issues (Galambos and Sturchio, 1998; Zucker and Darby, 1997), while others have built firm-level R&D capabilities through an ongoing investment strategy (Helfat, 1994a, 1994b). Furthermore, other firms have developed alliance capabilities through learning-by-doing that allows for superior selection of alliance partners, contracting, monitoring, managing and, if necessary, exiting of alliances (Anand and Khanna, 2000; Kale, Dyer, and Singh, 2002), while others 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 lever drives out exploration of alternative innovation mechanisms (Levinthal and March, 1993).

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, marketing, or human resources (Hitt et al., 1990; Hitt et al., 1991). Additionally, Hitt et al. (1990) find that a firm's acquisitions can potentially not only interrupt the R&D process, but also can alter an organizational culture focused on innovation and thus lower an employee's incentive to follow through

with the innovation process. The authors find that acquisitions can reduce both R&D expenditures and innovation outputs, thus pointing towards a substitution effect.

Prior research also indicates that different modes are often substituted for each other only when the current mode of innovation is determined to be ineffective. As an example, Higgins and Rodriguez (2005) found 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 the firm's need to invest in internal R&D. Additionally, alliances with universities can provide the firm with ancillary research services that would otherwise have to be developed internally (George et al., 2002). Indeed, the authors find that firms with ties to universities have lower R&D costs than those lacking such ties. Taken together, these observations suggest that different innovation mechanisms across multiple levels may substitute for one another.

Hypothesis 5: The interactions between individual and firm-level effects (H5a), between individual and network-level effects (H5b), and between firm and network-level effects (H5c) are <u>negative</u> such that the interactions across levels <u>substitute</u> for one another, and thus <u>decrease</u> a firm's innovative output within a new technological paradigm.

3.3 Methodology

3.3.1 Research Setting

To empirically test our multi-level theoretical model concerning the role of individual, firm, and network-level effects in building innovative capabilities within a new technological paradigm, we chose the global pharmaceutical industry as the research

setting for a number of reasons. The 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 researchers, because they can then observe whether or not, and if so, how the existing firms have accomplished innovation within the new technological paradigm. Traditionally, drug discovery within the chemical paradigm was based on random screening, whereas the new technological paradigm of biotechnology is informed by a more science-driven approach, which includes genetic engineering, genomics, and molecular biochemistry, among other disciplines. The scientific breakthroughs underlying biotechnology, such as recombinant DNA and hybridoma technology, were accomplished in the mid-1970s. The first new biotechnology drugs reached the market for pharmaceuticals in the 1980s. Since the emergence of biotechnology, around 2,000 new organizations have emerged to commercialize the new technology (*BioScan*, diverse years).

In their attempts to build innovative capabilities within the new biotechnology paradigm, the incumbent pharmaceutical firms made extensive use of all of the mechanisms described above. Unlike incumbents in other industries, which are often characterized by high levels of sunk costs, pharmaceutical incumbents have made a substantial investment in human capital, especially in the recruitment of star scientists (Zucker and Darby, 1997a, 1997b). Some researchers have postulated that through a re-focusing of human capital pharmaceutical incumbents have been able to stave off a "Schumpeterian destiny" (Galambos and Sturchio, 1998). Moreover, the pharmaceutical industry also exhibits one of the highest historical R&D intensities, since firm performance depends on continuous innovation through discovery and development of propriety 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, 2005). Considering these factors, we submit that the global pharmaceutical industry is an appropriate setting to test our multi-level theoretical model predicting innovation within a new technological paradigm.

3.3.2 Dependent Variable

The dependent variable for this study is the innovative output of pharmaceutical firms within the new biotechnology paradigm. We followed prior research that measured innovative output by a firm's patenting rate (e.g., Ahuja, 2000; Hagedoorn and Schakenraad, 1994; Henderson and Cockburn, 1994; Shan et al., 1994; Stuart, 2000). To specifically assess the pharmaceutical firm's innovative performance within the new biotechnology paradigm, however, we proxied their innovative output by the number of *biotechnology patents* applied for and granted in each year during our study period, 1980-2002, while explicitly controlling for non-biotechnology patents. The source for this information was the Technology Profile Report maintained by the U.S. Patent and Trademark Office (PTO), an agency of the U.S. Department of Commerce. Due to generous support from the PTO, we were able to obtain detailed data on the complete population of all biotechnology patents filed by and awarded to the global pharmaceutical companies in this sample annually over the 23-year study time frame. The PTO compiled these data based on all patents occurring in the biotechnology patent classes.[3] The average pharmaceutical firm in our sample applied for and was granted approximately 6 biotechnology patents per year.

[3] The complete set of biotechnology patent classes consists of: 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 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].

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 also closely correlated with other performance measures, such as new product development, profitability, and market value (Comanor and Scherer, 1969; Henderson and Cockburn, 1994). In sum, a pharmaceutical firm which patents heavily in biotechnology can be seen as innovative within the new technological paradigm of molecular biology.

A preliminary argument may point out 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).

The reliability of patent count data has been established empirically, because prior research shows that patent count data are highly correlated with citation-weighted patent measures, thus proxying the same underlying theoretical construct. The bivariate correlation between patent counts and citation-weighted patents has been shown to be above 0.77 ($p < 0.001$) in the pharmaceutical industry (Hagedoorn and Cloodt, 2003), which is especially relevant for this study, and above 0.80 ($p < 0.001$) in the semiconductor industry (Stuart, 2000), indicating some generalizability of this assertion.

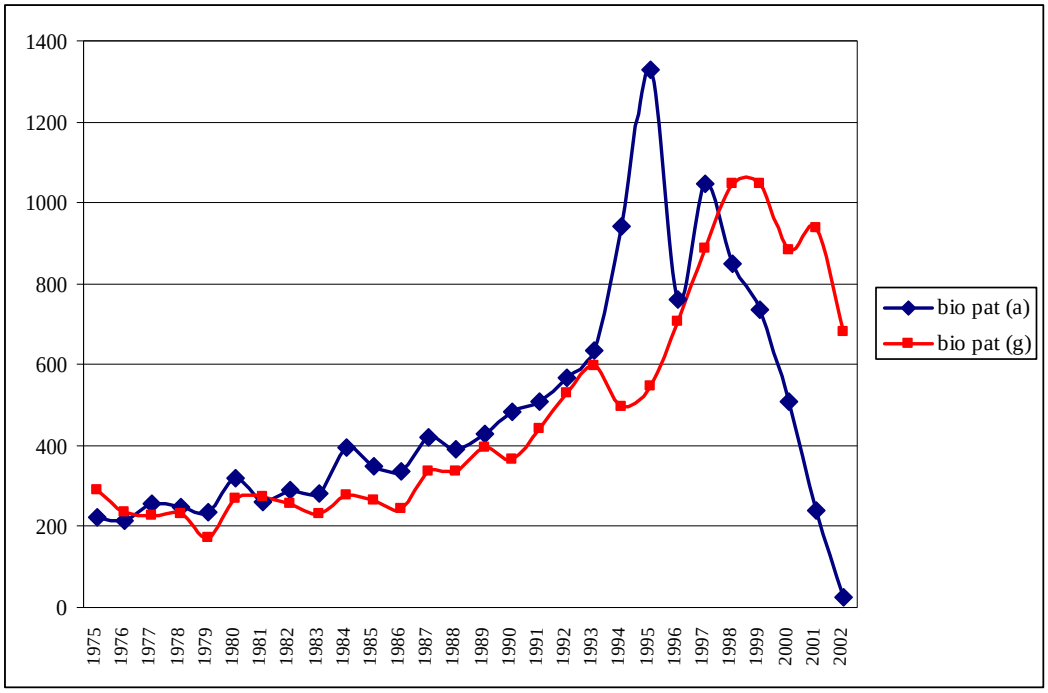

Figure 3.1: Biotechnology Patents Filed By and Assigned To Pharmaceutical Companies, 1975-2002

Figure 3.1 depicts the patenting behavior of the sample pharmaceutical firms in the new biotechnology between 1975 and 2002. Three observations are immediately apparent. First, both the time series for biotechnology patents applied and granted are highly correlated ($r = 0.61$, $p < 0.001$). Second, the patenting by large pharmaceutical firms in biotechnology did not really take off until the mid 1980s. Third, the 1990s witness an acceleration as well as a deceleration in biotechnology patenting.

3.3.3 *Independent Variables*

3.3.3.1 Intellectual Human Capital and Star Scientists. In their pioneering work on entrepreneurial biotechnology ventures, Zucker and her colleagues were one of the first to create a measure to proxy "star scientists" (Zucker and Darby, 1997; Zucker et al., 1998; Zucker et al., 2002). Zucker et al. 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. Recently, Lacetera et al. (2004) identified a star scientist as someone whose three year moving average of annual publications was greater than 5 for at least one year. To be even more conservative, we applied a more stringent definition of stardom than either Zucker et al. (1997) or Lacetara et al (2004). We constructed our star measure as follows.

We retrieved a sample of 125 pharmaceutical firms, representing the population of pharmaceutical firms active in the new biotechnology industry as listed in the various volumes of *BioScan* and in the *recap* database, maintained by *Recombinant Capital*, an independent research firm specializing in the life sciences. *BioScan* and *Recombinant Capital* appear to be the two most comprehensive publicly available data sources documenting the global biopharmaceutical industry. The validity of these data sources has been corroborated in prior research when focusing on different questions and employing only one of these two sources (e.g., Shan, et al. 1994; Lane and Lubatkin, 1998; Lerner et al. 2003; Powell, et al. 1996).

Using this sample of pharmaceutical firms, we then searched the ISI Science Citation Index database to identify academic journal articles published between 1980 and 2004 that had a keyword related to biotechnology research (to exclude non-human focused research, e.g., agricultural or veterinarian) and could be unambiguously connected with one of the pharmaceutical firms in the sample. This last step was important given the necessity of assuring that each of the authors was affiliated with at least one of the pharmaceutical firms. From the population of over 480,000 academic journal articles, we collected the following information: authors, authors' affiliations, article name, number of times cited, keywords, and publication year. Please note that

our time period to identify stars is by design somewhat longer than the study period (by two 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.

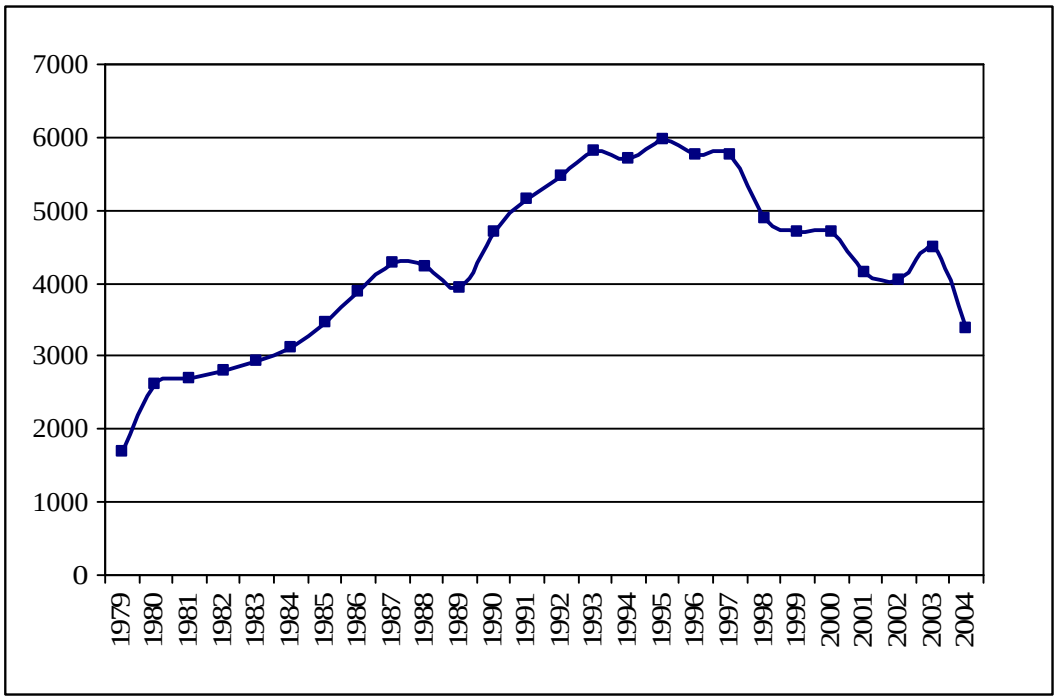

Figure 3.2: Total Annual Publications in Biotech by Pharmaceutical Firms,1979-2004

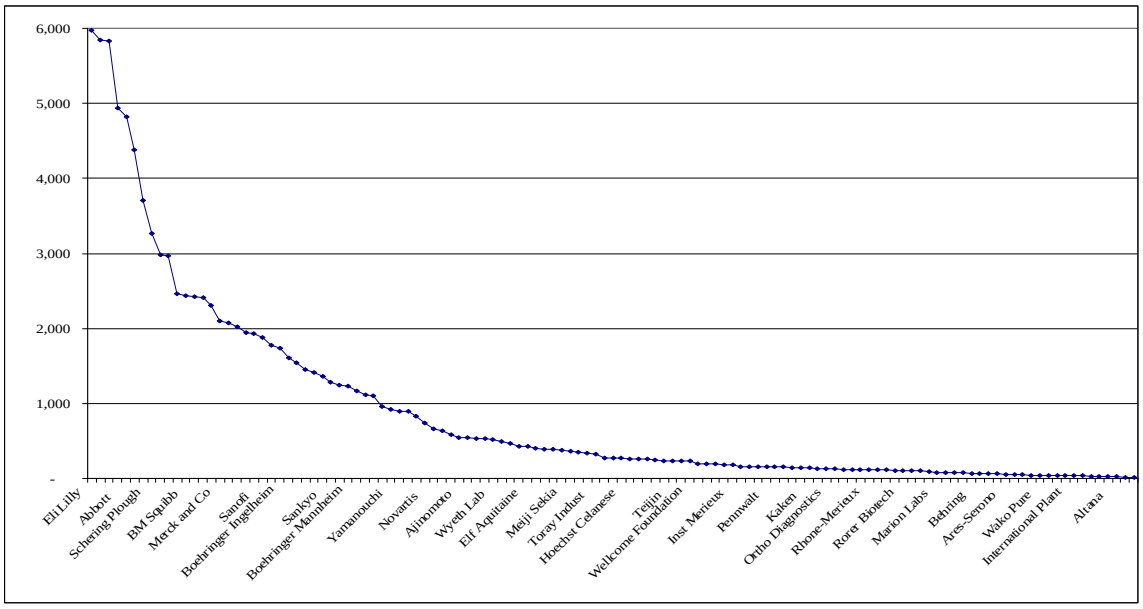

Figure 3.3: Distribution of Journal Publications in Biotechnology by Pharmaceutical Firms, 1973-2004

Figure 3.2 depicts the total number of annual publications in biotechnology by pharmaceutical firms between 1979 and 2004. The figure reveals that publishing in biotechnology by pharmaceutical firms did not take off until 1980. Since then, one can observe a drastic increase in publication activity until the mid 1990s, after which the rate of publication declines. This function has roughly a similar shape to the patenting functions introduced earlier; although, compared to patenting, both the increase and decline in publishing are less drastic. Nonetheless, both the publishing and patenting functions describe roughly an inverted U, thus highlighting that the study period under investigation (1980-2002) indeed captures a time period that represents the global pharmaceutical firms' attempts to innovate within the new biotechnology paradigm.

Figure 3.3 shows the variance in publication rates in biotechnology by pharmaceutical firms. This graph not only demonstrates the overall high variance among the firms' publication rates, but also its skewed distribution indicates that some

firms, like Eli Lilly, Abbott, or Schering Plough, are extremely active in publishing biotechnology research.

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 130,000 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 in academic journals was our proxy for a firm's intellectual human capital (*Scientists total).* The average firm in the sample employed 186 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, increasingly more stringent, approaches. The first method identified 2,392 "publication stars": scientists who published, on average, more than 27 papers (z-score > 3.0, i.e., 3 standard deviations above the mean) during the 25-year period, 1980-2004. 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. This process 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 publishes 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 represents a stringent and conservative approach to

identifying a star, we used it as our proxy for star scientists (*Star Scientists*).[4] This process also implies that the difference between *scientists total* 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 mean number of star scientists employed at a pharmaceutical firm in a given year was 13.3 over the study period.

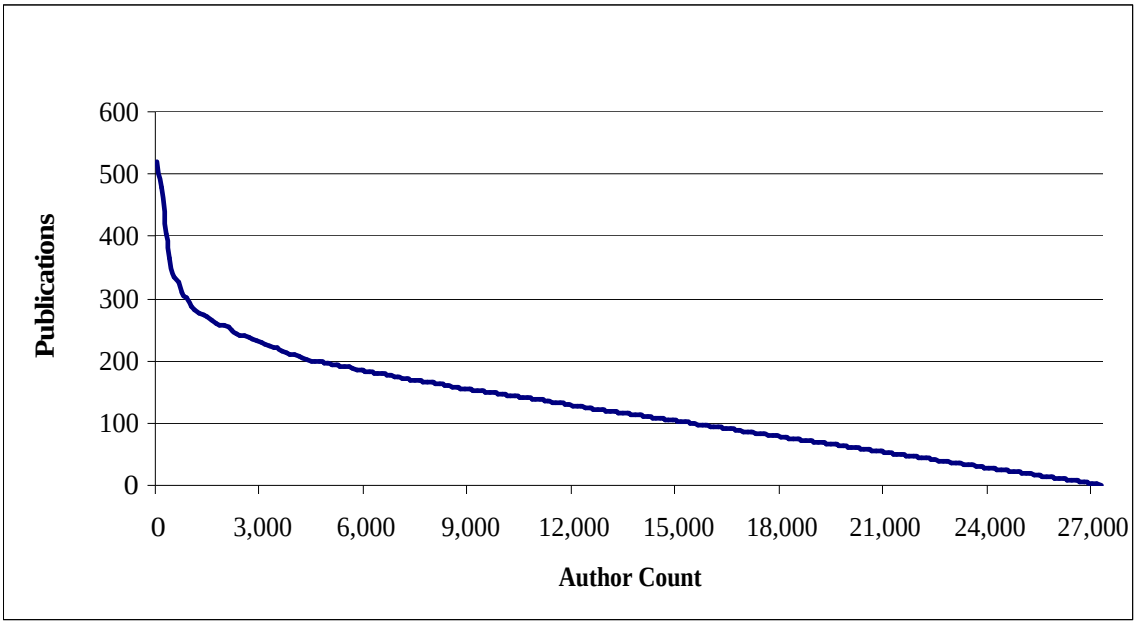

Figure 3.4: Distribution of Total Publications

[4] To the best of our knowledge, this paper is the first to employ citations as an additional filter used to identify star scientists. This is an important improvement over the few pioneering studies, because citations are generally seen as demonstrating the quality of the researchers' work. Thus, our measure of stardom identifies researchers that not only publish at a rate above 3 standard deviations above the mean, but are also cited at a rate of 3 standard deviations above the mean. This stardom measure captures both research quantity and quality.

