ESSAYS ON KNOWLEDGE SEARCH AND TECHNOLOGICAL PERFORMANCE IN THE BIOTECHNOLOGY INDUSTRY

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SUMMARY

This thesis comprises of three essays on the relationships among intellectual human capital, strategic alliances and technological performance. Earlier research has suggested that intellectual human capital and strategic alliances are key inputs to a firm's technological performance (Rothaermel and Hess, 2006). This dissertation investigates the means through which the above two factors influence a firm's technological performance, explores the mechanisms required for a firm to translate the benefits from these factors into better technological performance and finally, examines the interdependence between the two factors in influencing the technological performance.

The first essay seeks to understand if intellectual human capital and strategic alliances contribute to a firm's technological performance by assisting with the new knowledge search process. The second essay attempts to understand the importance of exploitation mechanism in converting the competencies of intellectual human capital into better technologies. The third essay investigates if intellectual human capital and alliances are substitutes or complements of each other in influencing firms' technological performance.

I test the theoretical models in the dissertation using the patent, publication and alliance data of 222 biotechnology firms from around the world. The results largely support the arguments presented in the dissertation. My first essay illustrates that intellectual human capital contributes to a firm's technological performance by embarking on the new knowledge search process. The results also confirm that strategic alliances assist a firm in successfully converting the new knowledge search into better technological performance. My second essay shows that a firm needs to have an

exploitation mechanism in place to ensure that the knowledge generated by its intellectual human capital is exploited for developing valuable technologies. My third essay suggests that intellectual human capital and alliances are both complementary and substitutive in nature, but that the relationship is contingent on the characteristics of intellectual human capital and the attributes of alliance partners.

Overall, the dissertation contributes to the managerial research on knowledge search, accumulation of intellectual human capital and strategic alliances in the following ways. Earlier studies have suggested that intellectual human capital and alliances are key mechanisms for knowledge search. My dissertation contributes to this stream of research by distinguishing the value of intellectual human capital and strategic alliances to new knowledge search. The findings augment the research on accumulation of intellectual human capital by suggesting that the kind of knowledge that can be accessed through different types of intellectual human capital differs depending on their characteristics. I contribute to the stream of research on strategic alliances by showing that a holistic understanding of benefits derived from alliance partners, warrants a careful examination of the alliance partners' attributes and their interaction with the focal firm's characteristics.

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CHAPTER ONE

INTRODUCTION

This chapter introduces the research questions investigated in the three essays of the dissertation, then summarizes the findings and contributions of each essay.

MOTIVATION AND RESEARCH QUESTIONS

A firm's ability to adapt, integrate and reconfigure its competencies in accordance with the dynamically changing environment is essential for its technological performance. Scholars studying the dynamics of technological performance believe that antecedents to technological performance can be found both in resources residing within a firm and in resources leveraged from external partners (Eisenhardt and Martin 2000). At the firm level, heterogeneous distribution of intellectual human capital across firms is shown to be a significant predictor of the variance in their technological performance (Subramaniam and Venkataraman, 2001). Similarly, the literature on social networks underlines that the resources leveraged through strategic alliance are a significant predictor of the variance in firms' technological performance (Powell, Koput and Smith-Doerr, 1996). Recognizing the importance of intellectual human capital and strategic alliances for technological performance, this thesis comprises of three essays on the relationships between intellectual human capital, strategic alliances and technological performance.

The first essay of this dissertation, presented in Chapter 2, seeks to understand the means through which intellectual human capital and strategic alliances contribute to technological performance. Specifically, the essay investigates if intellectual human capital and strategic alliances contribute to firms' technological performance by assisting with the new knowledge search process. The background and specific research question of this essay are elaborated upon below.

In high technology industries, firms' abilities in searching for new knowledge residing outside their organizational boundary are considered critical for their technological performance. It has been shown that through search organizations learn new skills (Huber, 1991) and adapt to environmental changes (Cyert and March, 1963). Thus, search for new knowledge is an important organizational learning mechanism for knowledge-creating companies. This is more so in the case of "competence destroying" biotech innovations (The biotechnology industry is the context in testing my research framework) because biotech innovations require established pharmaceutical firms to move away from their organic chemistry knowledge base and search for knowledge from immunology and molecular biology disciplines. In my dissertation, new knowledge search refers to a firm's endeavors in searching external knowledge with the anticipation that the knowledge can be recombined into valuable technologies.

The first step of the new knowledge search process is to search for and identify external knowledge. The second step is to acquire and exploit the searched knowledge. The literature on absorptive capacity identifies that existing knowledge forms the base for identifying valuable external knowledge (Cohen and Levinthal, 1990). Following the literature, I believe that the knowledge residing in intellectual human capital enables them to engage in research activities, knowledge transformation endeavors and to act as gatekeepers for the flow of external knowledge. Consequently, I propose that intellectual human capital plays an important role in searching and identifying new knowledge residing outside the organization, thereby assisting with the first stage of the new knowledge search process. In my dissertation intellectual human capital refers to "highly skilled and talented employees who hold advanced degrees".