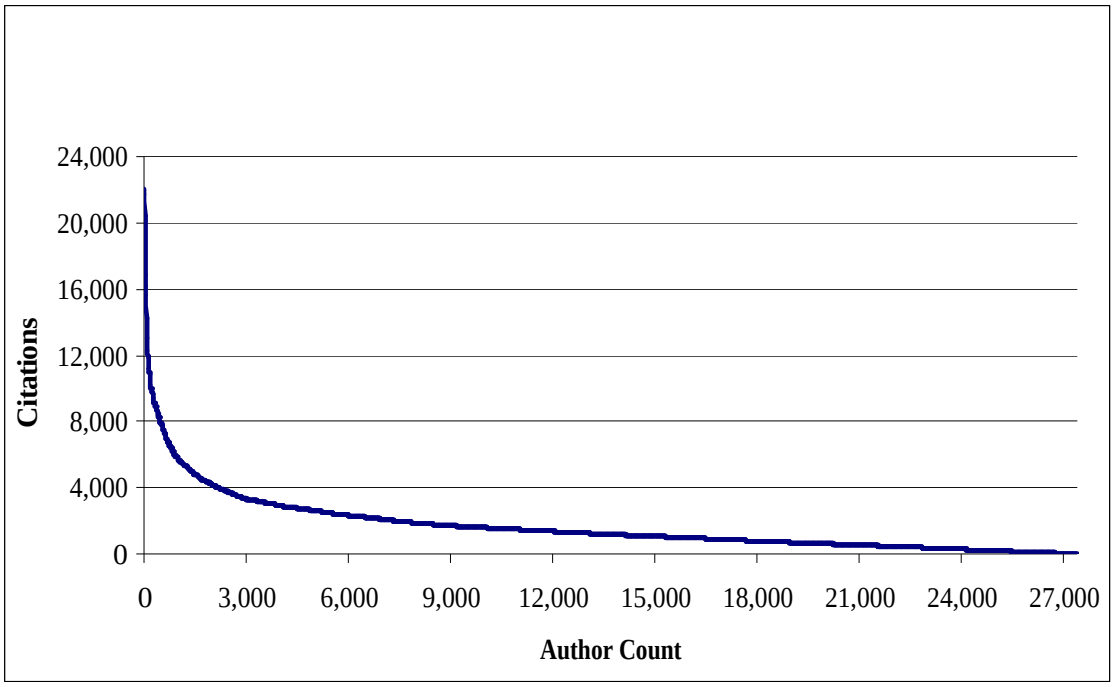

Figure 3.5: Distribution of Total Citations

Figures 3.4 and 3.5 depict the distribution of the authors' publication and citation counts. Given the extreme skewed distribution with an extended right tail, one can instantly glean that very few scientists account for a disproportionably large number of publications and citations, thus providing visual support for the concept of star scientists.

3.3.3.2 Absorptive Capacity. Following the seminal work by Cohen and Levinthal (1989, 1990), we proxied a firm's absorptive capacity by its R&D intensity, defined as R&D expenditures divided by sales (*R&D Intensity*). This proxy for absorptive has been widely used in the literature (e.g., Bierly and Chakrabarti, 1996; Steensma and Corley, 2000; Tsai, 2001) and is considered reflective of a firm's focus on discovery and innovation. We obtained the financial data used in this study from a number of sources including *Compustat, Datastream,* and *FIS Mergent*. The average pharmaceutical firm in the sample spent about 9.5% of its sales on R&D.

3.3.3.4 Biotech Alliances. To document the alliances that the pharmaceutical firms had entered with providers of biotechnology research, we tracked each firm's alliances with universities, research institutions, and biotechnology firms (Powell, et al. 1996). 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*. *BioScan* and *Recombinant Capital* are fairly consistent in their reporting. For example, we found the inter-source reliability to be greater than 0.90 when documenting alliances. The average sample firm entered more than two alliances per year with providers of biotechnology research.

3.3.3.5 *Biotech Acquisitions.* Following Higgins and Rodriguez (2005), among others, we used the *SDC Platinum* database, published by *Thomson Financial*, to identify the number of biotech 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 one biotechnology firm every two years.

3.3.4 Control Variables

3.3.4.1 Non-biotech Patents. To reduce the threat of unobserved heterogeneity when using biotech patents (applied and granted) as dependent variables, it is critical to control for non-biotech patents (applied and granted) to avoid spurious findings, because firms that patent heavily per se might also patent heavily in biotech, and vice versa. Thus, we include the number of non-biotech patents per year as a control variable (*Non-Biotech Patents Applied* and *Non-Biotech Patents Granted*). These data were obtained

from the U.S. PTO. The average pharmaceutical firm applied for and was granted approximately 57 non-biotechnology patents per year.

3*.3.4.2 Time to First Cohen-Boyer Patent Citation.* The Cohen-Boyer patent (U.S. Patent 4,237,224), disclosing recombinant DNA technology, is considered to represent 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 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).

3.3.4.3 Pharma 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 Monsanto or DuPont. A firm's level of diversification, therefore, may influence the extent to which it attempts to innovate within the new biotechnology framework. We controlled for the varying degree of diversification by coding the pharmaceutical companies as 1 if the company is a specialized pharmaceutical 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 (53%) were fully specialized pharmaceutical companies.

3.3.4.4 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 a comprehensive "family tree" by drawing on multiple industry sources to trace all firms in existence in 2002 back to their various "ancestors" alive in 1980. This allowed us to create a dummy variable indicating if a sample firm was the result of a horizontal merger or acquisition (1 = firm merged). About 7% of all sample firms engaged in at least one horizontal merger or acquisition during the study period.

3.3.4.5 Firm Nationality. We attempted to assess institutional and cultural difference by coding for the "nationality" of each pharma firm based on the location of its headquarters. Thus, one indicator variable takes on the value of 1 if the firm is headquarted 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 26% of the firms are headquarted in the U.S., while 37% are European, and the remaining 37% are Asian. Thus, we were able to overcome the U.S. centric bias prevalent in prior research.

3.3.4.6 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, 1934, 1942). To control for these effects, we inserted a firm's *Net Income* and *Total Assets* into to the regression equations.

3.3.4.7 Year Fixed Effects. Since we investigate a 23-year time period, it is prudent to control for time-varying factors that affect all firms, including macroeconomic conditions. We thus included annual time dummies for each year, with 1980 being the omitted year, and thus serving as 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, patenting rate, and the main regressors of interest.

3.3.5 Sample

The initial sample consisted of 125 pharmaceutical firms drawn form the *recap* database and annual volumes of *BioScan.* Based on the availability of panel data across the various datasets utilized and the lengthy time period under study, however, the final sample was reduced to 81 firms. It is important to note that the sample firms accounted for the vast majority of the sales in the 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 non-diversified pharmaceutical companies. These 35 focused pharmaceutical companies represent only 28% of the initial sample, but accounted for 69% of the total sales for pharmaceuticals at the end of our study period (*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.

We tracked annual data for each firm, beginning in 1980 until the end of 2002 (23 x 81 = 1,863 firm-year observations). The companies in the sample are primarily large organizations with a focus on the discovery of proprietary drugs. Firms in the sample include Ajinomoto (Japan), Aventis (EU), and Pfizer (U.S.). The sampled pharmaceutical companies represent a segment of the biotechnology industry that engages in research, development, and commercialization of biotechnology therapeutics that are placed inside the human body (*in-vivo*), as opposed to *in-vitro* therapeutics, which are used outside the human body. While biotechnology affects many different industries, the selected industry focus on in-vivo human therapeutics is reflective of its

economic importance and potential, its regulatory environment, and its consumer market. In our study, focusing on human therapeutics enabled us to create a homogenous sample, while at the same time controlling for industry idiosyncrasies.

We chose our study period to begin in 1980, because this was the year when biotechnology began to "take off" (see Figures 1 and 2). This can partly be explained by three important events that occurred in 1980 (Stuart, et al. 1999: 323): (1) the phenomenal successful IPO of Genentech, the first public biotechnology firm, which in 1980 "set a record for the fastest increase in stock price for an IPO, from $35 at offering to $89 in only 20 minutes;" (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, disclosing recombinant DNA, was granted to Stanford University in 1980, which non-exclusively licensed this breakthrough technology freely for a nominal fee.

3.3.6 Estimation Procedures

The majority of empirical work in strategic management relies on cross-sectional data, and therefore does not allow for causal inferences (Hitt, Gimeno, and Hoskisson, 1998). Moreover, cross-sectional data are not suitable to answer research questions that contain a dynamic component, such as the role of different antecedents to firm-level *dynamic* capabilities and innovation. To achieve a close match between our theoretical model and its empirical test, we chose a longitudinal research design in which we followed a given set of companies over time, while leveraging fine-grained panel data. The advantages of panel data include allowing the researcher to control for the initial values of the dependent variable, recognize time lags, enhance statistical power through the investigation of a larger sample size, and reducing the threat of collinearity among

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

independent variables, which in turn improve the econometric estimates (Hsiao, 2003).

The dependent variable of this study, a pharmaceutical firm's patenting rate in biotechnology, is a non-negative, integer count variable. Non-negative, integer count variables violate one of the main assumptions of the classical linear regression model, as this dependent variable cannot be normally distributed. For such data, count models provide an econometric improvement over the classical linear (OLS) regression models. The Poisson estimation is the simplest but most restricted count data model, because it assumes equity between the conditional mean and variance. Social science data, however, generally exhibit a greater variance than mean, and are thus characterized by over-dispersion. The over-dispersion in the biotechnology patenting variables are highlighted by the fact that the coefficient of variation (standard deviation/mean) is greater than 2, implying that the patenting rates differ by more than 200% from the averages across firms. The negative binomial estimation is an extension of the Poisson model and provides a mechanism for incorporating over-dispersion while allowing the variance to differ from the mean. In addition, negative binomial regression accounts for an omitted variable bias, while simultaneously estimating heterogeneity (Cameron and Trivedi, 1986; Hausman, Hall, and Griliches, 1984). We conducted a test for over-dispersion that revealed that a negative binomial estimation provides a significantly better fit for the data than the more restrictive Poisson model (Gourieroux, Montfort, and Trognon, 1984). A negative binomial regression analysis also represents a more conservative estimation procedure.

In theory, either fixed- or random-effects specification can be used to control for unobserved heterogeneity (Greene, 2003). Thus, we applied a Hausman specification

test (1978), and its result revealed that a random-effects estimation is indicated.[6] We therefore applied the following random-effects negative binomial model:

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

where *n* is a non-negative integer count variable capturing each pharmaceutical firm's patenting in biotechnology, and thus $P(n_{it} / \varepsilon)$ indicates the probability that pharmaceutical firm *i* files for or obtains *n* biotechnology patents 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 fairly 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 corrected for endogeneity (Hamilton and Nickerson, 2003).

Hypotheses 4 and 5 suggest, in a competing fashion, that the antecedents to firm innovation across levels either complement or substitute one another. These hypotheses indicate the application of hierarchical moderated regression (Cohen, et al. 2003). Moderated regression is considered to be a relatively conservative method for examining interaction effects, because the interaction terms are tested for significance after all direct effects have been entered into the regression equation (Jaccard, Wan, and Turrisi, 1990).

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 assess

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

the threat of multicollinearity, we calculated the variance inflation factors (VIFs) for each coefficient. The maximum estimated VIF for all direct effects across the two different dependent variables was 2.10, and for the interaction effects, it was 7.51. Thus, in both cases the VIFs were well below the recommended ceiling of 10 (Cohen, et al. 2003).

3.4 Results

The Table 3.1 in the appendix provides the descriptive statistics and the bivariate correlation matrix, while Table 3.2-3.6 present the regression results. It is important to note that, as revealed in Table 3.1, all of the bivariate correlations between the independent variables, with the exception of the correlation between total scientists and non-star scientists, fall below the 0.70 threshold, thus indicating acceptable discriminant validity (Cohen, et al. 2003). Moreover, the elevated correlation between the total number of scientists and non-star scientists is expected, because 99.35% of all scientists are non-stars, while only 0.65% are stars. This elevated correlation is not of any concern, furthermore, because these two variables are not entered simultaneously in the regression models. In addition, the key variables of interest exhibit considerable variance.

We applied a hierarchical moderated regression analysis. We first estimated a baseline model including the control variables only for biotech patents applied (Model 1) and biotech patents granted (Model 2), respectively. Each subsequent model represents a significant improvement over the respective baseline models at $p < 0.01$, or smaller. Models 3-6 contain all the direct effects simultaneously necessary to test Hypotheses 1-3, while Models 7-10 contain the interaction effects to assess Hypotheses 4 and 5.

3.4.1 Results – Direct Effect Hypotheses

The results obtained in Models 3 and 4 provide support for Hypothesis 1a (at $p < 0.01$ and $p < 0.001$, respectively), indicating that a firm's innovative output within a new technological paradigm is a positive function of its intellectual human capital. Recall that we proxied a firm's intellectual human capital by the total number of its research scientists that published in academic journals.

In Models 5 and 6, we split the total number of scientists into its constituent components of non-star and star scientists. This allows us to assess the effect of star scientists on innovative output, above and beyond non-star scientists. The results reveal, however, that a firm's non-star scientists are positively and significantly correlated with a firm's patenting rate ($p < 0.01$ and $p < 0.001$, respectively), while its number of star scientists are not. Thus, we reject Hypothesis 1b, predicting a positive relationship between a firm's stars and its innovation rate.

Models 3-6 allow us to assess Hypotheses 2 and 3. Contrary to our hypothesis, we find that a firm's absorptive capacity, proxied by its R&D intensity, is negative and significant (at $p < 0.01$ or smaller in Models 3-6) in predicting a firm's innovation rate. We find marginal support for Hypothesis 3a, suggesting that a firm's innovative output within a new technological paradigm is a positive function of its alliances with new technology providers, when proxying innovative output by the number of biotechnology patents granted ($p < 0.10$ in Models 4 and 6). The acquisition coefficients do not reach statistical significance in the fully specified direct effects models (Models 3-6), thus we fail to find support for Hypothesis 3b, positing that a firm's innovation rate is a positive function of its acquisitions.

3.4.2 Results – Interaction Hypotheses

We proposed two competing interaction hypotheses, which we evaluate in Models 7-10. In Hypothesis 4 we posited that the different innovation antecedents

across levels complement one another, while in Hypothesis 5 we suggested 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 absorptive capacity are substitutes for one another, because the interaction between these two variables is negative and significant ($p < 0.05$ in Model 7 and $p < 0.01$ in Model 8). When splitting a firm's intellectual human capital into star and non-star scientists, the results in Models 9 and 10 reveal a firm's non-star scientists and its absorptive capacity, proxied by R&D intensity, serve as substitutes for one another ($p < 0.05$ in Model 9). In Model 10, we find marginal support for the hypothesis that firm's star scientists and its absorptive capacity complement one another ($p < 0.10$). Taken together, the results support Hypothesis 4a, positing that the individual and firm-level antecedents to innovation are substitutes. This result appears also to hold for the relationship between a firm's non-star scientists and its absorptive capacity. Yet, when investigating the interaction between a firm's star scientists and its absorptive capacity, we find some tentative support for Hypothesis 5a, indicating that these two mechanisms complement one another.

When assessing the interaction between individual and network-level antecedents, we find that a firm's intellectual human capital and its biotech alliances serve as substitutes, as indicated by the negative and significant interaction terms ($p < 0.01$ in Model 7, $p < 0.10$ in Model 8). A substitution relationship also appears to hold when splitting a firm's intellectual capital into star and non-star scientists, because the interactions remain negative and significant ($p < 0.05$ in Model 9, $p < 0.01$ in Model 10). Taken together, we find support for Hypothesis 4b, suggesting that individual and network-level antecedents to innovation serve as substitutes. This statement, however, needs to be qualified in the sense that it only holds for alliances, and not acquisitions.

The results reveal support for Hypothesis 5c, postulating that firm- and network-level antecedents to innovation are complements. The interactions between a firm's absorptive capacity and its biotech alliances are positive and significant ($p < 0.001$ in Models 7 and 9, $p < 0.01$ in Model 8). The interactions between a firm's absorptive capacity and its biotech acquisitions are also positive and significant ($p < 0.10$ in Models 7 and 9, $p < 0.05$ in Model 10). A firm's absorptive capacity and its alliances or acquisitions positively reinforce one another in generating innovative output.

3.4.3 Results of Control Variables

Some of the results of the control variables are also noteworthy. We assess them in the baseline models 1 and 2. With regard to the annual indicator variables, we see that the year dummies appear to capture a trend acceleration and eventual deceleration in biotechnology patenting over time. Patenting activity accelerates in the mid-1980s, while it slows down significantly towards the end of the study. This observation matches closely the graphical depiction of the biotechnology patenting trend in Figure 1.

The results also indicate that firms that are heavily engaged in patenting overall, as proxied by their non-biotech patents, are also very active in biotech patenting ($p < 0.001$ in both Models 1 and 2). Including a variable that captures a firm's overall inclination to engage in the focal activity is a common way to control for unobserved heterogeneity (Heckman and Borjas, 1980). The results obtained are assuring as they capture unobserved heterogeneity, because they rule out the explanation that the findings with regard to the key independent variables might be caused by a firm's strategy focused on innovation. The results presented above are robust to an assessment of a firm's overall innovation orientation that might lead to variance in a firm's underlying competences, capabilities, or dispositions to patent.

Moreover, firms that have exhibited superior performance ($p < 0.10$) and firm's that have merged during our study period ($p < 0.001$) are more active in biotech patenting. Larger firms ($p < 0.001$), and European firms ($p < 0.001$), tend to be laggards with respect to innovation. Finally, as expected, firms that take a longer time to incorporate the breakthrough Cohen-Boyer patent in their firm knowledge ($p < 0.001$), exhibit an overall lower innovation rate within the new biotechnology framework.

3.5 Discussion

Following recent theoretical developments emphasizing that the antecedents to dynamic capabilities can be found at the individual, firm, and network level of analysis (Eisenhardt and Martin, 2000; Teece, et al. 1997), we set out to answer the question pertaining to their locus. Questions pertaining to the locus of dynamic capabilities go to the heart of strategic management, as they lead into the question of the locus of competitive advantage. In particular, we were motivated by the question of whether the antecedents to dynamic capabilities can be found primarily at a specific level of analysis or at the intersection across different levels. To answer these important but under-explored questions, we developed a set of hypotheses that were tested on an unusually comprehensive and detailed panel dataset tracking the innovative output of existing pharmaceutical companies within the newly emerging biotechnology paradigm. We began by developing a set of three direct effect hypotheses to assess the relative importance of different antecedents to dynamic capabilities located at different levels of analysis. Since we were careful to include individual, firm, and network-level predictors simultaneously in the regression analysis, we could overcome the threat of unobserved heterogeneity, frequently documented in prior research (Felin and Hesterly, 2005).

We found that most of the variance in biotechnology patenting is explained by individual and firm-level factors, while network-level factors did not exert a direct effect

when applying a traditional 95% significance cut-off. A firm's intellectual human capital was the strongest predictor of firm patenting. In particular, when splitting a firm's intellectual human capital into its two components, star and non-star scientists, we found that the positive direct effect of intellectual human capital on patenting could be attributed to a firm's non-star scientists, while its star scientists did not exert a direct effect on patenting.[7] 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 scientists, rather than the relevance of elite scientists, which is emphasized in the few prior studies in this area (Lacetera, et al. 2004; Zucker, 1997a, 1997b). Thus, the role of the star scientist seems to be to help cue the firm to potential shifts in the environment (Kaplan, Murray, and Henderson, 2003), rather than to facilitate its adaptation to the change itself.

A possible explanation of the somewhat discrepant findings in our study is that prior research neglected to control for non-star scientists when assessing the effect of stars on different outcome variables, or that prior research neglected to control for a potential heterogeneity across levels by including firm and network-level determinants. Given that our results show heterogeneity rather than homogeneity across levels of analysis, both scenarios open the door for unobserved heterogeneity, and thus can lead to spurious findings and attributional errors. Considering our detailed and fine-grained controls across different levels, we are fairly confident in attributing the direct effect of intellectual human capital to non-star scientists.

We also found that a firm's R&D intensity, our proxy for firm-level absorptive capacity, consistently had a significant negative effect on the pharma firms' patenting

[7] This result cannot be attributed reasonably to collinearity, because the bivariate correlation between stars and non-stars is $r = 0.57$. This indicates discriminant validity because the bivariate correlation is well below the conventional ceiling of $r = 0.70$. Moreover, all variance inflation factors for stars and non-stars were below 4.0, thus well below the traditional cut-off ceiling of 10 (Cohen et al., 2003).

rate in biotechnology. This result is surprising, because it runs counter to what we had hypothesized. A first reaction to this finding is that our measure of firm-level absorptive capacity is fairly narrow, since the theoretical construct of a firm-level absorptive capacity clearly goes beyond firm-level R&D intensity. Thus, our result might be a reflection of an adequate, albeit widely accepted, proxy for absorptive capacity (Cohen and Levinthal, 1990). A second possible explanation for this finding is that although the pharmaceutical firms engaged heavily in R&D spending, their R&D dollars were spent within the old technological paradigm of chemical screening, thus hampering their attempts to innovate within the new biotechnology paradigm.

Given the strong precedent in the literature documenting a positive effect of a firm's alliances and acquisitions on innovative output (e.g., DeCarolis and Deeds, 1999; Higgins and Rodriguez, 2005; Rothaermel, 2001; Shan, et al. 1994), we were surprised not to find any strong effects of either alliances or acquisitions on a pharma firm's patenting rate in biotechnology, albeit alliances were found to be marginally significant in predicting a firm's patenting rate as proxied by biotech patents granted. This result confirms our cautionary note expressed above. Future research must make greater strides towards controlling for confounding factors at different levels of analysis, especially at the individual level, to avoid spurious results due to unobserved heterogeneity (Felin and Hesterly, 2005).

Going beyond simple, though comparative, direct effects, we next attempted to answer the question of whether the locus of the antecedents to dynamic capabilities lies within the intersection of any of these levels; in other words, does it lie across multiple levels of analysis? And if the locus of the antecedents to dynamic capabilities is indeed found across multiple levels of analysis, are the different mechanisms to innovate complements or substitutes? The results obtained here are interesting in the sense that we find support for both a complementarity and a substitutability hypothesis, depending

on which levels of analysis are interacted with one another. Given that we found significant moderating effects, the direct effects presented above also need to be interpreted contingent upon a potential moderating effect, because firms generally pursue several innovation mechanisms in tandem.

Broadly speaking, we found that individual-level antecedents to innovation are substitutes to firm or network-level antecedents to innovation, and vice versa, because the interactions between a firm's intellectual human capital and its absorptive capacity and its alliances, respectively, were negative and significant. It is noteworthy that this assertion also held when considering non-star scientists, rather than the firm's entire intellectual human capital. Stars, too, seem to be substitutes for alliances. This implies some equifinality when using individual or firm and network-level mechanisms to innovate, because intellectual human capital seems to compensate for R&D intensity and alliances, respectively. On the other hand, we also found support for a complementarity hypothesis, because the interactions between a firm's R&D intensity and its alliances and acquisitions were positive and significant. This implies that firm- and network-level mechanisms of innovation positively reinforce one another. Taken together, the antecedents to dynamic capabilities clearly seem to lie *across* different levels of analysis. This implies that we not only reject the assumption of homogeneity across levels, but also that we reject the assumption of independence from different levels of analysis (Felin and Hesterly, 2005).

One could argue that we did not find consistent star effects because our proxy definition of a star is too restrictive. Going beyond prior research that relied only on publication productivity (Lacetera, et al. 2004; Zucker, 1997, 1997), we defined a star as someone who is above three standard deviations of the mean for both the frequency of journal publications and citations. This result opens the door for the general and

important question of how do you define a star? What criteria should you be looking at?[8] Does it need to be a dichotomous variable as used in prior research, or can we measure stardom as a continuous variable? For example, our variable for intellectual human capital is a continuous measure, which exhibited significant predictive power. Yet, it does not account for individual-level heterogeneity. These are important issues, since prior research has highlighted that some companies have policies in place that do not allow their employees to publish research findings, which in turn retarded their innovation (Henderson and Cockburn, 1994). It would be helpful if future research could resolve some of these issues.

An important caveat to the interpretation of our results involves the potential generalizability of the results. Specifically, our results may not be applicable beyond our setting of large, incumbent pharmaceutical firms. One reason for this concern centers on is considered to be included in the R&D expense of a firm. This is of concern because despite our relatively low correlation between R&D expense and total scientists (0.2), general accounting guidelines suggest that the salaries of R&D personnel should be included in R&D expense. My study looks at publishing scientists in pharmaceutical firms, which represent only a small subset of the total researching scientists and lab employees in large pharmaceutical firms. My research indicates that the overlap between R&D expense and publishing scientists is more significant with smaller firms, which have fewer non-publishing research employees. This suggests that one should be cautious in generalizing our results to a sample of smaller firms, even in the pharmaceutical industry.

[8] 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 little for any meaningful econometric analysis.

3.6 Conclusion

In this paper we have made an initial attempt to disentangle the multi-level effects associated with the various mechanisms firms use to adapt to a new technological paradigm. Through this analysis, we have made a contribution to our understanding of how firms build and refine dynamic capabilities in order to adapt to change. Prior research on the development of dynamic capabilities has focused on the collective level, investigating the importance of firm or network-level attributes. Our research demonstrates that individuals matter and that it is inappropriate to attempt to investigate firm adaptation and innovation without the consideration of its intellectual human capital. Our investigation of the various interactions between the levels of analysis seems to explicate the importance of the individual. That is, while the antecedents to dynamic capabilities occur across different levels, the firm and collective-level mechanisms are complementary in nature, while human capital seems to compensate 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 the paradigm shift and assemble the requisite human assets that are ultimately capable of developing the necessary dynamic capabilities.

Managers face the added burden of time constraints when attempting to innovate within a new technological paradigm. It is tantamount, therefore, to firm success that a manager be able to not only weigh the strengths and weaknesses of the available 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 the knowledge of

possible deleterious interaction effects. Our research demonstrates that, due to the constraints imposed on a firm's financial, managerial, and research-related resources, this tandem approach may actually lead to decreases in innovative output. In other words, when investigating the number of mechanisms a manager can employ, more is not always better.

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CHAPTER 3 APPENDIX

TABLE 3.1: 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.
1. Biotech Patents Applied	5.55	11.90																
2. Biotech Patents Granted	5.63	11.46	0.606															
3. Net Income (MM$)	32,907	648,153	0.032	0.052														
4. Total Assets (MM$)	10,268	12,211	0.142	0.181	-0.019													
5. US Firm	0.26	0.44	0.121	0.135	-0.036	0.044												
6. EU Firm	0.37	0.48	0.033	0.023	0.066	0.158	-0.462											
7. Firm Merged	0.07	0.26	0.051	0.082	-0.013	0.194	0.104	0.056										
8. Pharma Firm	0.53	0.50	0.053	0.071	0.047	-0.316	-0.096	0.219	-0.129									
9. Time to First Cohen-Boyer Patent Citation (years)	6.55	2.90	-0.212	-0.225	-0.069	0.032	-0.107	0.065	-0.036	0.009								
10. Non-Biotech Patents Applied	55.71	104.18	0.237	0.190	0.007	0.535	0.132	0.074	0.004	-0.313	0.010							
11. Non-Biotech Patents Granted	57.90	104.93	0.180	0.228	0.014	0.540	0.146	0.070	0.018	-0.325	0.008	0.927						
12. Scientists (total)	186.46	282.61	0.427	0.455	-0.036	0.232	0.232	0.100	0.381	0.124	-0.159	0.250	0.263					
13. Non-Star Scientists	173.13	260.58	0.414	0.445	-0.036	0.242	0.220	0.120	0.387	0.118	-0.158	0.250	0.266	0.995				
14. Star Scientists	13.34	35.85	0.363	0.356	-0.019	0.084	0.232	-0.077	0.196	0.119	-0.103	0.154	0.138	0.654	0.572			
15. R&D Intensity	0.09	0.07	0.111	0.113	-0.030	-0.065	-0.073	0.230	0.070	0.359	-0.001	-0.035	-0.048	0.197	0.205	0.074		
16. Biotech Alliances	2.41	6.12	0.250	0.155	-0.009	0.121	0.185	-0.004	0.310	0.045	-0.152	0.089	0.043	0.413	0.390	0.417	0.068	
17. Biotech Acquisitions	0.51	1.63	0.183	0.165	-0.013	0.196	0.142	0.056	0.381	0.070	-0.114	0.101	0.080	0.377	0.360	0.360	0.089	0.514

N = 1,863 firm-years.

Table 3.2: Regression Results

	Model 1		Model 2	
	Biotech Patents Applied		Biotech Patents Granted	
	beta	s.e.	beta	s.e.
Constant	-0.0556	(0.2323)	0.1216	(0.2000)
Year is 1981	-0.2720	(0.2896)	0.0079	(0.2281)
Year is 1982	0.1951	(0.2610)	-0.2121	(0.2489)
Year is 1983	0.0192 *	(0.2799)	-0.3389 †	(0.2576)
Year is 1984	0.3151	(0.2565)	-0.0654	(0.2368)
Year is 1985	0.2037	(0.2629)	0.0539	(0.2297)
Year is 1986	0.3477 †	(0.2567)	-0.1261	(0.2411)
Year is 1987	0.5408 *	(0.2473)	0.0098	(0.2346)
Year is 1988	0.5408 *	(0.2511)	0.1316	(0.2267)
Year is 1989	0.5840 **	(0.2372)	0.2129	(0.2096)
Year is 1990	0.8419 ***	(0.2276)	0.2738 †	(0.1989)
Year is 1991	0.8776 ***	(0.2271)	0.5027 *	(0.1964)
Year is 1992	0.9167 ***	(0.2272)	0.5875 ***	(0.1942)
Year is 1993	1.1491 ***	(0.2253)	0.7113 ***	(0.1918)
Year is 1994	1.4643 ***	(0.2265)	0.6142 ***	(0.1987)
Year is 1995	1.6436 ***	(0.2276)	0.6813 ***	(0.1996)
Year is 1996	1.3595 ***	(0.2289)	0.7892 ***	(0.1968)
Year is 1997	1.4457 ***	(0.2268)	1.0444 ***	(0.1937)
Year is 1998	1.3906 ***	(0.2312)	1.1856 ***	(0.1940)
Year is 1999	1.3419 ***	(0.2345)	1.1771 ***	(0.1983)
Year is 2000	1.0461 ***	(0.2403)	0.9651 ***	(0.2024)
Year is 2001	0.5101 *	(0.2547)	1.1134 ***	(0.2026)
Year is 2002	-0.7438 *	(0.3270)	0.8589 ***	(0.2083)
Net Income	0.0288 †	(0.0192)	0.0203	(0.0193)
Total Assets	-0.3356 ***	(0.0680)	-0.2199 ***	(0.0619)
US Firm	-0.0892	(0.1151)	-0.1503	(0.1192)
EU Firm	-0.5458 ***	(0.1271)	-0.8738 ***	(0.1321)
Firm Merged	0.1766 ***	(0.0333)	0.1085 ***	(0.0346)
Pharma Firm	-0.0154	(0.0892)	0.0693	(0.0938)
Time to First Cohen-Boyer Patent Citation	-0.4259 ***	(0.0782)	-0.5317 ***	(0.0818)
Non-Biotech Patents Applied	0.3927 ***	(0.0388)		
Non-Biotech Patents Granted			0.4853 ***	(0.0439)
Scientists (total)				
Non-Star Scientists				
Star Scientists				
R&D Intensity				
Biotech Alliances				
Biotech Acquisitions				
Scientists (total) x R&D Intensity				
Scientists (total) x Biotech Alliances				
Scientists (total) x Biotech Acquisitions				
Non-Star Scientists x R&D Intensity				
Non-Star Scientists x Biotech Alliances				
Non-Star Scientists x Biotech Acquisitions				
Star Scientists x R&D Intensity				
Star Scientists x Biotech Alliances				
Star Scientists x Biotech Acquisitions				
R&D Intensity x Biotech Alliances				
R&D Intensity x Biotech Acquistions				
Log likelihood	-2521.08		-2465.30	
Chi Square	895.91 ***		705.77 ***	

† $p < .10$* $p < .05$; ** $p < .01$; *** $p < .001$; Standard errors are in parentheses.

Table 3.3: Regression Results

	Model 3 Biotech Patents Applied		Model 4 Biotech Patents Granted	
	beta	s.e.	beta	s.e.
Constant	0.0506	(0.2410)	0.1763	(0.2135)
Year is 1981	-0.2723	(0.2859)	-0.0215	(0.2305)
Year is 1982	0.1695	(0.2585)	-0.2278	(0.2497)
Year is 1983	0.0163	(0.2762)	-0.3443 †	(0.2578)
Year is 1984	0.0163 †	(0.2558)	-0.0932	(0.2429)
Year is 1985	0.0163	(0.2689)	0.0448	(0.2347)
Year is 1986	0.3371	(0.2553)	-0.1727	(0.2460)
Year is 1987	0.1126 *	(0.2464)	-0.2178	(0.2372)
Year is 1988	0.3268 *	(0.2479)	0.0169	(0.2334)
Year is 1989	0.5573 **	(0.2380)	0.1449	(0.2183)
Year is 1990	0.7944 ***	(0.2277)	0.1761	(0.2052)
Year is 1991	0.8201 ***	(0.2276)	0.4087 *	(0.2050)
Year is 1992	0.8503 ***	(0.2287)	0.4935 †	(0.2041)
Year is 1993	1.0636 ***	(0.2279)	0.6290 ***	(0.2025)
Year is 1994	1.3946 ***	(0.2298)	0.4831 *	(0.2115)
Year is 1995	1.5679 ***	(0.2324)	0.5882 **	(0.2143)
Year is 1996	1.2506 ***	(0.2355)	0.6405 **	(0.2125)
Year is 1997	1.4089 ***	(0.2352)	0.9675 ***	(0.2172)
Year is 1998	1.4149 ***	(0.2427)	1.2112 ***	(0.2159)
Year is 1999	1.3471 ***	(0.2456)	1.2829 ***	(0.2189)
Year is 2000	1.0901 ***	(0.2475)	1.0169 ***	(0.2307)
Year is 2001	0.6384 ***	(0.2754)	1.3182 ***	(0.2320)
Year is 2002	-0.7258 *	(0.3818)	0.9886 ***	(0.2453)
Net Income	0.0195	(0.0200)	0.0065	(0.0210)
Total Assets	-0.3865 ***	(0.0729)	-0.3384 ***	(0.0709)
US Firm	-0.2883 *	(0.1413)	-0.3204 **	(0.1368)
EU Firm	-0.6229 ***	(0.1541)	-0.8459 ***	(0.1510)
Firm Merged	0.1582 ***	(0.0348)	0.1110 ***	(0.0361)
Pharma Firm	-0.0791	(0.0975)	-0.0088	(0.0980)
Time to First Cohen-Boyer Patent Citation	-0.4889 ***	(0.0828)	-0.5792 ***	(0.0843)
Non-Biotech Patents Applied	0.3909 ***	(0.0420)		
Non-Biotech Patents Granted			0.4878 ***	(0.0489)
Scientists (total)	0.1257 **	(0.0421)	0.1901 ***	(0.0457)
Non-Star Scientists				
Star Scientists				
R&D Intensity	-0.1225 **	(0.0525)	-0.1561 **	(0.0608)
Biotech Alliances	0.0161	(0.0214)	0.0327 †	(0.0226)
Biotech Acquisitions	0.0094	(0.0222)	-0.0232	(0.0227)
Scientists (total) x R&D Intensity				
Scientists (total) x Biotech Alliances				
Scientists (total) x Biotech Acquisitions				
Non-Star Scientists x R&D Intensity				
Non-Star Scientists x Biotech Alliances				
Non-Star Scientists x Biotech Acquisitions				
Star Scientists x R&D Intensity				
Star Scientists x Biotech Alliances				
Star Scientists x Biotech Acquisitions				
R&D Intensity x Biotech Alliances				
R&D Intensity x Biotech Acquistions				
Log likelihood	-2251.41		-2147.90	
Chi Square	914.46 ***		817.81 ***	
Improvement over Base ($\Delta\chi^2$)	18.55 ***		112.04 ***	

† $p < .10$* $p < .05$; ** $p < .01$; *** $p < .001$; Standard errors are in parentheses.

Table 3.4: Regression Results

	Model 5 Biotech Patents Applied			Model 6 Biotech Patents Granted		
	beta		s.e.	beta		s.e.
Constant	0.0557		(0.2414)	0.1748		(0.2137)
Year is 1981	-0.2727		(0.2861)	-0.0212		(0.2304)
Year is 1982	0.1699		(0.2586)	-0.2274		(0.2497)
Year is 1983	0.0166		(0.2764)	-0.3440	†	(0.2578)
Year is 1984	0.3377	†	(0.2561)	-0.0926		(0.2428)
Year is 1985	0.1120		(0.2692)	0.0447		(0.2347)
Year is 1986	0.3292	†	(0.2556)	-0.1731		(0.2460)
Year is 1987	0.5178	*	(0.2467)	-0.0213		(0.2372)
Year is 1988	0.4247	*	(0.2481)	0.0154		(0.2336)
Year is 1989	0.5579	**	(0.2382)	0.1449		(0.2182)
Year is 1990	0.7956	***	(0.2280)	0.1756		(0.2052)
Year is 1991	0.8198	***	(0.2279)	0.4090	*	(0.2050)
Year is 1992	0.8481	***	(0.2290)	0.4933	**	(0.2041)
Year is 1993	1.0635	***	(0.2280)	0.6292	***	(0.2025)
Year is 1994	1.3931	***	(0.2299)	0.4835	*	(0.2115)
Year is 1995	1.5653	***	(0.2326)	0.5891	**	(0.2144)
Year is 1996	1.2458	***	(0.2360)	0.6415	**	(0.2127)
Year is 1997	1.3994	***	(0.2367)	0.9703	***	(0.2181)
Year is 1998	1.4082	***	(0.2435)	1.2129	***	(0.2162)
Year is 1999	1.3398	***	(0.2466)	1.2852	***	(0.2194)
Year is 2000	1.0805	***	(0.2589)	1.0192	***	(0.2312)
Year is 2001	0.6303	*	(0.2766)	1.3195	***	(0.2321)
Year is 2002	-0.7361	*	(0.3830)	0.9921	***	(0.2464)
Net Income	0.0194		(0.0200)	0.0066		(0.0210)
Total Assets	-0.3874	***	(0.0731)	-0.3369	***	(0.0717)
US Firm	-0.2891	*	(0.1415)	-0.3191	**	(0.1370)
EU Firm	-0.6273	***	(0.1546)	-0.8448	***	(0.1511)
Firm Merged	0.1583	***	(0.3452)	0.1109	***	(0.0361)
Pharma Firm	-0.0773		(0.0975)	-0.0102		(0.0985)
Time to First Cohen-Boyer Patent Citation	-0.4824	***	(0.0841)	-0.5805	***	(0.0849)
Non-Biotech Patents Applied	0.3919	***	(0.0420)			
Non-Biotech Patents Granted				0.4872	***	(0.0491)
Scientists (total)						
Non-Star Scientists	0.1278	**	(0.0485)	0.1714	***	(0.0510)
Star Scientists	0.0022		(0.0345)	0.0286		(0.0330)
R&D Intensity	-0.1250	**	(0.0531)	-0.1552	**	(0.0611)
Biotech Alliances	0.0169		(0.0215)	0.0320	†	(0.0231)
Biotech Acquisitions	0.0104		(0.0223)	-0.0235		(0.0229)
Scientists (total) x R&D Intensity						
Scientists (total) x Biotech Alliances						
Scientists (total) x Biotech Acquisitions						
Non-Star Scientists x R&D Intensity						
Non-Star Scientists x Biotech Alliances						
Non-Star Scientists x Biotech Acquisitions						
Star Scientists x R&D Intensity						
Star Scientists x Biotech Alliances						
Star Scientists x Biotech Acquisitions						
R&D Intensity x Biotech Alliances						
R&D Intensity x Biotech Acquistions						
Log likelihood	-2251.32			-2147.89		
Chi Square	915.06	***		817.54	***	
Improvement over Base ($\Delta\chi^2$)	19.15	**		111.77	***	

† $p < .10$* $p < .05$; ** $p < .01$; *** $p < .001$; Standard errors are in parentheses.