While the literature on evolutionary search acknowledges the difficulty of acquiring external knowledge, the literature on social networks proposes inter-organizational collaborations as an important mechanism for the inflow of external knowledge (Mowery et al., 1996). Hence, I propose that strategic alliances play an important role at the second stage of the new knowledge search process of acquiring and exploiting the searched knowledge, thereby helping a firm translate its new knowledge search into better technologies.

There are also notable examples in the biotechnology industry that emphasize the importance of intellectual human capital and alliances for new knowledge search. The success of Merck in its search for the root cause of AIDS is attributed to a group of scientists employed by the organization. The advancement of genetic research is closely tied to the Nobel Prize winning scientist Kary Mullis's search of polymerization chain reaction techniques. With respect to alliances, Genentech, a leading biotech firm, claims that their recent R&D collaboration with Abbott technologies will assist the firm in converting their apoptosis research into anti-cancer compounds[1]. A recent survey conducted in this industry highlights that alliances contribute to the success of biotech firms in translating their search for new knowledge into useful discoveries[2].

To better understand the significance of intellectual human capital and alliance to new knowledge search, the first essay of this dissertation concentrates on the research question:

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[1] http://www.lifesciencesworld.com/news/view/37908

[2] Global pharmaceutical company partnering capabilities survey 2000 http://www.biocouncilontario.com/media/Summary_Report.pdf

(1) How does (a) intellectual human capital help a firm in its search for new knowledge, and how does (b) alliance portfolio help a firm in translating its new knowledge search into better technologies?

In investigating the above question, I classify new knowledge search into (1) technological search, (2) geographical search and (3) science search, depending on the knowledge that is searched, and classify intellectual human capital into (1) pure scientists, (2) bridging scientists and (3) pure inventors, depending on their specialization. Similarly, I concentrate on three attributes of alliance portfolio: (1) technological diversity, (2) geographical diversity and (3) number of partners from a university background. The above classifications are used to examine how different characteristics of intellectual human capital and different attributes of alliance portfolio contribute to the three dimensions of new knowledge search in varied ways.

While the first essay emphasizes the importance of intellectual human capital and alliances, realizing the benefits of these factors is not simple and straightforward. Intellectual human capital is inclined to work on intellectually challenging questions, even if the findings are not capable of generating economic rents. Since intellectual human capital, like scientists, believe that their primary obligation is the advancement of research rather than making their skills available to the organization, it is especially difficult for a firm to translate their competencies into better technologies. Similarly, the difficulty of benefiting from alliances is demonstrated by a survey[3] conducted in 2000 which projected that about 40% of alliances failed to produce their desired effect. Though a number of scholars have delved into the means of leveraging alliance partners'

[3] Global pharmaceutical company partnering capabilities survey 2000
http://www.biocouncilontario.com/media/Summary_Report.pdf

capabilities (Dyer and Singh, 1998; Lane and Lubatkin, 1996; Grant and Braden-Fuller, 2004), the question of how firms realize the benefits of their intellectual human capital has not gained enough attention in the literature. Hence, the second essay of this dissertation, presented in Chapter 3, investigates the research question:

(2) How can a firm benefit from the competencies of its intellectual human capital?

Specifically, the study looks at mechanisms for converting the competencies of intellectual human capital, such as scientists, into better technological performance.

The third essay of this dissertation, presented in Chapter 4, investigates the interdependency between (1) intellectual human capital and (2) alliances in explaining the technological performance of firms. Two different perspectives exist regarding the interdependency of these two factors. The first perspective argues that the two factors are complementary, whereas the second one perceives the factors to be substitutes of each other (Liebeskind et al., 1996; Rothaermel and Hess, 2007). However, neither perspective has paid attention to the characteristics of intellectual human capital and alliances that might alter the nature of their interdependencies. As the nature of information flow from alliance partners and the kind of knowledge that flows through intellectual human capital is known to depend on their characteristics (Owen-Smith and Powell, 2004), I believe that the attributes of intellectual human capital and alliances play an important role in determining their interdependency. Hence, the third essay of this dissertation, presented in Chapter 4, pursues the question:

(3) How do the characteristics of intellectual human capital and alliances alter the nature of their interdependency (complements/substitutes)?

To examine this question the essay classifies intellectual human capital into (1) pure scientists, (2) bridging scientists and (3) pure inventors, depending on their specialization, and alliances into (1) firm alliances and (2) university alliances, based on the institutional regime, and then investigates their interdependency.

The next section elaborates on the research models, findings, and contributions of each of the three essays that comprise this dissertation.

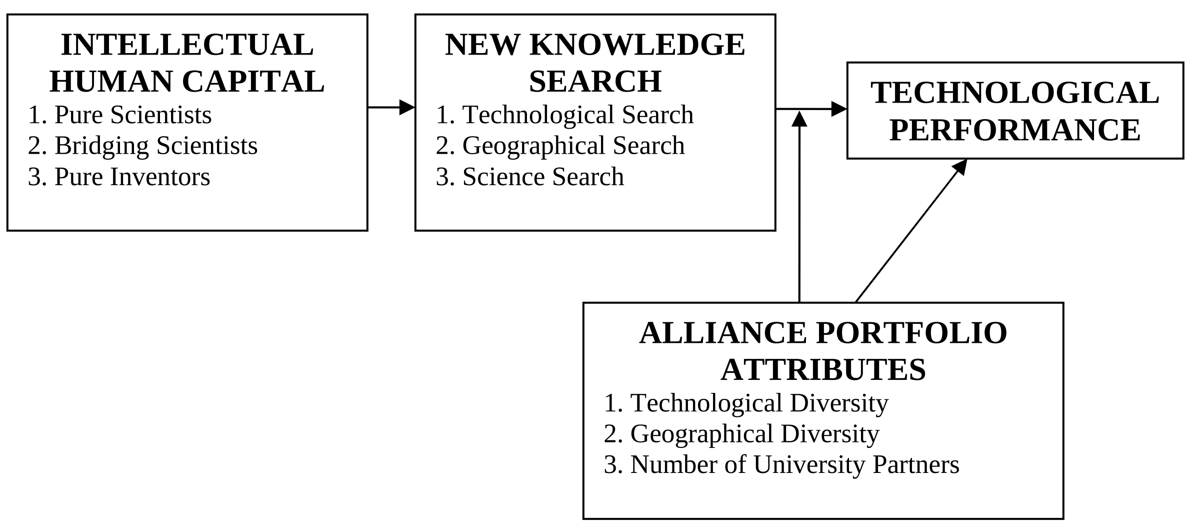
RESEARCH MODELS, FINDINGS AND CONTRIBUTIONS

As outlined above, the first essay of this dissertation investigates the importance of intellectual human capital to new knowledge search and how alliances help a firm in translating its new knowledge search into better technologies. The research model tested in this essay is presented in Figure 1.1. In my study, a firm's attempt to search for knowledge outside its organizational boundary is termed as new knowledge search. Depending on the knowledge that is searched, new knowledge search is classified into (1) technological search, (2) geographical search and (3) science search.

Intellectual human capital and alliances are categorized into three types in order to better understand their contributions to new knowledge search and technological performance. In high technology industries, intellectual human capital is known to differ based on whether they specialize in the science domain, technology domain or both (Gittelman and Kogut, 2003). Hence, I classify intellectual human capital into three types: (1) pure scientists (only science domain), (2) bridging scientists (both science and technology domains) and (3) pure inventors (only technology domain), depending on their domain of specialization. Similarly, the benefits from alliances are known to depend on their attributes, not just by their size (Stuart, 2000). Accordingly, I look at three attributes of alliance portfolio: (1) technological diversity, (2) geographical diversity and (3) number of partners from a university background. The three attributes of alliance portfolio are consistent with the three dimensions of new knowledge search.

The research question, unit of analysis and key results of the first essay are presented in the first column of Table 1.1. I use the patent, publication and alliance data of 222 biotech firms in testing the research model. The results show that bridging scientists and pure inventors directly contribute to new knowledge search and technological performance, but pure scientists do not. The findings further demonstrate that the contributions of pure scientists to new knowledge search are indirect by helping bridging scientists in their search process. With regard to alliances, all three attributes of alliance portfolio have a positive influence on technological performance. A technologically and geographically diverse alliance portfolio is observed to enhance the contributions of technological and geographical searches to technological performance.