Table 3.5: Regression Results

	Model 7 Biotech Patents Applied			Model 8 Biotech Patents Granted		
	beta		s.e.	beta		s.e.
Constant	0.1538		(0.2396)	0.2080		(0.2128)
Year is 1981	-0.2863		(0.2809)	-0.0059		(0.2243)
Year is 1982	0.1544		(0.2534)	-0.2027		(0.2433)
Year is 1983	-0.0031		(0.2702)	-0.3330	†	(0.2530)
Year is 1984	0.3179		(0.2503)	-0.0709		(0.2378)
Year is 1985	0.1013		(0.2645)	0.0703		(0.2293)
Year is 1986	0.3029		(0.2510)	-0.1715		(0.2418)
Year is 1987	0.5088	*	(0.2437)	0.0109		(0.2323)
Year is 1988	0.3805	†	(0.2457)	0.0365		(0.2299)
Year is 1989	0.5019	*	(0.2388)	0.1617		(0.2194)
Year is 1990	0.7226	***	(0.2256)	0.1514		(0.2028)
Year is 1991	0.7512	***	(0.2262)	0.4029	*	(0.2037)
Year is 1992	0.7685	***	(0.2275)	0.4876	**	(0.2024)
Year is 1993	0.9611	***	(0.2277)	0.6116	***	(0.2018)
Year is 1994	1.3035	***	(0.2289)	0.4649	*	(0.2104)
Year is 1995	1.5131	***	(0.2330)	0.6070	**	(0.2141)
Year is 1996	1.1693	***	(0.2353)	0.6411	**	(0.2126)
Year is 1997	1.3334	***	(0.2380)	1.0332	***	(0.2183)
Year is 1998	1.3001	***	(0.2427)	1.2153	***	(0.2153)
Year is 1999	1.2833	***	(0.2436)	1.3178	***	(0.2154)
Year is 2000	0.9711	***	(0.2567)	1.0388	***	(0.2266)
Year is 2001	0.4998	*	(0.2761)	1.2545	***	(0.2310)
Year is 2002	-0.8552	*	(0.3846)	1.0109	***	(0.2448)
Net Income	0.0176		(0.2000)	0.0067		(0.0206)
Total Assets	-0.3708	***	(0.0721)	-0.3550	***	(0.0704)
US Firm	-0.2897	*	(0.1425)	-0.3086	*	(0.1403)
EU Firm	-0.6127	***	(0.1539)	-0.8442	***	(0.1509)
Firm Merged	0.1441	***	(0.0351)	0.0932	**	(0.0371)
Pharma Firm	-0.0791		(0.0975)	0.0107		(0.1002)
Time to First Cohen-Boyer Patent Citation	-0.4772	***	(0.0848)	-0.6071	***	(0.0876)
Non-Biotech Patents Applied	0.3879	***	(0.0421)			
Non-Biotech Patents Granted				0.5106	***	(0.0490)
Scientists (total)	0.2202	***	(0.0531)	0.2453	***	(0.0552)
Non-Star Scientists						
Star Scientists						
R&D Intensity	-0.1395	**	(0.0557)	-0.1246	*	(0.0627)
Biotech Alliances	0.0279		(0.0355)	0.0471	†	(0.0347)
Biotech Acquisitions	0.0227		(0.0346)	-0.6128	†	(0.0389)
Scientists (total) x R&D Intensity	-0.0919	*	(0.0421)	-0.1111	**	(0.0396)
Scientists (total) x Biotech Alliances	-0.0355	**	(0.0149)	-0.0209	†	(0.0148)
Scientists (total) x Biotech Acquisitions	-0.0160		(0.0154)	0.0019		(0.0165)
Non-Star Scientists x R&D Intensity						
Non-Star Scientists x Biotech Alliances						
Non-Star Scientists x Biotech Acquisitions						
Star Scientists x R&D Intensity						
Star Scientists x Biotech Alliances						
Star Scientists x Biotech Acquisitions						
R&D Intensity x Biotech Alliances	0.1775	***	(0.0502)	0.0544	**	(0.0453)
R&D Intensity x Biotech Acquistions	0.0594	†	(0.0402)	0.1267		(0.0466)
Log likelihood	-2240.25			-2139.36		
Chi Square	976.34	***		860.74	***	
Improvement over Base ($\Delta\chi^2$)	80.43	***		154.97	***	

† $p < .10$* $p < .05$; ** $p < .01$; *** $p < .001$; Standard errors are in parentheses.

Table 3.6: Regression Results

	Model 9 Biotech Patents Applied		Model 10 Biotech Patents Granted	
	beta	s.e.	beta	s.e.
Constant	0.1624	(0.2411)	0.2538	(0.2154)
Year is 1981	-0.2881	(0.2808)	-0.0032	(0.2235)
Year is 1982	0.1527	(0.2533)	-0.2064	(0.2425)
Year is 1983	0.0052	(0.2703)	-0.3366 †	(0.2518)
Year is 1984	0.3158	(0.2503)	-0.0770	(0.2366)
Year is 1985	0.0988	(0.2648)	0.0508	(0.2288)
Year is 1986	0.3026	(0.2512)	-0.1846	(0.2413)
Year is 1987	0.4991 *	(0.2440)	-0.0079	(0.2320)
Year is 1988	0.3622 †	(0.2477)	-0.0097	(0.2326)
Year is 1989	0.4764 *	(0.2412)	0.1526	(0.2205)
Year is 1990	0.7139 ***	(0.2264)	0.1133	(0.2035)
Year is 1991	0.7403 ***	(0.2274)	0.3591 *	(0.2053)
Year is 1992	0.7569 ***	(0.2287)	0.4541 *	(0.2039)
Year is 1993	0.9517 ***	(0.2287)	0.5767 **	(0.2031)
Year is 1994	1.2953 ***	(0.2294)	0.4350 **	(0.2106)
Year is 1995	1.5019 ***	(0.2340)	0.5770 **	(0.2150)
Year is 1996	1.1576 ***	(0.2366)	0.6148 **	(0.2135)
Year is 1997	1.3337 ***	(0.2396)	1.0076 ***	(0.2191)
Year is 1998	1.2931 ***	(0.2450)	1.1576 ***	(0.2183)
Year is 1999	1.2709 ***	(0.2458)	1.2721 ***	(0.2188)
Year is 2000	0.9641 ***	(0.2592)	1.0015 ***	(0.2287)
Year is 2001	0.4953 **	(0.2766)	1.2216 ***	(0.2305)
Year is 2002	-0.8816 *	(0.3872)	0.9550 ***	(0.2509)
Net Income	0.0178	(0.0200)	0.0088	(0.0202)
Total Assets	-0.3574 ***	(0.0754)	-0.3063 ***	(0.0759)
US Firm	-0.2922 *	(0.1423)	-0.3129 *	(0.1413)
EU Firm	-0.6156 ***	(0.1548)	-0.8599 ***	(0.1522)
Firm Merged	0.1436 ***	(0.0356)	0.0810 *	(0.0374)
Pharma Firm	-0.0752	(0.0984)	0.0198	(0.1014)
Time to First Cohen-Boyer Patent Citation	-0.4801 ***	(0.0862)	-0.6063 ***	(0.0890)
Non-Biotech Patents Applied	0.3871 ***	(0.0421)		
Non-Biotech Patents Granted			0.5147 ***	(0.0487)
Scientists (total)				
Non-Star Scientists	0.2132 ***	(0.0560)	0.2352 ***	(0.0644)
Star Scientists	0.0105	(0.0489)	0.0192	(0.0539)
R&D Intensity	-0.1388 **	(0.0573)	-0.1021 *	(0.0618)
Biotech Alliances	0.0332	(0.0361)	0.0409	(0.0363)
Biotech Acquisitions	0.0197	(0.0350)	-0.0675 *	(0.0394)
Scientists (total) x R&D Intensity				
Scientists (total) x Biotech Alliances				
Scientists (total) x Biotech Acquisitions				
Non-Star Scientists x R&D Intensity	-0.0906 *	(0.0551)	-0.1573	(0.0531)
Non-Star Scientists x Biotech Alliances	-0.0467 *	(0.0233)	-0.0164	(0.0230)
Non-Star Scientists x Biotech Acquisitions	-0.013	(0.0205)	0.0188	(0.0211)
Star Scientists x R&D Intensity	-0.0005	(0.0683)	0.1000 †	(0.0715)
Star Scientists x Biotech Alliances	0.0038	(0.0105)	-0.0014 **	(0.0103)
Star Scientists x Biotech Acquisitions	-0.0007	(0.0090)	-0.0095	(0.0088)
R&D Intensity x Biotech Alliances	0.1835 ***	(0.0541)	0.0263	(0.0524)
R&D Intensity x Biotech Acquistions	0.0557 †	(0.0418)	0.1031 *	(0.0507)
Log likelihood	-2239.84		-2137.38	
Chi Square	977.77 ***		879.96 ***	
Improvement over Base ($\Delta\chi^2$)	81.86 ***		174.19 ***	

† $p < .10$* $p < .05$; ** $p < .01$; *** $p < .001$; Standard errors are in parentheses.

CHAPTER 4

AMBIDEXTERITY AND INNOVATIVE PERFORMANCE: THE ROLE OF INTELLECTUAL HUMAN CAPITAL AND STRATEGIC ALLIANCES

4.1 Introduction

How do organizations identify and react to changes that originate outside their boundaries? This question is fundamental to both organization theory and strategic management. Organization theory scholars that draw on the organizational learning literature suggest that the ability to simultaneously explore new knowledge and to exploit existing knowledge allows an organization to continuously adapt to changing environments (Levinthal and March, 1993; March, 1991). The ability of an organization to concurrently pursue exploration and exploitation has been described as ambidexterity (O'Reilly and Tushman, 2007), because engaging in exploration requires fundamentally different routines, processes, and skills than those necessary for exploitation.

To answer the question of how organizations identify and react to changes that originate outside their boundaries, strategy scholars have recently begun to advance a dynamic capabilities perspective. They suggest 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 not only adapt to changing environments (Teece, Pisano, and Shuen, 1997: 516), but also to introduce favorable market change (Eisenhardt and Martin, 2000). Thus, a dynamic capability has been defined as "the capacity of an organization to purposefully create, extend, or modify its resources base" (Helfat et. al, 2007: 4). Key to understanding dynamic capabilities, therefore, is the organization's ability to alter its resource base in a repeatable and reliable fashion, as guided by the organization's strategic intent.

In their recent theoretical treatise, O'Reilly and Tushman (2007) synthesized these two theoretical perspectives to suggest that ambidexterity is an important dynamic capability. The creation and maintenance of this dynamic capability, therefore, requires that an organization not only engages in exploration to create new capabilities, but also that the organization builds on and exploits current capabilities as well. While it is readily apparent that managers have at their disposal multiple mechanisms to build dynamic capabilities (for an overview see Helfat, et al., 2007), we have virtually no understanding of the nuanced contingency effects that arise when different antecedents to dynamic capabilities *within* and *across* the dimensions of the exploration-exploitation framework are employed simultaneously. The critical theoretical dimension that we highlight, therefore, is whether the different dynamic capability mechanisms that firms use to build and change their resources are exploratory or exploitative in nature.

We focus herein on two different mechanisms that firms can employ to build dynamic capabilities: 1) recruiting and retaining of intellectual human capital and 2) engaging in strategic alliances, while explicitly controlling for acquisitions. Our choice in focusing on these two mechanisms stems from the fact that expertise in these activities are representative of dynamic capabilities that allow firms to access and build new capabilities in order to change their existing resource base (Gulati, 1998; Cockburn and Henderson, 2001), and thus to develop new processes, products, or services. While some of these mechanisms have been studied in isolation in prior research (Zucker and Darby, 1997a; Rothaermel, 2001; Gardner, 2005), we know very little about the simultaneous effects of these mechanisms on innovative performance in general (Rothaermel and Hess, 2007). We know practically nothing about the simultaneous effects of leveraging different types of intellectual human capital and different types of strategic alliances in an effort to modify a firm's existing resources or to create new resources.

We suggest that both strategic alliances and different types of intellectual human capital can be categorized within the exploration-exploitation framework of organizational learning. This decomposition allows us to derive falsifiable hypotheses. While the exploration-exploitation lens has been applied to strategic alliances based on their strategic motivation (Koza and Lewin, 1998), we propose that it can also be applied to a firm's intellectual human capital based on a noted bifurcation of "star" versus "staff scientists" (Rothaermel and Hess, 2007; Zucker and Darby, 1996). It has long been demonstrated that not all intellectual human capital is created equally (Lotka, 1926), indicating that significant heterogeneity exists even within highly specialized intellectual human capital.

We propose that different antecedents to building dynamic capabilities *within* the same activity (either indented for exploration or exploitation) compensate for one another, and thus are *substitutes*. Conversely, we hypothesize that different dynamic capability antecedents *across* exploration or exploitation activities positively reinforcing one another, and thus are *complements*. We empirically test this contingency framework of ambidexterity across exploration and exploitation on an unusually detailed and comprehensive panel of data. In particular, we followed 108 global pharmaceutical firms' innovative performance in biotechnology for over three decades (1974-2003). The pharmaceutical industry experienced a radical technological transformation with the advent of biotechnology based on the arrival of genetic engineering, genomics, and other novel research since the mid-1970s (Kenney, 1986; Pisano, 2006). To track the adaptation of incumbent pharmaceutical companies to biotechnology, we leverage fine-grained longitudinal data on 3,100 alliances, 3,500 new drug introductions, 36,000 biotechnology patents that have been cited 80,000 times, 147,000 non-biotechnology patents, 171,000 publishing scientists, 672,000 journal publications, and 9.9 million journal citations.

4.2 Theory and Hypotheses Development

In high velocity industries antecedents to innovation often come from outside of the organizational boundaries (Powell, et al., 1996). Therefore, in such industries, an organization's innovative performance is inextricably linked to its ability to create and manage connections with other organizations. Prior research investigating the importance of this connectivity has primarily focused on the important role strategic alliances play in developing an organization's ability to access sources of external knowledge (Hagedoorn, 1993; Gulati, 1999; Rothaermel and Deeds, 2004). It is important to note however, that this capability is also related to the firm's scope of collaborations; both formal (strategic alliances) and informal (interpersonal) relationships (Powell, et al., 1996). Thus, analysis of an organization's connectivity requires knowledge not only of its strategic alliances, but also its intellectual human capital, which fosters, as indicated by the CEO of Centocor: "…dozens of handshake deals and informal collaborations, as well as probably hundreds of collaborations by our company's scientists with colleagues elsewhere" (Powell, et al. 1996: 120). Thus, within high velocity industries, both strategic alliances and intellectual human capital are antecedents to innovation (Rothaermel and Hess, 2007).

The relationship between these antecedents to innovation is complex because the interdependence between them depends on the innovative intent with which they are utilized. This intent relates to the type of knowledge the organization is attempting to access. More specifically, is the organization seeking to explore for new knowledge or exploit an existing knowledge base? This distinction is critical because the relationship between exploration and exploitation lies at the foundation of understanding how organizations not only gain, but also sustain long term innovative performance (Tushman and O'Reilly, 1996). As we will develop further, the importance of understanding this relationship stems from the analysis of both the type of knowledge

transmitted and the types of partners an organization attempts to connect with; depending on whether its innovative intent of the effort is to exploration or exploitation. Our hypotheses development will progress by next briefly describing the explore/exploit framework of organizational learning and why it represents an appropriate lens for the analysis of organizational connectivity. Our theoretical development will describe how prior research has applied this framework to an organization's strategic alliances and why we suggest it is also appropriate for the analysis of an organization's human capital. Finally, the typology developed through this theoretical argument will be utilized to illustrate the differential interaction between alliances and intellectual human capital; depending on whether they are focused on exploration or exploitation activities.

It is important to note that prior research has provided some key insights pertaining to exploration and exploitation activities when using the *same* mechanism, i.e., when focusing either on alliances *or* scientists. What we lack, however, is a nuanced understanding of the contingency effects of *different* exploration and exploitation mechanisms. In this study, therefore, we focus on the interactions between micro- and macro-levels, and thus focus on the different permutations between a firm's intellectual human capital, bifurcated into star and staff scientists, and its strategic alliances, dichotomized into exploration alliances and exploitation alliances.

4.2.1 The Exploration/Exploitation Framework

March (1991: 71) explained that "exploration includes things captured by terms such as search, variation, risk taking, experimentation, play, flexibility, discovery, innovation. Exploitation includes such things as refinement, choice, production, efficiency, selection, implementation, execution." Thus, the "essence of exploration is experimentation with new alternatives," while the "essence of exploitation is the refinement and extension of existing competences." Subsequently, Levinthal and March

(1993: 105) defined exploration as “the pursuit of new knowledge, of things that might come to be known,” and exploitation as “the use and development of things already known.” In order understand the relationship both within and between the organization’s functional groups, we next turn to describe how the explore/exploit framework relates to both an organization’s strategic alliances, as well as its intellectual human capital.

4.2.1.1 Strategic Alliances

In their conceptual treatment, Koza and Lewin (1998) were the first to apply to exploration-exploitation framework to a firm’s strategic alliances. In particular, they suggested that alliances can be categorized whether they are entered with the motivation to exploit an existing capability or to explore for new opportunities. In this functional view based on the value-adding position of an alliance along the value chain, exploration alliances are understood as knowledge-generating R&D alliances, while exploitation alliances are understood as knowledge-leveraging production and marketing alliances (Lavie and Rosenkopf, 2006).

Firms that conduct upstream research alliances to discover something new are engaged in exploration, allowing the partners to share and acquire tacit knowledge. Exploration alliances are usually undertaken with universities and other research institutions and are often characterized by high uncertainty and frequent failure (Rothaermel and Deeds, 2006). On the other hand, firms that conduct downstream alliances to leverage complementary assets are engaged in exploitation through the leveraging of explicit knowledge Teece, 1992). Unlike exploration alliances, exploitation or downstream alliances are generally formed with larger, more well-established firms that provide manufacturing capabilities, regulatory know-how, market knowledge and access (Rothaermel and Deeds, 2006).

When studying alliance formation, Park, et al. (2002) found that, in turbulent industries, a firm's propensity to enter exploration or exploitation alliances relates to its resource endowment, with resource-poor firms preferring exploitation over exploration alliances. Rothaermel and Deeds (2004) documented that biotechnology firms that are able to conceive of and implement an alliance strategy based on exploration and exploitation alliances to form an integrated system of new product development are rewarded with enhanced performance. More recently, Lavie and Rosenkopf (2006) demonstrated how firms in the software industry simultaneously balance exploration and exploitation in alliance formation across the value chain function of alliances, specific partner attributes, and the partners' network positions.

Several empirical studies, across different types of firms, industries, and time frames, have provided robust support for the viability of applying the exploration-exploitation lens to strategic alliances (Rothaermel, 2001; Park, et al., 2002; Rothaermel and Deeds, 2004; Lavie and Rosenkopf, 2006). Following this established line of theoretical and empirical research, we dichotomize a firm's strategic alliances into exploration and exploitation alliances based on this functional view to reflect their differential motivation to leverage different types of knowledge along the value chain.

4.2.1.2 Intellectual Human Capital

Sociologists have investigated the disparate roles that individuals of varying talent within the scientific community play in the identification, as well as in adopting or rejecting new scientific paradigms (Kuhn, 1962). Such research, however, has generated conflicting viewpoints regarding the importance of key individuals to the development of scientific knowledge. A central question to the sociology of science is whether science itself advances through the accumulation of marginal contributions from large armies of average scientists or through seminal contributions by an eminent few. One perspective, referred to as the Ortega Hypothesis (Ortega y Gasset, 1932; Cole and

Cole, 1972), supports the former argument by positing that breakthroughs by exceptional scientists are built on the shoulders of smaller, incremental discoveries by 'non-star' researchers. Accordingly, in his analysis of scientific advancement, Kuhn (1962) emphasizes the role of these non-star scientists in 'mopping up' after significant paradigm shifts, and suggests that this activity is so integral to the progression of science that it serves as the basis for normal science itself.

A second perspective, referred to as the Lotka-Price Law, suggests that a few elite scientists are responsible for determining those scientific ideas that are acceptable for propagation (Cole and Cole, 1972; Lotka, 1926; Price, 1963). This research suggests that without these scientific 'stars', the institution of science itself would sever into a multitude of fragmented and disconnected pieces and eventually stifle scientific progress altogether. Polanyi (1963) believes that without these elite scientists, young scientists would lack direction because they would be overwhelmed with too many conflicting and under-developed theories; Cole and Cole (1973) even go so far as to suggest that most of these so-called 'average' scientists are expendable, and that scientific progress may even be accelerated if there were fewer of these 'average' scientists because more resources would then be available for the 'stars'.

The tension between the Ortega Hypothesis and the Lotka-Price Law can be alleviated by considering how scientific knowledge is acquired and codified within the setting of a firm's effort to innovate. A synthesis of these viewpoints provides not only a clearer picture of the role of the individual in a firm's innovation efforts, but also the relationship between different antecedents to innovation. Building on Kuhn (1962), we suggest that rather than being competitive or substitutive in nature, elite and average scientists actually play discrete but highly complementary roles in facilitating firm innovation.

The notion that different individuals play different roles in the innovation process has its roots in sociological research that investigates the relationship between a scientist's talent, status, and conformity. While, it may appear at first glance to be tangential to our central argument relating to the explore/exploit framework, synthesizing the work of Zuckerman, Phillips, Dittes, and Kelly (Dittes and Kelley, 1956; Zuckerman and Phillips, 2001) with the organizational learning literature examining gate-keeping and boundary spanning (Allen and Cohen, 1969; Aldrich and Herker, 1977; Tushman, 1977) allows for insight into the motivations that underpin the roles of the individual scientist or researcher within a commercial enterprise. Within these commercial enterprises, the analysis of the overlap between scientific and commercial opportunities available to researchers provides a fertile ground for investigation into the similarities between the process of organizational learning and the process through which scientific revolutions spread in society.

When scientific and commercial opportunities converge, the skills and motivations of individuals will lie on a continuum between scientific (associated with the creation and dissemination of tacit knowledge) and commercial opportunities (reflecting the commercial interests of the organization). We suggest that an individual's position on this continuum may in part be due to the status and talent of the individual. Specifically, related to Dittes and Kelley (1956), high-status or star actors will tend to be confident in their position within the organization and thus often will be emboldened to deviate from conventional behavior (Zuckerman and Phillips, 2001). Within the setting of knowledge-intensive, commercial entities, this deviant behavior may involve a more active participation in the academic or pure research pursuits of the profession. The importance of this pursuit is that the star actors are more likely to pursue more tacit research streams that are a higher risk/reward potential and thus not directly related to the dominant research streams of the organization. Such activities are often rewarding

for the individual scientist, but because of the tacit nature of the generated knowledge, often do not lead to commercially viable products (Gittelman and Kogut, 2003). Within the organization, these individuals may serve as gatekeepers or boundary spanners. These individuals bridge organizational/environmental boundaries to act as information filters by evaluating and organizing knowledge flows from external sources. They are able to gather and understand external information, and then to translate and disseminate this information into terms that are meaningful and useful to other organization members (Allen and Cohen, 1969; Aldrich and Herker, 1977; Tushman, 1977).

In contrast to the star researchers, *middle* status actors (differentiated from *low*-status individuals who are not likely to be employed[9]) do not experience the same level of freedom. Whether because of tenure or talent, these individuals are likely to be more conservative given the tensions between their aspirations and fear of disenfranchisement (Zuckerman and Phillips, 2001). We suggest that the middle status or staff scientists will pursue activities that are closer to the commercial end of the scientific/commercial continuum. In contrast to the stars, staff scientists are more likely to pursue research activities that are more codified in nature and thus more likely to result in patents and new products. In addition, the general conformity of the middle status individual suggests that the chosen research or knowledge streams will be more inline with that of the organization's current knowledge base than that chosen by a star researcher. Further, there is an element of institutional restriction which may dictate the direction staff researcher projects are allowed to go. These individuals are often part of

[9] The authors suggest there is an inverted U-shaped relationship between status and conformity, with low-status actors also feeling free to defy accepted practice because they are excluded regardless of their actions (Zuckerman and Philips, 2001)

a larger research team, and thus less likely to have as much freedom to pursue their own research interests.

In support for this notion, Furukawa and Goto (2006) documented that the stars in science are, as expected based on the Lotka-Price Law, responsible for a disproportional large number of publications in scientific journals, but that it is the staff scientists, who translate this tacit knowledge into patents, and thus transform tacit knowledge not only into codified knowledge, but also knowledge that is legally protected and provides a basis for commercial exploitation. Similarly, Rothaermel and Hess (2007) documented that staff scientists fully mediate any effect stars have on a firm's patenting in new technological field. Both studies seem to implicitly suggest that a balance between explorative activities of stars and exploitative activities of staff scientists is necessary when building new competences.

As defined by the Lotka-Price Law, a star scientist is by an order of magnitude, both, more productive and more influential than a staff scientist, in a specific field of research. Parallel to the bifurcation of intellectual human capital into star and staff scientists, we propose that star scientists are primarily engaged in exploratory work through identifying future promising research areas, conducting basic research, and so on, while staff scientists tend to be engaged in exploitative work primarily as bench scientists in laboratories, for example. Our identification of star scientists is similar to the one made by Furukawa and Goto (2006), where they highlight the importance of "corporate scientists," who are mainly engaged in exploratory activities. For example, the scientific activities by corporate scientists, such as the publication of papers and presentation of findings at academic meetings serve to keep these individuals connected to the external developments in basic research. On the other hand, the staff scientists were found to be primarily engaged in internal exploitative activities such as codifying new basic knowledge gained by corporate scientists into commercially viable patents.

Thus, we describe intellectual human capital as consisting of two groups: star scientists, who primarily engage in exploration activities, and staff scientists, who primarily engage in exploitation activities.

4.2.2 Dynamic Capability Antecedents Within and Across Exploration and Exploitation Functional Groups

Given exploration and exploitation activities represent fundamentally different strategic initiatives, they are often driven by different norms, cultures, and compensation plans (Tushman and O'Reilly, 1996). Tushman et al.(2004) indicate that the differences between the groups focused on exploration and exploitation are so dramatic as to affect organizational structure and decentralize the decision making process. Given this, competencies developed through organizational learning relating to an organization's ability to manage its alliances or intellectual human capital may be developed at the functional group level (e.g., exploration or exploitation focused group) rather than at the firm level. This suggests that analysis of the relationship between the different antecedents to innovation is more appropriately done at the less-aggregated, functional group level of analysis.

Analysis at this level of analysis allows us to investigate the relationship between antecedents to innovation both within functional groups as well as between functional groups. Based on this conceptualization, we propose the following typology based on the combinations of intellectual human capital and strategic alliances. As explicated above, we understand intellectual human capital to consist of star scientists who primarily engage in exploration, and staff scientists who primarily engage in exploitation. Further, prior research categorized alliances into exploration or exploitation alliances based on their respective strategic intent. Joining these two categories along

exploration-exploitation framework leads to four possible permutations, as depicted in Figure 4.1.

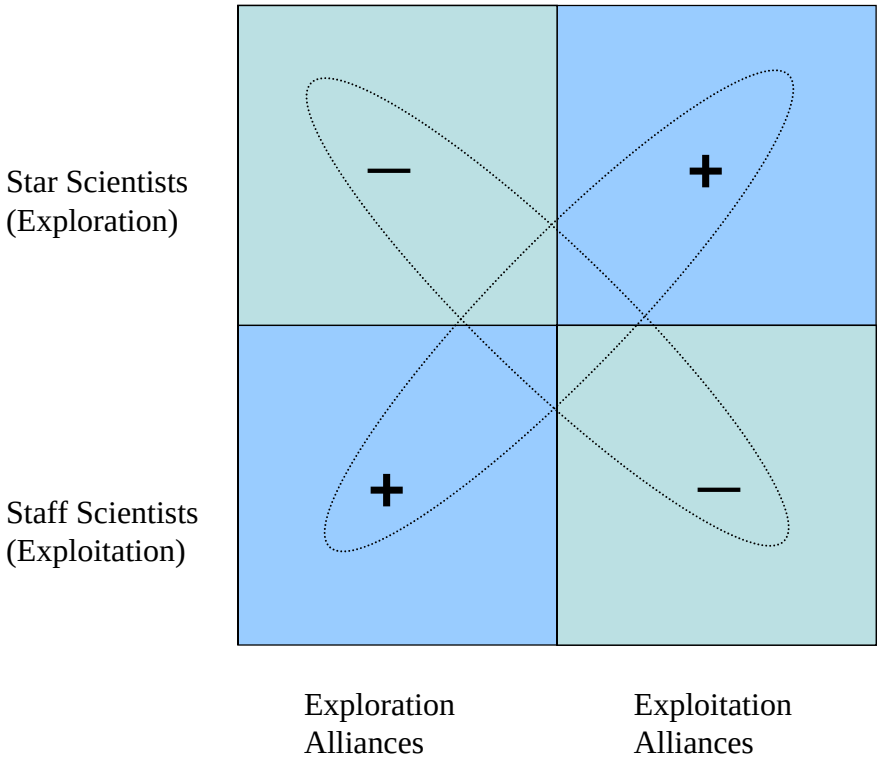

Figure 4.1: Dynamic Capability Antecedents *Within* and *Across* Exploration and Exploitation

Of interest here are the northwest/southeast and southwest/northeast diagonals. The northwest quadrant combines star scientists and exploration alliances. Since both activities are targeted towards exploration, we expect them to be substitutive, at the margin. A similar picture emerges in the southeast quadrant, which combines staff scientists and exploitation alliances. Since management intends both for exploitation, we expect them to be substitutive, at the margin. Thus, along the northwest/southeast diagonal, we expect substitutive relationships between the different mechanisms that are employed to modify and develop a firm's resource base. In contrast, we expect

complementary relationships along the southwest/northeast diagonal. In particular, the northeast quadrant combines star scientists with exploitation alliances, while the southwest quadrant combines staff scientists with exploration alliances. The southwest/northeast diagonal represents ambidexterity due to the simultaneous engagement in exploration and exploitation activities. It is important to note, however, that firms that employ star scientists and exploitation alliances and/or staff scientists and exploration alliances concurrently in their quest for innovation, must be able to manage the trade-offs inherent in the simultaneous pursuit of exploration and exploitation to capture the benefits of ambidexterity (O'Reilly and Tushman, 2007).

4.2.3 Dynamic Capability Antecedents Within Exploration or Exploitation Functional Groups

The propensity of firms to choose one mechanism to either explore or to exploit over another tends to be history dependent given the accumulated skills an organization develops in a specific innovation mechanism. Investments in building the various dynamic capabilities tend to be path-dependent (Cohen and Levinthal, 1990), and as such, early decisions affect outcomes distant in the future due to time compression diseconomies (Dierickx and Cool, 1989). As an example, investing in human resources to create an alliance management capability produces different results if this training is stretched out over six months with a given budget versus a compressed management training format that is executed over two months with a budget thrice the original size. In the pharmaceutical industry, for example, Merck tends to leverage their own star scientists when exploring for new therapeutic areas, whereas Lilly tends to rely more on exploration alliances (Galambos and Sturchio, 1998). By developing expertise in certain exploration or exploitation mechanisms, such as recruiting and retaining star scientists or alliance management, switching costs between the different mechanisms can be

substantial, and thus make the use of more than one mechanism difficult and costly (Levinthal and March, 1993). The critical point to this discussion is that given the differences between exploration and exploitation activities, these competencies and path-dependencies are likely to be *functional group- specific,* rather than *firm-specific* in nature. In support of this, prior research suggests that the decentralization of the organizational structure may lead to a situation where knowledge stocks within the firm may differ across these organizational subunits or functional groups (Lenox and King, 2004).

The importance of this point stems from the fact that while there are clearly some important differences between staff scientists engaged in knowledge exploration and exploitation alliances, there is also some element of equifinality that may be present with respect to both the type of knowledge generated and type of partner with which the knowledge is shared. This implies that within the functional groups, investments in different exploration or exploitation mechanisms can lead to similar outcomes. Simply put, a firm may be able to acquire and access similar codified knowledge through either employing staff scientists or engaging in exploitation alliances. In a similar sense, exploration alliances and star scientists allow a firm to be connected to similar upstream, research-focused partners in the hope of gaining highly tacit and new knowledge.

Previous empirical research documents equifinality in the context of other innovative activities. For example, Cockburn, Henderson, and Stern (2000) illustrate how pharmaceutical firms arrive at a similar endpoint with regard to pro-publication incentives to disseminate research in scientific journals, used as a proxy for external linkages to open science, despite remarkably different starting points and different strategic paths. Cohen and Levinthal (1990: 136) suggest that for knowledge to be valuable, it must be "must be fairly diverse to permit effective creative utilization of the

new knowledge" by the firm. Given this, the marginal benefit of investing simultaneously in multiple exploration- or exploitation-focused mechanisms will actually be negative.

Taken together, an element of equifinality, combined with path dependence and non-trivial switching costs, leads us to posit that the mechanisms used to build dynamic capabilities *within* exploration or exploitation activities are substitutive in nature, which implies that a simultaneous use of different exploration or exploitation mechanisms reduces a firm's innovative performance at the margin.[10] This theoretical notion is strengthened by the observation that firms tend to have a preference for one exploration or exploitation mechanism over another, and thus exhibit a lower cost in their preferred mode of executing exploration or exploitation.

Hypothesis 1a: Different exploration activities substitute for one another, such that the interaction between star scientists and exploration alliances is negative, and thus decrease a firm's innovative performance at the margin.

Hypothesis 1b: Different exploitation activities substitute for one another, such that the interaction between staff scientists and exploitation alliances is negative, and thus decrease a firm's innovative performance at the margin.

Hypothesis 1a can also be expressed in a more technical fashion. If we define star scientists as $Star_{Explore}$, exploration alliances as $All_{Explore}$, and innovative performance as π, it follows that

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

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

,

where *prime* indicates that a firm does not engage in that specific activity. The formula states that the innovative performance of firms that engage in exploration through star scientists *and* exploration alliances simultaneously is lower than for firms that engage in exploration through either star scientists *or* exploration alliances, holding all else constant. The same is true if we were to express this substitutive relationship for staff scientists and exploitation alliances (Hypothesis 1b).

4.2.4 Dynamic Capability Antecedents Between Exploration and Exploitation Functional Groups

The overarching hypothesis in the organizational learning literature is that firms ought to maintain a balance between exploration and exploitation: "The basic problem confronting an organization is to engage in sufficient exploitation to ensure its current viability and, at the same time, to devote enough energy to exploration to ensure its future viability," yet, "the precise mix of exploitation and exploration that is optimal is hard to specify" (Levinthal and March, 1993: 105). Accentuating this is the fact that firms are generally constrained by their resources, and managers often face a trade-off when allocating scarce resources to exploration and exploitation activities. This perspective resonates with the recent theoretical contribution by O'Reilly and Tushman (2007: 2), where they defined ambidexterity as "the ability of a firm to simultaneously explore and exploit." The simultaneous pursuit of exploration and exploitation, however, is difficult to accomplish and to maintain, because exploration and exploitation require distinctively different organizational designs, with different incentives, cultures, structures, and leadership styles (Tushman, et al., 2004).

A much more commonly observed phenomenon is an organization's preference to focus predominantly on either exploration or exploitation. Repeated failure, for example, tends to drive organizations towards extensive exploration (failure trap). A dynamic of failure turns organizations into "frenzies of experimentation, change, and innovation" (Levinthal and March, 1993: 105). Firms that engage in exploration at the expense of exploitation incur the substantial costs of experimentation without reaping the commensurate benefits thereof (March, 1991). These firms, for example, may pursue too many distinctly different scientific avenues without developing the competences required to exploit any new knowledge gained, and thus fail to transform it into commercially viable products, processes, or services.

While failure tends to lead organizations further down the exploration paths, success, on the other hand, tends to reinforce an organization's existing competence, and thus leads to stronger emphasis of exploitation at the expense of exploration. Firms that engage in repeated exploitation run the risk of falling into a competency trap (Levitt and March, 1988): firms further enhance their competency in a narrow area, through continued incremental innovation, for example, while simultaneously increasing their opportunity cost of engaging in exploration (Levinthal and March, 1993). As this dynamic plays out over time, firms become trapped by their own competences with potentially devastating consequences, because core competences can turn into core rigidities (Leonard-Barton, 1992). Such a self-destructive dynamic has been documented by Sorensen and Stuart (2000), who show that firms in the biotechnology and semi-conductor industries that focused more strongly on exploitation at the expense of exploration albeit produced more innovations; however, these innovations tended to be merely incremental, and thus eventually led to the firms' obsolescence.

The ability to be ambidextrous allows a firm to simultaneously explore and exploit. Ambidexterity, however, necessitates accommodating trade-offs in

organizational alignments because organizations must manage exploration and exploitation activities differently. Exploitation has short time horizons with fairly reliable paybacks based on efficiency and incremental improvements, where exploration has long time horizons with unpredictable returns, but also the potential for greater variance in outcomes (Benner and Tushman, 2003). Ambidexterity allows organizations to creatively harness this tension to continuously take advantage of changes that originate outside their boundaries.

Managers in ambidextrous firms act as jugglers to simultaneously balance experimentation and flexibility with efficiency and structure (O'Reilly and Tushman, 2007). While ambidextrous organizational designs can impose higher costs, we suggest that the benefits associated with ambidexterity outweigh these costs. In support of this notion, Tushman, et al. (2004) demonstrate that firms that are able to integrate and reconcile both exploratory and exploitative activities produced a continuous stream of innovations, encompassing both incremental and radical ones and thus accomplished higher performance. Moreover, He and Wong (2004) provide evidence for the notion that ambidexterity in exploiting existing product-market positions versus exploring new product-market domains enhances firm performance. Taken together, we propose that organizations that pursue ambidexterity through combining exploration and exploitation activities achieve better innovation performance. In our context that relates to firms pursuing ambidexterity through star scientists that are engaged in exploration combined with exploitation alliances or through staff scientists that are engaged in exploitation combined with exploration alliances.

Hypothesis 2a: Ambidexterity in exploration and exploitation activities complement one another, such that the interaction between star scientists and exploitation

alliances is positive, and thus increases a firm's innovative performance at the margin.

Hypothesis 2b: Ambidexterity in exploration and exploitation activities complement one another, such that the interaction between staff scientists and exploration alliances is positive, and thus increases a firm's innovative performance at the margin.

As above, Hypothesis 2a can also be expressed in a more technical fashion. If we define star scientists as $Star_{Explore}$, exploitation alliances as $All_{Exploit}$, and innovative performance as π, it follows that

$$\pi\left(Star_{Explore}, All_{Exploit}\right) - \pi\left(\overline{Star_{Explore}}, All_{Exploit}\right) > \pi\left(Star_{Explore}, \overline{All_{Exploit}}\right) - \pi\left(\overline{Star_{Explore}}, \overline{All_{Exploit}}\right)$$

,

where *prime* again indicates that a firm does not engage in that specific activity. The formula states that the innovative performance of firms that engage in exploration through star scientists and exploitation alliances simultaneously is higher than for firms that engage in exploration through either star scientists *or* exploitation alliances alone, holding all else constant. The same holds true if we were to express this complementary relationship for staff scientists and exploration alliances (Hypothesis 2b).

4.3 Methodology

4.3.1 Research Setting

To empirically test our theoretical model relating different dynamic capability antecedents within and across exploration and exploitation activities to innovative performance, we selected the global pharmaceutical industry as the research setting.

The emergence of biotechnology in the mid-1970s presented a new technological paradigm with respect to drug discovery and development for incumbent pharmaceutical companies (Kenney, 1986; Pisano, 2006). This new paradigm challenged the traditional drug discovery modes associated with random screening in the traditional chemical paradigm. A more scientific approach, including genetic engineering, genomics, and molecular biochemistry drives drug discovery and development process associated with biotechnology.

We tracked annual data for 108 incumbent pharmaceutical firms over 30 years, beginning in 1974 until the end of 2003 (108 x 30 = 3,240 firm-year observations as sampling frame).[11] We define an incumbent pharmaceutical firm as a firm that focuses on human *in-vivo* therapeutics and was founded prior to the emergence of biotechnology. This segment of the biotechnology industry is comprised of pharmaceutical companies that engage in research, discovery, development, and commercialization of biotechnology therapeutics that are placed inside the human body (*in-vivo*), as opposed to *in-vitro* therapeutics, which are used outside the human body. While biotechnology affects many different industries, the focus on *in-vivo* human therapeutics is reflective of its economic importance and potential, its regulatory environment, and consumer market. Moreover, focusing on human therapeutics enables us to create a homogenous sample while controlling for industry idiosyncrasies.

The time frame for our study is appropriate given that the scientific breakthroughs underlying biotechnology were accomplished in the mid-1970s. In 1973, a research team led by Stanley Cohen and Herbert Boyer demonstrated that genetic engineering through recombinant DNA was possible; since they discovered a set of techniques for "cutting and pasting" different DNA fragments outside the human body (*in-vitro*) (Cohen,

[11] As described further below, given the breadth and number of variables that were used, the size of the panel was necessarily adjusted downwards based on the specific model being investigated.

et al., 1973). Subsequently, Georges Köhler and Cesar Milstein (1975) discovered monoclonal antibodies, a second important second breakthrough that helped launch the biotechnology revolution. The first new biotechnology drugs reached the market for pharmaceuticals in the 1980s. A review of over 100 annual reports for the sample firms revealed that by the early 1980s most of the incumbent pharmaceutical firms were pursuing attempts to innovate in the new biotechnology paradigm. In their attempts to modify their existing resource base to build a new innovative capability within biotechnology, the incumbent pharmaceutical firms made extensive use of both intellectual human capital and strategic alliances (Hagedoorn, 1993; Zucker and Darby, 1997a). Considering these factors, we submit that our sample and time frame within the global pharmaceutical industry is an appropriate setting to test our theoretical model advanced above.

4.3.2 Empirical Analysis

In the few prior empirical studies attempting to track dynamic capabilities, their existence is often proxied by dependent variables related to the exploration of new knowledge, such as simple patent counts in a new area for the firm (Rothaermel and Hess, 2007) or by a combination of patent and publication measures (Lacetera, Cockburn, and Henderson, 2004). Ambidexterity, as the key dynamic capability of interest in this study, however, requires that an organization not only discovers and creates new knowledge, but also that the organization builds on and exploits current capabilities as (O'Reilly and Tushman, 2007). Given their upstream locus in the innovative process, it is unlikely that measurements of new knowledge acquisition would capture the effects of a firm's exploitation efforts adequately.

In an attempt to overcome this shortcoming, we utilize a number of dependent variables that represent different knowledge stages along the innovative process,

including biotech patent counts, citation-weighted biotech patents, new drug development, and adjusted stock market returns.[12] The first three dependent variables capture different types of knowledge, while market returns capture economic performance. Moreover, we view the new product development cycle as a process of discovering new knowledge with the intent of transforming and embodying it in a final product (Madhavan and Grover, 1998). We employ the first three dependent variables in an attempt to capture these different types of knowledge. While simple patent counts proxy for more basic knowledge exploration, and citation-weighted patent counts add a quality dimension to this measure, the number of new drugs developed is a measure not only of successful knowledge exploration, but also successful knowledge exploitation.[13]

Using multiple dependent variables that capture different types of knowledge underlying innovative performance along the value chain allows us to apply the two yardsticks that Helfat et. al (2007) put forth when evaluating the effectiveness of dynamic capabilities: technical and evolutionary fitness. Simply put, technical fitness denotes how well a specific capability performs its intended function, holding all else constant. In an illustrative sports analogy imported from track and field, the capability of an athlete to perform in the long jump refers to his or her technical fitness. To beat the respective world records, a woman must jump more than 7.52 meters and a man must jump more

[12] Considering multiple different dependent variables along the value chain also helps us to overcome the risk of generating idiosyncratic findings based on a single innovation measure, as frequently done in prior research.

[13] Prior research demonstrated that a simple count of patents is representative of other measures of innovation, including citation-weighted patents, new product development, as well as innovative performance (Comanor and Scherer, 1969; Stuart, 2000; Hagedoorn and Cloodt, 2003). While our data indicate that the bivariate correlation between patent counts and citation-weighted patents is, as expected, elevated ($r = 0.70$), it is much lower when correlated other measures of innovative performance, including new product development ($r = 0.21$) and adjusted stock market performance ($r = 0.06$). Based on these correlations, we suggest that within this setting, an analysis of the innovation process requires more than the consideration of simple patent counts. Using multiple dependent variables to capture different dimensions of knowledge exploration and exploitation in the pharmaceutical industry resonates with Graham and Higgins' (2006) recent study showing that a simple relationship between patenting and new drug development no longer holds.

than 8.95 meters. In parallel, our first three dependent variables measure the technical fitness of firm's dynamic capabilities: counts of biotech patents, citation-weighted biotech patents, and number of new drugs developed, while again holding all else constant.

While these are all objective measures of innovative performance, they do not capture the evolutionary fitness of a firm's dynamic capabilities, because evolutionary fitness refers to how well a dynamic capability enables a firm to perform in the marketplace by continuously altering its resource base (Helfat, 2007). Specifically, adaptation to biotechnology requires from pharmaceutical companies to continuously change their existing resource base, and thus the evolutionary fitness of their dynamic capabilities can be proxied by a market-based performance metric.

We chose adjusted stock market return (annual firm stock return less return of S&P index of global pharmaceutical firms) as the proxy for the evolutionary fitness of a firm's dynamic capabilities, because it captures firm-specific performance rather than overall movements of an industry (Kerr and Bettis, 1987). This measure represents an abnormal return to the shareholder; a return above what shareholders would expect to receive on the basis of industry risk alone. This logic is based on the efficient-markets hypothesis (Fama, 1976), which assumes that security prices reflect all available information. As such, a stock price change is considered an unbiased estimate of the present value of the change in future cash flows to the firm associated with managerial actions. This change in the present value of future cash flows captures the growth, value creation and competitive advantage dimension that have been associated with evolutionary fitness (Helfat, et al., 2007). Given the importance of innovation in the pharmaceutical industry, we submit that this measure of adjusted stock market return represents and a suitable measurement of a firm's innovative performance. In addition, unlike the proposed measurements of technical fitness outlined above, this proxy of evolutionary fitness can be negative.

This aspect of the measurement is important because the concept of adaptation or evolution is broader than that of the innovation associated with technical fitness. For this reason a measurement of evolutionary fitness must take into account the relationship between capabilities, while technical fitness is solely associated with the innovation of a particular capability (Helfat, et al., 2007). As illustrated in this paper, the path dependent nature of capabilities indicates that this relationship can often be negative. Finally, by including two of the dependent variables (biotech patenting and new product development) to proxy technical fitness in the regression models predicting stock market returns, we are able to examine the evolutionary fitness of an organization's dynamic capabilities, while specifically controlling for its technical fitness.[14] We thus explicitly acknowledge the fact that technical fitness is frequently endogenous to evolutionary fitness (Helfat, et al., 2007). Anecdotally, one of the few variables that was found to be positive and significant ($p < 0.05$) in the stock market return models was the count of biotechnology patents. Numerous prior studies have utilized this this measure has been used in numerous prior studies as a dependent variable associated with a pharmaceutical firm's ability to adapt to a new paradigm .

Table 1 illustrates the different dependent variables and the respective regression models that we use to empirically test our hypotheses. Below, we briefly describe each dependent, independent and control variable. Because we employ different dependent variables in different regression estimations, we also include a description of several key model-specific controls that we included to further control for unobserved heterogeneity.

[14] To address serious concerns of collinearity, citation-weighted biotech patents were excluded from the regressions predicting stock market returns given their expected high bivariate correlation with biotech patent counts ($r = 0.70$).

Table 4.1: Summary of Model Parameters

Dependent Variables	Key Independent Variables	Interactions	Base Controls
Count of Biotech Patents, Citation-Weighted Biotech Patents, New Drug Development, Adj. Stock Market Returns	Exploration Alliances, Exploitation Alliances, Star Scientists, Staff Scientists	Star Scientists x Exploration Alliances, Staff Scientists x Exploitation Alliances, Stars Scientists x Exploitation Alliances, Staff Scientists x Exploration Alliances	Year Effects, Merged Firm, Diversified, Nationality, Net Income, Revenues, % Equity Alliances, R&D Expense, R&D Acquisitions

4.3.2.1 Biotech Patent Counts

A potential methodological contribution of this paper is that we utilize a number of dependent variables that represent various knowledge stages along the value chain. The most tacit of these outputs is represented by a firm's patenting rate (e.g., Ahuja, 2000; Hagedoorn and Schakenraad, 1994; Henderson and Cockburn, 1994; Shan et al., 1994; Stuart, 2000). Patents have been a rich source of data for studying innovation and technical change (Griliches, 1990). To specifically assess the pharmaceutical firm's innovative performance within the biotechnology paradigm, we measure innovative output by the number of *biotechnology patents granted by application year (BPA)*. Tracking patents granted by application date provides a closer link in time between the invention and its recording (Hall, Jaffe, and Trajtenberg, 2001). The time lag between the completion of an invention and the patent application date is no more than 2-3 months (Darby and Zucker, 2007), while the time lag between patent application by the firm and granting of the patent by the U.S. PTO is on the average 3 years in the population of biotechnology patents.

To assure that a firm's patenting in biotechnology is not the result of an organization's overall patenting strategy, we explicitly control for the granting of all non-biotech patents in a given year. The source for this information was the Technology

Profile Report maintained by the U.S. Patent and Trademark Office (PTO), an agency of the U.S. Department of Commerce. Due to generous support from the U.S. PTO, we obtained detailed data on the complete population of all biotechnology patents filed by and awarded to the global pharmaceutical companies in this sample annually over the 30-year study time frame. The U.S. PTO compiled these data based on a complete set of biotechnology patents.[15] The average pharmaceutical firm in our sample was granted 14 biotechnology patents by application year.

4.3.2.2 Citation-Weighted Biotechnology Patents

While prior research indicates that patents are an important measure of innovative output, innovations vary enormously in their technological and economic importance. Thus, simple patent counts are inherently limited in the extent to which they can capture this heterogeneity (Griliches, et al., 1987). Given this, we collected the forward citation-weighted biotechnology patent information (*Citation-Weighted BPA)* for the sample firms following the procedure similar to that used in Hall, Jaffe, and Trajtenberg (2005). Prior research demonstrated that patents that are highly cited patents tend to be perceived by experts in a technological area as having been the most important inventions in that area (Albert, et al., 1991; Stuart, 1998)

The data collected allow us to more closely measure the heterogeneity in quality and technological novelty in a firm's patents. Prior research has found that in general citation-weighted stocks of patents are a more accurate predictor of value than simple patent counts (Hall, et al., 2001). In addition, patent citations have been used to proxy for spillovers and to describe research trajectories (Jaffe, et al., 1993). Following Hall et

[15] The complete set refers to biotechnology patents (as identified by the U.S. PTO) 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 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].

al. (2005), our window for the weighting calculation of forward citations was 10 years. We submit that this timeframe is appropriate given that prior research suggests most citations occur within 10 years of patent granting, with a mode of approximately 3.5 years (Hall et al. (2005). We find that only 20% of our patents did not receive any citation, compared to the 25% figure reported by Hall et al. (2005).

These data were obtained primarily through the original as well as updated NBER patent data provided by Hall, Jaffe, and Trajtenberg (2001). In addition, we used the U.S. PTO database to both confirm the values obtained from the Hall et al. data and to update the measures that were not available for all of our sample firms. In total, we are able to obtain a 10-year citation-weighting window for 86 of our sample firms between the years 1974-1997.[16]

4.3.2.3 New Product Development

To investigate outputs of the innovation process that are less explorative but more exploitative in nature, we collected data reflecting the count of new drug names that enter a pharmaceutical firm's pipeline in a given year (*New Drugs)*. These counts represent the introduction of a new drug into the firm's pipeline at the pre-clinical stage of development. We chose this new product development measure to reduce concerns associated with the time lags between dependent and independent variables caused by the lengthy development and approval process for drugs from discovery to market introduction (Galambos and Sturchio, 1998). The average firm in our sample introduced

[16] While the sample sizes for the regression models employing the citation-weighted biotechnology patents (86 firms), new drug development (56 firms), and stock market returns (42 firms) are by necessity less than the 108 firms in the sample firm when using biotech patent counts as dependent variable, we are confident that this does not introduce a systemic sample selection bias, because the industry structure of the global pharmaceutical industry is fairly oligopololistic, and it has become more concentrated over time. As an example, we tracked the pharmaceutical sales of 52 sample firms that were not diversified outside pharmaceuticals. The annual revenues of these focused pharmaceutical companies represent only 44% of the initial sample but accounted for 75% of the total sales for pharmaceuticals worldwide (*IMS Health,* 2003). Moreover, we also explicitly control for this concentration effect trough tracking horizontal mergers between pharma firms in the sample. We further control explicitly for firm revenues, which captures firm growth (both organic and through horizontal mergers; more details on the measures are provided below).

just over 6 new drug development indications per year. While we collected data regarding the development of new products associated with biotechnology only, there is, at this early stagy of the industry's evolution, an insufficient number of biotechnology products (157) to generate any significant variation in our large-scale panel, and thus we could not include this variable in our regression analyses. We thus had to fall back on an examination of the new product development across all therapy areas, which allows us to examine the effects of different exploration and exploitation mechanisms on building their new product development capability in a more general sense, while the two patent measures are specific to biotechnology only.

We obtained the new product development information from the *PharmaProjects* database, which was available for 56 of our sample firms from 1980-2003. These data are comprised of 4,018 new drug indications with explicit controls for therapy category designations (specifically we control for the percentage of firm projects that are related to oncology). Following Guedj and Scharfstein (2004), if a drug compound was associated with multiple therapy indications, we counted each therapy indication as a unique drug introduction. We are comfortable with this calculation because under FDA guidelines the manufacturer must conduct separate studies to determine if this drug is effective in treating diseases associated with the different indications. Only if the FDA determines that there is enough evidence to approve the drug for the indication (treatment of the disease) can the manufacturer claim that the drug is effective for the approved indication, and use this information to market their new drug to patients and physicians.[17]

4.3.2.4 Organizational Financial Performance

[17] Our analysis only includes such 'on-label' uses, which can be very difficult to obtain from the FDA. In 2004, Pfizer/Warner-Lambert paid $430 million to the federal government to settle a whistleblower case that alleged the company engaged in a scheme to promote the epilepsy drug, Neurontin, for 'off-label' uses such as for patients with bipolar disorder and Lou Gehrig's disease.

Finally, to assess the evolutionary fitness of the pharmaceutical companies' dynamic capabilities in the marketplace, we collected data relating to an organization's stock market returns. We calculated annual returns for each organization as the total return (stock price change plus reinvested dividends) weighted by the company's market value for a given year (Porac, et al., 1999).[18] This method implicitly controls for stock splits during the timeframe. Given the nature of this measurement, our sample of firms was reduced to 42 firms with data from 1974-2004. As previously mentioned, our interest was in capturing a measurement that controlled for the stock movement of the overall pharmaceutical industry. As such, we subtracted the annual return from the S&P Pharmaceutical Index from our sample firm's annual return *(Adjusted Stock Return)*. As would be expected, this index contained many of the firms in our sample. On average, firms in our sample had a return of 8.9% over the study period, which was slightly lower than the industry average of 9.1%. The similarity of these numbers lends additional assurance that the firms in our sample are representative of the global pharmaceutical industry.[19] In addition, to control for unobserved heterogeneity associated with the specific exchange on which a firm's stock is traded we included four stock exchange dummy variables (S*tock Market Exchange*).

4.3.3 Independent Variables

4.3.3.1 Star and Staff Scientists

In collecting the information relating to a pharmaceutical firm's intellectual human capital, we followed the process described in detail by Lacetera, et al. (2004) and Rothaermel and Hess (2007). Using several sources including *BioScan* and *Recombinant Capital* databases, we identified a population of 125 pharmaceutical

[18] The source for the stock return data was the Compustat/Center for Research in Security Prices (CRSP).
[19] A *t*-test revealed that these means are not statistically significant.

firms.[20] Using this sampling frame of pharmaceutical firms, we then searched the *Web of Science ISI* database to identify journal publications that appeared between 1974 and 2005, had a keyword related to science research (excluding social science research and non-human focused research, e.g., agricultural or veterinarian), and could be unambiguously connected with one of the pharmaceutical firms in the sample. This last step was important given the necessity of assuring that each of the authors was affiliated with one of the pharmaceutical firms at the time of the article publication. From the population of over 672,000 publications we collected the following information: author's name, author's affiliations, journal name, article title, keywords, publication year, number of times cited.

From this extensive database, we compiled a list of authors with an aggregate number of publications and times cited for each year. This query yielded the records of over 171,000 authors who on average published 3.9 papers and which were cited 66.3 times. We then tied back each author to the pharmaceutical firms in our sample based on the authors' affiliations as indicated in the journal article(s).

Based on the distributions of citations and publications we identified star scientists from the population of scientists. In particular, we followed Rothaermel and Hess (2007) by identifying stars as researchers who had *both* published *and* been at a rate of three standard deviations above the mean (z-score > 3.0). To qualify for this elite group of star scientists based on the both the quantity and quality of their work, a star scientist must have published more than 28 papers during the study period and had to

[20] We constructed a detailed "family tree" for each of these 125 firms for the 1974-2003 time period. We used multiple industry publications to construct the family tree, including *Dun and Bradstreet's 'Who Owns Whom'?* and annual *Standard & Poor's Industry Reports.* Through this method, we identified 17 horizontal mergers among the pharmaceutical firms. Taking the 17 horizontal mergers into account, the sample for final analysis is 108 firms. Noteworthy is that we tracked the pharmaceutical firms *forward* beginning in 1974 to avoid a survivor bias. All 108 firms in the initial sample were included in the sample drawn to construct the measures for intellectual human capital. More details below when we describe horizontal mergers by sample firms.

be cited at least 861 times. Based on this intersection, we identified 1,071 scientists (*Star Scientists)*. These stars represent 0.63% of the total population of scientists in this sample, but produced 12.2% of all publications and garnered 22.1% of all citations. This made star scientists 19 times more productive in terms of research output and 35 times more impactful in terms influencing other scientists' research.

We calculated the number of "non-star" scientists employed by a firm by taking the difference between the total scientists and star scientists (*staff scientists)*. The average pharmaceutical firm employed about 23 star scientists and 211 non-star scientists in a given year over the study period. Note that our time period to identify stars is by design two years longer than the study period to allow us to account, to some extent, for a "rising star" effect associated with the potential right censoring of the data.[21]

4.3.3.2 Biotech Alliances

To document the alliances that the pharmaceutical firms had entered with different sources of biotechnology knowledge, we tracked each firm's alliances with universities, research institutions, and biotechnology firms (Powell, et al., 1996). To obtain accurate alliance data as possible, we used various issues of the *BioScan* industry directory and the *recap* database provided by *Recombinant Capital*.[22] *BioScan* and *Recombinant Capital* appear to be the two most comprehensive publicly available data sources documenting alliance activity in the global biopharmaceutical industry, and they have been used frequently in prior research, although not together, but in isolation (e.g., Shan, et al., 1994; Lane and Lubatkin, 1998; Powell, et al., 1996). The average sample firm entered approximately one biotechnology alliance per year.

In a next step, we content-analyzed each alliance description to ensure that the focal alliance indeed pertained to biotechnology and to decompose a firm's total biotech

[21] The timeframe for the data used in the regression analysis is 1974-2003.
[22] *BioScan* and *Recombinant Capital* are fairly consistent in their reporting. We found their inter-source reliability to be greater than 0.90 when documenting alliances.

alliances into exploration and exploitation agreements. Following a well-established coding procedure in prior research (Koza and Lewin, 1998; Rothaermel, 2001; Park, et al., 2002; Lavie and Rosenkopf, 2006), we coded grants, research and R&D alliances as exploration alliances (*Exploration Alliances)*, since they focus on the basic-research oriented upstream knowledge discovery activities of the value chain. By contrast, we identified licensing, development and supply alliances as exploitation in nature (*Exploitation Alliances*), because they focus on the downstream knowledge-leveraging activities of the value chain. Accordingly, we identified 2,041 exploration alliances and 1,061 exploitation alliances. Research assistants that were blind to each other and the theory to be tested coded the alliance data. In addition, in an attempt to insure the accuracy of this coding, two additional research assistants independently coded 100 randomly selected alliance agreements. The inter-rater reliability was 98%, and thus well above the recommended threshold of 70% (Cohen, et al. 2003).

4.3.4 Control Variables

We include a detailed set of control variables to account for potential heterogeneity at the drug, firm, network, and industry level. The use of several of the controls we implemented relating to nationality (*US, EU*, *or Japan*)*,* financial performance (*net income*), size (*total revenues*), and temporal effects (*year dummy variables*) is well-established and has been validated by prior research. We collected financial data from a number of sources including *Compustat* and annual financial reports. In addition, all financial data is inflation adjusted in constant 2000 U.S. dollars.

While the controls above are fairly standard in prior research, there are a number of unique controls that we included to further reduce the threat of unobserved heterogeneity. Organizations attempting to innovate can choose to either make (*R&D Expenditures*) or buy (*R&D Acquisitions*) the requisite capabilities. As such, in order to

control for the focus and scale of an organization's innovative efforts, we included both the firm's R&D expenditures as well as its R&D acquisitions. In addition, this later control is important given that prior research has indicated acquisitions may be alternatives to alliances for innovating organizations (Higgins and Rodriguez, 2006). We used the SDC Platinum database, published by Thomson Financial, to identify the number of R&D acquisitions a pharmaceutical firm had consummated during the study period. Here, we studied each acquisition description in detail to ensure that organizations undertook the focal acquisitions with the intent of sourcing R&D. The average pharmaceutical firm in the sample acquired about one biotechnology firm every three years.

To overcome an unnecessary contamination of the measures for R&D expenditures and R&D acquisitions, we identified the magnitude of the R&D spending devoted to R&D acquisitions, which accountants label "in-process R&D spending."[23] The amount of in-process R&D spending in the pharmaceutical industry is around 2.5% of total R&D expenditures (Rothaermel and Thursby, 2007). The commensurate expenses for R&D alliances tend to be significantly smaller, since these are mainly executed through contractual rather than equity agreements (about 88% of all alliances in this sample are contractual). Thus, the magnitudes of the in-process R&D spending devoted to R&D acquisitions and R&D alliances are too small to introduce a systematic error.

Given the consolidation in the pharmaceutical industry over the lengthy study period, we created a comprehensive "family tree" to track the merger history of each sample firms. We were thus able to trace back all firms in existence at the end of 2004 to their various "ancestors" alive in 1974. We used multiple industry publications to

[23] Compustat defines in-process R&D as "the portion of R&D considered to be 'purchased' and written off immediately upon acquisition if the R&D items are deemed not to have an alternative use. This item includes purchased technology [through acquisitions]."

construct the family tree from 1980 onwards, including *Dun and Bradstreet's 'Who Owns Whom?'* and annual *Standard & Poor's Industry Reports.* We further triangulated this process through also tracking all pharmaceutical firms in existence in 1974 forward when constructing the initial sample for this study. This procedure enabled us to explicitly control for horizontal mergers among sample firms. About 15% of all sample firms engaged in at least one horizontal merger during the study period, and thus we identified 16 horizontal mergers among the pharmaceutical firms. Accordingly, we inserted a dummy variable that takes on the value of 1 beginning in the year that two firms in the sample merged horizontally (1 = *Merged Firm*). Both firms are tracked individually until the merger year and then all data are joined and updated annually using the new firm's identity.

Additionally, for all alliances, we collected information regarding whether an alliances was based on an equity exchange. This represents a proxy of a firm's propensity for entering into equity agreements that are considered to be stronger ties (Gulati, 1995). Given that our panel observations are at the firm level, we calculated a control variable equal to the percentage of total alliances that are equity agreements *(% Equity Alliances*). While non-equity alliances are contract-based cooperative agreements to exchange knowledge and resources, equity alliances are based on taking an equity stake in a partner, exchanging equity, or setting up a third organization as a joint venture. In our sample, about 12% of all alliances are equity based.

In addition to these controls we also included information regarding the non-biotech patenting associated with firms that patent heavily in general (*Non-biotech patents*), a pharmaceutical firm's level of diversification (*Diversified*), and a 'strategy' control associated with the first time the organization cited the Cohen-Boyer patent (*Time to 1st Cohen-Boyer Citation*). This patent is influential, and is often associated with the commencement of the biotechnology movement (Fabrizio, 2004). Finally, our

calculations indicate the proportion of oncology projects in the NDA Pipeline and *PharmaProjects* over the time period 1990 to 2001 (4.5%), was significantly less than that of other groups. Given this, we included a control variable equal to percentage of sample firm drugs that were identified as oncology projects (*% Cancer Drugs).* Table 2 depicts which additional control variables, based on the respective dependent variable, we included in the regression estimations.

Table 4.2: Additional Model Controls

	Model 1a & 1b	**Model 2a & 2b**	**Model 3a & 3b**	**Model 4a & 4b**
Dependent Variable	Count of Biotech Patents	Citation-Weighted Biotech Patents	New Drug Development	Adjusted Stock Market Return
Model-Specific Additional Controls	Time to First Cohen-Boyer Citation	Time to First Cohen-Boyer Citation	% of Cancer Drugs	Stock Market Exchange Dummies
	Count of Non-Biotech Patents	Count of Non-Biotech Patents		Count of Biotech and Non-Biotech Patents
				New Drugs in Pipeline

4.3.5 Estimation Procedure

Three of the four dependent variables (biotech patents, citation-weighted biotech patents and new drug indications) are count variables, and thus take on only non-negative integer values (e.g., the number of biotech patents or new drugs for a firm in a particular year). Poisson estimation provides a natural baseline model for such count data (Hausman, Hall, and Griliches, 1984). A Poisson specification, however, requires that the mean and variance of the event count are equal. This restrictive assumption is unlikely to hold for pooled cross-section count data in the social sciences. Indeed, we conducted tests for over-dispersion on each of three count-data dependent variables (Gourieroux, et al., 1984), and found that the data violated the assumption of mean and

variance equality. In such cases, 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 (Hausman, et al., 1984; Cameron and Trivedi, 1986).

Moreover, based on econometric theory, the use of either a fixed- or a random-effects specification permits one to control for unobserved heterogeneity (Greene, 2003). Accordingly, we applied a Hausman specification test (1978), and its results revealed that there was not a systematic variation between the random and fixed-effects estimations. Taken together, we applied the following random-effects negative binomial model:

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

where *n* is a non-negative integer count variable capturing each pharmaceutical firm's innovative output and thus technical fitness (i.e., biotech patents, citation-weighted biotech patents, or new drug development). Accordingly, $P(n_{it} / \varepsilon)$ indicates the probability that pharmaceutical firm *i* develops the expected number of these outputs *n* in year *t.*

We estimated the models proxying for a firm's evolutionary fitness using stock market returns as dependent variable. Given the underlying nature of the dependent variable, we applied a generalized least-squares estimation. As above, we conducted a Hausman test, which revealed that a random-effects approach was appropriate for these estimations.[24] Not only does the application of a random-effects estimation procedure addresses concerns of heterogeneity, but it also enables us to include covariates that tend to be (fairly) time invariant (Hsiao, 2003), such as the firm's time to first citation of the Cohen-Boyer patent, national origin, or degree of diversification. Moreover, we

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

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 endogeneity concerns (Hamilton and Nickerson, 2003). Additional robustness checks, including using firm-clustered standard errors and zero-inflated negative binomial estimations were used and the results reported remained robust to these treatments.

The hypotheses that we developed highlight different dynamic capability antecedents within and across exploration and exploitation activities. Such a theoretical approach requires the application of hierarchical moderated regression. Moderated regression is a relatively conservative method for examining the interaction between variables, requiring that the interaction terms are statically significant after inclusion of all direct effects. In addition, to enhance the interpretability of the results, we standardized all independent variables prior to both entering them into the various regression models and creating their cross products to test the interaction hypotheses. As illustrated by Table 4.3 in the appendix, all of the bivariate correlations are below the recommended 0.70 threshold. To further assess the threat of multicollinearity, we calculated the variance inflation factors (VIFs) for each coefficient. The maximum estimated VIF for was 7.2, well below the recommended ceiling of 10 (for a discussion of these issues see Cohen, et al., 2003).

In the estimation of the various regression models we paid significant attention to appropriate time lags between our independent and dependent variables. In an attempt to compensate for a potential simultaneity bias and to allow for potential claims of causality, we lagged the financial measures (net income, revenues, and R&D expenditures) as well as alliances and acquisitions by one year (Hall, et al., 1986; Stuart, 1998; Gulati, 1999). We do not lag our measures of star and staff scientists because of the close temporal link between the date at which at article was published (this was the

basis for our measure of star and non-star scientists) and the innovative output associated with the publication (Murray, 2002).[25]

4.4 Results

In the appendix Table 4.3 provides the descriptive statistics and the bivariate correlation matrix, while Tables 4.4-4.5 present the regression results using the four different dependent variables. In each case, we first estimated a baseline model including the control variables and direct effects only. Next, we added the interaction effects. Each subsequent model represents a significant improvement over the respective baseline models at $p < .05$, or smaller. Models 1a-4a each contain all the controls as well as model-specific controls as detailed in Tables 4.1 and 4.2, as well as all direct effects, while Models 1b-4b contain additionally each of the four interaction terms simultaneously to assess the theoretical model advanced.

Hypotheses 1a and 1b posit that dynamic capability antecedents that represent a similar strategic intent in regards to exploration or exploitation (see northwest/southeast diagonal in Figure 1) are substitutes. We thus expect the interaction between star scientists and exploration alliances (H1a), as well as the interaction between staff scientists and exploitation alliances (H1b) to be negative (and statistically significant). We find general support for Hypothesis 1a, because the interactions between star scientists and exploration alliances are negative and are statistically significant: In Models 1b ($p < .10$ when predicting biotech patent counts), 2b ($p < .001$ when predicting citation-weighted biotech patents at), 3b ($p < .05$ when predicting new product development), and 4b ($p < .01$ when predicting adjusted stock market returns). We find

[25] 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 (Stern and Murray, 2005).

some tentative support for Hypothesis 1b predicting that staff scientists and exploitation alliances are substitutes. All four interactions in Models 1b-4b are negative as predicted, however, they reach statistical significance only in Model 1b ($p < .05$ when predicting biotech patents).

In Hypothesis 2a and 2b, we suggest that ambidexterity across exploration and exploitation activities complement one another (southwest/northeast diagonal in Figure 1). We thus expect the interactions between star scientists and exploitation alliances (H2a) and between staff scientists and exploration alliances (H2b) to be positive (and statistically significant). We find broad support for an ambidexterity hypothesis; all of the interactions along the southwest/northeast diagonal are positive as expected, and statistically significant in all but one case. Specifically we find support for complementarity between star scientists and exploitation alliances (H2a) in all of the four models (at $p < .05$ or smaller). In addition, we find support for the complementarity between staff scientists and exploration alliances (H2b) in three out of the four models: In Models 2b ($p< .05$ when predicting citation-weighted patents), 3b ($p < .01$ when predicting new product development), and 4b ($p<.05$ when predicting adjusted stock market returns). Taken in aggregate, these results provide support for the notion that ambidexterity across exploration and exploitation enhances a firm's innovative performance.

We summarized the results in an overview fashion in Table 4.6. The depiction reveals that we find strong support for an ambidexterity hypothesis (H2a-b). Pursing exploration and exploitation simultaneously by leveraging star scientists and exploitation alliances, on the one hand, and staff scientists and exploration alliances, on the other, enhances innovative performance. We also find strong support for a substitutability hypothesis when firms pursue exploration through star scientists and exploration

alliances simultaneously (H1a). The support for a substitutability effect between staff scientists and exploitation alliances (H1b) is tentative at best.

Table 4.6: Summarized Results of Interaction Models

Interaction	Hypothesized Direction	Summarized Results M1b	M2b	M3b	M4b
Star Scientists x Exploration Alliances	-	-	-	-	-
Staff Scientists x Exploitation Alliances	-	-			
Star Scientists x Exploitation Alliances	+	+	+	+	+
Staff Scientists x Exploration Alliances	+		+	+	+

Of particular interest is that the dynamic capability of ambidexterity is important to both the technical and evolutionary fitness of the organization. That is, our results discussed above are generally consistent regardless of the innovative output utilized in the model. As support for this consistency, seven of the possible eight complementarity hypotheses illustrated in Table 6 were supported at a level of $p < .05$. Thus, while research asserts that dynamic capabilities need not perform equally well on both technical and evolutionary fitness measures (Helfat et. al, 2007), our findings suggest that the dynamic capability of ambidexterity is reflected in both, a technical as well as an evolutionary fitness. This suggests that while ambidexterity is a critical component of innovation at the process or capability level, the market also seems to reward this capability as representative of the strong growth opportunities associated with evolutionary fitness. As previously indicated, in our model investigating evolutionary fitness of an organization's dynamic capabilities, we explicitly controlled for the technical fitness of the dynamic capabilities. Interestingly, our results in Model 4a and 4b illustrate that the market values tacit measurements of technical fitness (e.g., count of biotech patents) in its appraisal of an organization's evolutionary fitness, pointing to the fact that technical

fitness is frequently endogenous to evolutionary fitness. Beyond these direct effects however, the results of the interactions in Model 4b clearly highlight the value of developing the dynamic capability of ambidexterity.

4.5 Discussion

Dynamic capabilities allow organizations to modify their existing resource base to ensure continued survival and competitiveness. At the core of this resource transformation is the ability for an organization to simultaneously exploit its current capabilities as well as to explore future opportunities (March, 1991; Levinthal and March, 1993). We offer a unique theoretical perspective on ambidexterity, and empirical validation of the importance of this balance. In addition, through the use of multiple innovative outputs, we are able to decompose the aggregate notion of innovative output into the constituent components of technical and evolutionary fitness to offer unique empirical insights.

From a practical perspective, our results point to the need for researchers and managers alike to understand the heterogeneity of intellectual human capital and the differential roles these individuals play within the organization's adaptation process. By analyzing this dichotomy of individuals within the exploration-exploitation framework we demonstrate that pursuing exploration and exploitation activities in tandem (despite their inherent differences and unique managerial challenges) can result in improved innovative performance. As hypothesized, the benefits of this ambidexterity outweigh the costs associated with being able to manage the disparate processes of exploration and exploitation simultaneously. This result is interesting because prior research illustrates that these costs are not insignificant to the organization. Specifically, they are a result of the different organizational structures, incentives, and competencies that are

associated with exploratory and exploitive activities (Nadler and Tushman, 1997; Benner and Tushman, 2002; Benner and Tushman, 2003).

By contrast, we find that the pursuit of redundant mechanisms (e.g., both activities represent either exploration or exploitation) simultaneously results in a marginal decrease in innovative performance. This substitutability may be reflective of an organization that is overly focused on either exploration or exploitation. Prior research illustrates that pursuing either exploration or exploitation activities, at the cost of the other, can have deleterious implications (Levitt and March, 1988; Levinthal and March, 1993). Our results suggest that the costs of such a focus apparently outweigh the potential benefits that have been posited to exist when there exists a level of commonality between alliance partners (Lane and Lubatkin, 1998). In a study on alliance formation in the semi-conductor industry, Stuart (1998) documented that the most valuable alliances are those between firms with similar technological foci. In our setting, this would suggest that firms with more star scientists would be able to select and manage exploratory alliances. Our results demonstrate that, in this case, the costs of this similarity outweigh its potential benefits.

In an attempt to further our understanding of the nature of the interdependence between different antecedents to dynamic capabilities, we illustrate the importance of considering the appropriate level of analysis for two reasons. The first relates to importance of considering the heterogeneity of the individual members of an organization's intellectual human capital base. In our expansion of the explore/exploit framework, we encapsulate the innovative activities of individuals and in doing so attempted to synthesize seminal sociological work investigating individual status, talent, and conformity with the more applied and aggregated literature focusing on organizational learning. It is through this analysis that we shed light not only on the different roles that star and staff scientists play in developing dynamic capabilities but

also on the more interesting question of 'why'. While we are only able to generalize on the motivations of the individual researcher, the notion of an individual's research conformity allows us to view the individual's knowledge as constituent component of the much larger knowledge base of the organization. It is only once this foundation is in place that one is able to aggregate the efforts of the individual so they can representative of an organization's resource and innovative activities.

The second means through which we highlight the importance of considering the appropriate level of analysis relates to the locus of innovation within the organization. The work of Tushman, O'Reilly, and colleagues suggests that given the fundamental differences between exploration and exploitation, the activities focused on strategic directions should reside in different organizational subunits or functional groups. Based on this observation, a study that analyzes innovative activities by aggregating exploratory and exploitive intent may suffer from the aggregation bias associated with ignoring the potential variance that exists between these disparate activities. As our study has shown, this bias may be especially costly in the analysis of the development of capabilities, as their history- and path-dependent nature seems to be functional-group specific, rather than firm-specific, as indicated in prior literature.

4.6 Conclusion

As this study represents an initial attempt to understand the relationship between the antecedents to dynamic capabilities, there are several limitations of our investigation that provide fertile ground for future research. The first of these limitations relates to the setting of the study. We suggest that the pharmaceutical industry represents an interesting and appropriate setting for investigating the knowledge acquisition and accumulation associated with dynamic capability formation. However, given the idiosyncrasies associated with the biopharmaceutical industry, in terms of the

importance of scientific knowledge and new product development, future studies are needed to enhance the external validity of our findings. In a related manner, future analyses may also expand on our findings by developing and testing new measurements of stardom. While the bibliographic methodology used in this study is established in the literature, future investigations may look to identify stars based on different important metrics, including patents, new products developed or potentially other more subjective measures of performance.

Finally, future studies may expand on our methodological contributions. More specifically, research may look for alternative measurements to proxy for technical and evolutionary fitness of an organization's dynamic capabilities. As indicated above, we believe the breadth of measurements used in the current study is appropriate for our setting, yet complexity theorists may extend our analysis by looking at fitness landscapes, for example. NK modeling may provide a unique avenue for such a study in which the relationship between activities is analyzed in terms of optimization of the relationship by assessing local maxima and minima.

Despite these limitations, we offer that the current paper extends our understanding of an important construct in the organization theory and the strategic management literatures. The focus of our investigation has been on understanding the relationship between the mechanisms organizations employ to build dynamic capabilities. The key aspect of the construct of dynamic capabilities is that it extends the resource-based view (RBV) of the firm beyond consideration of simple resource existence, to the more complex issues associated with resource emergence and resource combinations. While the RBV focuses on how organizations select between appropriate resources, dynamic capabilities emphasizes resource development and renewal. Thus, while consideration of selection is important, of import is not the choice between resources, but rather the choice between the different mechanisms that

managers employ to develop and change these capabilities. This distinction is critical, because it allows us to more fully understand the origins and performance consequences of dynamic capabilities.

In conclusion, it is important to note that continued survival and any potential competitive advantage is not a direct outflow of ambidexterity, but rather ambidexterity as dynamic capability allows managers to reconfigure and extend a firm's resources that facilitates survival and performance (Eisenhardt and Martin, 2000; Winter, 2000; O'Reilly and Tushman, 2007). By considering the relationship between these choices, not only across different antecedents to dynamic capabilities, but also across different levels of analysis, we have attempted to both refine as well as extend our theoretical and empirical understanding of the formation of dynamic capabilities.

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CHAPTER 4 APPENDIX

Table 4.3: Descriptive Statistics and Correlations

	Variables	Mean	Median	St.Dev	Min	Max	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.	16.	17.	18.	19.
Dependent	**1.** Biotech Patents (BPA)	14.3	6.2	21.6	0.0	243.0																			
	2. Citation-Weighted BPA	54.8	14.2	74.7	1.0	613.0	0.698																		
	3. New Drugs	6.0	2.2	10.4	0.0	89.0	0.214	0.035																	
	4. Adj. Stock Return	0.0	0.0	0.2	-0.6	3.5	0.055	0.033	0.016																
Control	**5.** Merged Firm	0.2	0.2	0.4	0.0	1.0	0.306	0.350	0.353	0.066															
	6. Diversified	0.5	0.3	0.5	0.0	1.0	0.080	0.046	0.031	0.060	0.012														
	7. US	0.3	0.3	0.5	0.0	1.0	0.217	0.295	0.100	0.117	0.175	-0.073													
	8. EU	0.3	0.1	0.5	0.0	1.0	0.083	0.034	0.065	-0.020	0.091	0.094	-0.476												
	9. Net Income	710.8	240.2	1575.0	-6680.3	28596.3	0.213	0.276	0.256	0.070	0.147	0.005	0.117	0.007											
	10. Revenue	10275.7	5133.1	14807.0	0.0	158768.8	0.198	0.088	0.212	-0.025	0.083	-0.333	0.074	0.175	0.300										
	11. % Equity Alliances	0.1	0.2	0.5	0.0	10.0	0.059	0.073	-0.037	-0.013	0.002	-0.008	0.122	-0.010	0.002	0.025									
	12. Non-Biotech Patents	41.5	12.3	73.4	0.0	688.0	-0.462	-0.310	-0.192	-0.034	-0.211	-0.386	0.031	0.041	-0.007	0.361	-0.002								
	13. R&D Expense	627.9	257.8	1473.3	0.0	33433.2	0.220	0.314	0.144	0.059	0.275	0.086	0.089	0.041	0.143	0.048	0.020	0.130							
	14. R&D Acquisitions	0.3	0.4	1.2	0.0	30.0	0.295	0.310	0.142	0.023	0.146	-0.035	-0.066	0.161	0.170	0.354	0.003	0.050	-0.167						
	15. Cohen-Boyer Citation	23.5	26.3	6.6	0.0	26.0	-0.211	-0.203	0.036	-0.019	-0.021	0.004	-0.062	0.062	-0.008	0.019	-0.026	-0.028	-0.152	0.158					
	16. % Cancer Drugs	0.1	0.1	0.2	0.0	1.0	-0.044	-0.037	0.098	-0.042	-0.037	-0.098	-0.025	-0.084	0.002	0.016	-0.090	0.059	-0.030	0.028	-0.112				
Independent	**17.** Exploration Alliances	0.6	0.5	1.4	0.0	17.0	0.352	0.285	-0.047	0.042	0.197	0.017	0.127	0.004	0.101	0.062	0.091	0.104	0.242	-0.223	-0.133	-0.079			
	18. Exploitation Alliances	0.3	0.3	1.0	0.0	13.0	0.221	0.229	-0.035	0.054	0.132	0.080	0.095	-0.030	0.051	-0.021	0.043	0.049	0.125	-0.182	-0.140	-0.048	0.515		
	19. Star Scientists	23.0	4.4	52.3	0.0	655.0	0.524	0.512	0.092	0.021	0.221	0.197	0.130	-0.067	0.130	-0.001	0.031	0.080	0.188	-0.455	-0.169	-0.051	0.312	0.226	
	20. Staff Scientists	211.2	86.3	325.7	0.0	4354.0	0.475	0.517	0.381	0.081	0.286	0.075	0.109	0.058	0.217	0.086	0.015	0.191	0.274	-0.289	-0.178	-0.023	0.317	0.217	0.652

Table 4.4: Regression Results

Models	Biotech Patent Count				Forward Citation Weighted Biotech Patents			
	Model 1a		Model 1b		Model 2a		Model 2b	
	beta	s.e.	beta	s.e.	beta	s.e.	beta	s.e.
Year Effects	*Included*		*Included*		*Included*		*Included*	
Constant	-1.0542	(0.2773)	-0.9579	(0.2758)	0.0367	(0.2488)	0.2277	(0.4721)
Merged Firm	0.0723	(0.0527)	0.0648	(0.0521)	-0.0895	(0.0858)	-0.0510	(0.0850)
Diversified	0.1371	(0.1155)	0.1454	(0.1178)	-0.0661	(0.1144)	-0.0421	(0.1150)
US Firm	-0.2591	(0.1596)	-0.2552	(0.1594)	0.6208 ***	(0.1545)	0.6128 ***	(0.1523)
EU Firm	-0.4143 **	(0.1639)	-0.3484 *	(0.1652)	0.4798 **	(0.1744)	0.4932 **	(0.1728)
Net Income	-0.0275	(0.0279)	-0.0226	(0.0275)	0.0749	(0.0504)	0.0896 *	(0.0494)
Total Revenues	0.0614 *	(0.0297)	0.0637 *	(0.0292)	-0.0468	(0.0414)	-0.0507	(0.0414)
% Equity Alliances	0.0052	(0.0133)	0.0030	(0.0134)	0.0227	(0.0162)	0.0214	(0.0162)
Non-Biotech Patents	-0.3118 ***	(0.0165)	-0.3210 ***	(0.0174)	-0.0859 **	(0.0326)	-0.0784 **	(0.0323)
R&D Expense	0.0442	(0.0325)	0.0434	0.03198	0.2069 ***	(0.0432)	0.2138 ***	(0.0423)
R&D Acquisitions	-0.0096	(0.0111)	-0.0143	(0.0110)	-0.0290	(0.0256)	-0.0465 *	(0.0272)
Time to First Cohen-Boyer Patent Citation	-0.0804 *	(0.0391)	-0.0702 *	(0.0395)	-0.2057 ***	(0.0411)	-0.1961 ***	(0.0411)
Exploration Alliances	0.0138	(0.0118)	0.0441 ***	(0.0137)	0.0268	(0.0205)	0.0356	(0.0242)
Exploitation Alliances	0.0079	(0.0105)	-0.0005	(0.0137)	0.0012	(0.0151)	-0.0047	(0.0174)
Star Scientists	-0.0187	(0.0149)	-0.0106	0.0152	-0.0090	(0.0289)	0.0217	(0.0296)
Staff Scientists	0.0609 **	(0.0217)	0.0781 ***	(0.0213)	0.1158 **	(0.0448)	0.1256 **	(0.0456)
Star Scientists x Exploration Alliances			-0.0091 †	(0.0059)			-0.0424 ***	(0.0126)
Staff Scientists x Exploitation Alliances			-0.0165 *	(0.0093)			-0.0188	(0.0215)
Star Scientists x Exploitation Alliances			0.0121 **	(0.0051)			0.0176 *	(0.0103)
Staff Scientists x Exploration Alliances			-0.0083	(0.0072)			0.0445 *	(0.0217)
Log likelihood	-4441.47		-4383.71		-3465.32		-3432.34	
Chi Square	1398.23 ***		1424.54 ***		405.50 ***		448.76 ***	
Improvement over Base ($\Delta\chi^2$)			19.25 ***				8.25 **	

† p < .10* p < .05; ** p < .01; *** p < .001; Standard errors are in parentheses.

Table 4.5: Regression Results

Models	New Drug Development				Adjusted Stock Market Performance			
	Model 3a		Model 3b		Model 4a		Model 4b	
	beta	s.e.	beta	s.e.	beta	s.e.	beta	s.e.
Year Effects	*Included*		*Included*		*Included*		*Included*	
Constant	2.7414	(0.2340)	2.9258	(0.2525)	0.1156	(0.0703)	0.1395	(0.0713)
Merged Firm	0.1566	(0.1242)	0.2414 *	(0.1276)	0.0573 **	(0.0332)	0.0592 **	(0.0337)
Diversified	0.1046	(0.1513)	0.0498	(0.1508)	-0.0500	(0.0285)	-0.0471	(0.0283)
US Firm	0.3830 *	(0.1995)	0.3133	(0.1997)	NA		NA	
EU Firm	0.1902	(0.1988)	0.1579	(0.1967)	NA		NA	
Net Income	0.0267	(0.0346)	0.0229	(0.0342)	0.0400 *	(0.0235)	0.0478 *	(0.0237)
Total Revenues	0.0928	(0.0752)	0.1137	(0.0741)	-0.0758 *	(0.0374)	-0.0734 *	(0.0376)
% Equity Alliances	-0.0362	(0.0368)	-0.0454	(0.0367)	-0.0055	(0.0147)	-0.0049	(0.0147)
R&D Expense	0.0335	(0.0400)	0.0502	0.04346	-0.0410	(0.0289)	-0.0422	(0.0288)
R&D Acquisitions	0.0287	(0.0209)	0.0271	(0.0206)	0.0002	(0.0092)	-0.0016	(0.0092)
Biotech Patents	NA		NA		0.0312 *	(0.0156)	0.0285 *	(0.0156)
Non-Biotech Patents	NA		NA		0.0298	(0.0213)	0.0300	(0.0214)
New Drugs	NA		NA		0.0076	(0.0129)	0.0029	(0.0130)
Stock Market Exchange Dummies	NA		NA		*Included*		*Included*	
% Anti-Cancer Drugs	0.0480	(0.0415)	0.0424	(0.0411)	NA		NA	
Exploration Alliances	-0.0398 *	(0.0220)	-0.0515 *	(0.0285)	0.0092 *	(0.0075)	0.0063	(0.0094)
Exploitation Alliances	0.0366 *	(0.0193)	0.0291	(0.0324)	0.0005	(0.0067)	0.0027	(0.0097)
Star Scientists	-0.0924 ***	(0.0281)	-0.0916 **	0.03178	-0.0088	(0.0096)	0.0077	(0.0131)
Staff Scientists	0.0976 ***	(0.0278)	0.0970 ***	(0.0290)	0.0102	(0.0130)	-0.0010	(0.0163)
Star Scientists x Exploration Alliances			-0.0228 *	(0.0121)			-0.0118 **	(0.0043)
Staff Scientists x Exploitation Alliances			-0.0087	(0.0109)			-0.0052	(0.0045)
Star Scientists x Exploitation Alliances			0.0179 *	(0.0080)			0.0058 *	(0.0033)
Staff Scientists x Exploration Alliances			0.0287 **	(0.0117)			0.0112 *	(0.0055)
Log likelihood (R-Sq in Model 4)	-965.55		-939.53		0.25		0.28	
Chi Square	801.49 ***		868.85 ***		93.90 ***		103.2 ***	
Improvement over Base ($\Delta\chi^2$)			8.67 **					

† p < .10* p < .05; ** p < .01; *** p < .001; Standard errors are in parentheses.

Table 4.7: Incidence Rate Ratios for Interaction Models

	beta		Incidence Rate Ratio = exp(beta)	Factor Change = IRR-1
Biotech Patent Count Model				
Stars X Exploration Alliances	NS			
Staff Scientists X Exploitation Alliances	-0.0165	*	0.98	-0.02
Stars X Exploitation Alliances	0.0121	**	1.01	0.01
Staff Scientists X Exploration Alliances	NS			
Citation Weighted Patent Model				
Stars X Exploration Alliances	-0.0424	***	0.96	-0.04
Staff Scientists X Exploitation Alliances	NS			
Stars X Exploitation Alliances	0.0176	*	1.02	0.02
Staff Scientists X Exploration Alliances	0.0445	*	1.05	0.05
New Drug Development Model				
Stars X Exploration Alliances	-0.0228	*	0.98	-0.02
Staff Scientists X Exploitation Alliances	NS			
Stars X Exploitation Alliances	0.0179	*	1.02	0.02
Staff Scientists X Exploration Alliances	0.0287	**	1.03	0.03
Adjusted Stock Market Performance				
Stars X Exploration Alliances	-0.0124	**	0.99	-0.01
Staff Scientists X Exploitation Alliances	NS			
Stars X Exploitation Alliances	0.0056	*	1.01	0.01
Staff Scientists X Exploration Alliances	0.0115	*	1.01	0.01

* $p < .05$; ** $p < .01$; *** $p < .001$; Standard errors are in parentheses
odds ratio is the same as multiplier factor, b/c variables are standardized

CHAPTER 5

CONCLUSION

By developing a multi-level system of dynamic capability formation, I have attempted to demonstrate that dynamic capabilities emerge at the firm-level through interactions at the individual level. In particular, the interactions between different types of boundary spanners, in conjunction with top management, allow the formation of dynamic capabilities at the firm level. While this process of dynamic capability formation can be initiated through managerial action and formalization of roles, the formation of dynamic capabilities need to be explained by the notion of emergence (Goldstein, 1999), where the observed outcome at a macro level is the product of the interactions at a micro level. For example, just as interactions among molecules result in cells, interactions among neurons result in brains, and interactions among species result in ecosystems, interactions among different types of boundary spanners can result in dynamic capabilities.

Emerging properties stem from the interaction of agents, and are not found in individual parts of the system. For instance, a single neuron does not have consciousness, but a human brain in its entirety does exhibit consciousness. The resulting dynamic capabilities, therefore, cannot simply be explained by the sum of the inputs provided by each individual. Rather, they exhibit emergent properties arising from the continuous interactions of specific boundary spanners attempting to overcome different knowledge gaps in the innovation process. This conclusion echoes Teece's (1982: 44) sentiment that capabilities do not vest in a single individual, nor are they capable of being articulated by an individual; rather, they are supra-individual and not "reducible to individual memory."

The focus of my dissertation echoes the recent call for a stronger micro foundation in strategic management research (Felin and Hesterly, 2005). Since innovation is, by its nature, a knowledge intensive activity, the question turns to the issue of how firms learn. Simon suggests that intellectual human capital, especially the recruitment of scientists can be an effective way to learn and innovate, as 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, I believe, 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 specific individuals, here scientists, have a direct bearing on the innovative performance of firms, while controlling for alternative explanations across different levels. This result resonates with Teece's (2003) recent finding that experts and professionals are the locus of knowledge in service-oriented firms. Taken together, we submit that future research needs to consider the role of individuals when studying antecedents to a firm's dynamic capabilities.

As, previously mentioned, while the setting for this investigation offers unique insights into the knowledge acquisition and assimilation process, the numerous idiosyncrasies of the pharmaceutical industry call into question the potential generalizability of the my findings. While indeed a limitation of any single-industry study, I feel that the question of generalizability can be better thought of as offering insights into future areas of investigation. As I have described within the chapters of my dissertation, the findings of this dissertation suggest numerous paths for future consideration. Preliminary findings of research into one such path reveal interesting aspects of the

nature of 'stardom' in science-based industries. As part of an ongoing research into the generalizability of my findings, I have collected the publication record for more than 165K authors publishing in over 2,300 biotechnology firms. As illustrated by the chart below, preliminary analysis of this data illustrates that the role of the star scientists may not be as idiosyncratic as originally indicated.

Table 5.1 – Comparison of 'Stars in Pharmaceutical and Biotechnology Firms

	Average Pubs		*To be a star*		*Stars*				*Times more impactful*	
Setting	*Pubs*	*Cites*	*Pubs*	*Cites*	*#*	*% of total*	*% of all pubs*	*% of all cites*	*Pubs*	*Cites*
Pharma	3.9	66.3	28	861	1071	0.63%	12.20%	22.10%	**19.4**	**35.1**
Biotech	3.3	50.5	24	770	570	0.31%	6.00%	15.80%	**19.4**	**51.0**

The figure above reveals a striking similarity between the 'stardom' of elite scientists in pharmaceutical and biotechnology firms. T-tests between the means reveal no significant ($p<0.05$) difference between the publication impact of biotech and pharma stars but a significant ($p<0.05$) difference between the citation impact of the different stars. As previously indicated, this result is preliminary but lend support to the ideas presented in chapter 2 of the dissertation that examine the role of star scientists through the lens of the sociology of science. The similarity between the populations of scientists suggests a connection between these individuals that transcends the boundaries of the firm. Following the work of Merton, Zuckerman, Kuhn and others, this extension of my dissertation suggests that while these individuals are employees of organizations, they are more importantly actors in the larger institution of the scientific community. Further research within this domain will hopefully help to substantiate and generalize the findings and positions of this dissertation.