Figure 1. 1. Research Model of the First Essay



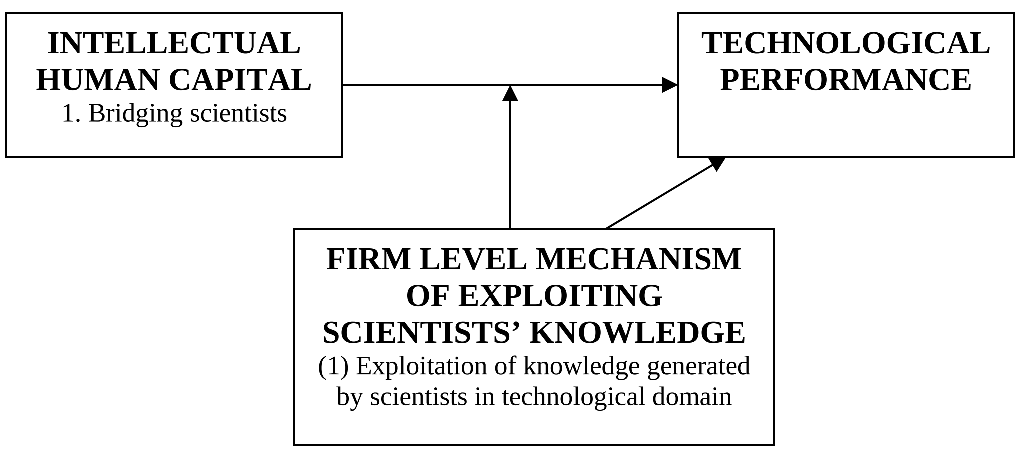
The first essay of this dissertation makes the following contributions. The findings contribute to the research on knowledge search by distinguishing the value of intellectual human capital and strategic alliances to new knowledge search. The essay contributes to studies on intellectual human capital - technological performance link by showing that new knowledge search is one of the means through which intellectual human capital contributes to technological performance. The findings of this essay help in illustrating that the contributions of intellectual human capital to technological performance and new knowledge search differ depending on their characteristics. Specifically, I demonstrate the contingent value of intellectual human capital, such as scientists, by differentiating between the contributions of scientists who play the bridging role (in bridging science and technology domains) and scientists who do pure research. The results pertaining to alliance portfolio are useful in proposing an alliance strategy to a firm that best fits with the firm's knowledge search strategy. The findings also suggest that the strategic advantage derived from alliance partners depends on the partners' attributes and their interaction with the focal firm's characteristics.

The results from the first essay underline the importance of scientists and inventors for better technological performance. As inventors are solely involved in technology development activities, it should not be very difficult for a firm to translate competencies of its inventors into better technologies. This is not so in the case of scientists, as scientists are involved in scientific research that is not a ready-made input to technological development. Hence, the second essay investigates two mechanisms for translating competencies of a firm's intellectual human capital into better technologies.

The first mechanism is an individual level mechanism of letting intellectual human capital, such as scientists, work on both upstream scientific research and downstream technology development activities. The second one is the firm's exploitation mechanism of letting scientists do the upstream scientific research while also encouraging technology developers to exploit the knowledge produced by in-house scientists. The research model tested in this essay is presented in Figure 1.2. The key results of this essay are presented in the second column of Table 1.2.

The findings of this study support the importance of bridging scientists. Nevertheless, exploitation mechanism turns out to be of greater significance than bridging scientists because the results indicate that in the absence of an exploitation mechanism, bridging scientists have no role to play in converting the scientific competency of a firm into better technologies. While existing studies view individuals as movers of knowledge across boundaries, my findings illustrate that bridging the science and technology domain within a firm is not a simple human capital story of having scientists do both. A firm should have an appropriate exploitation mechanism in place to achieve this.

Figure 1. 2. Research Model of the Second Essay



The third essay of this dissertation investigates the interdependency between intellectual human capital and alliances. The research model tested in this essay is presented in Figure 1.3. Similar to the second essay, intellectual human capital is subdivided into (1) pure scientists, (2) bridging scientists and (3) pure inventors. Alliances are categorized into (1) firm alliances and (2) university alliances, depending on their institutional affiliation. The key findings of this essay are presented in the third column of Table 1.1.

In examining their interdependency, the results show that bridging scientists and pure scientists substitute university alliances because they are also involved in an external scientific network with a free flow of knowledge from academic communities adhering to the norm of openness. However, with respect to firm alliance partners that believe in a proprietary model of sharing knowledge, all three types of intellectual human capital act as complements to each other. While prior studies have found support for either a substitutive or complementary story in explaining the interdependency between intellectual human capital and alliances, I support both perspectives. Further, I show that the exact nature of interdependency (complements/substitutes) is contingent on the nature of intellectual human capital and attributes of alliance partners. The findings also suggest that benefits from a formal partnership depend on whether or not it is an extension of the social relationships of human capital residing within the firm.

This dissertation is organized as follows. Chapters 2, 3 and 4 present the three essays of this dissertation. Chapter 2 investigates the means through which intellectual human capital and strategic alliances influence a firm's technological performance. Chapter 3 examines mechanisms required for a firm to translate benefits from its intellectual human capital into better technological performance. Chapter 4 explores the interdependency between intellectual human capital and strategic alliances in influencing the technological performance. Chapter 5 integrates the findings of the three essays and links these findings with the extant literature on knowledge search, human capital and strategic alliances. I also discuss the limitations and future research directions of this dissertation in Chapter 5.

Figure 1.3. Research Model of the Third Essay

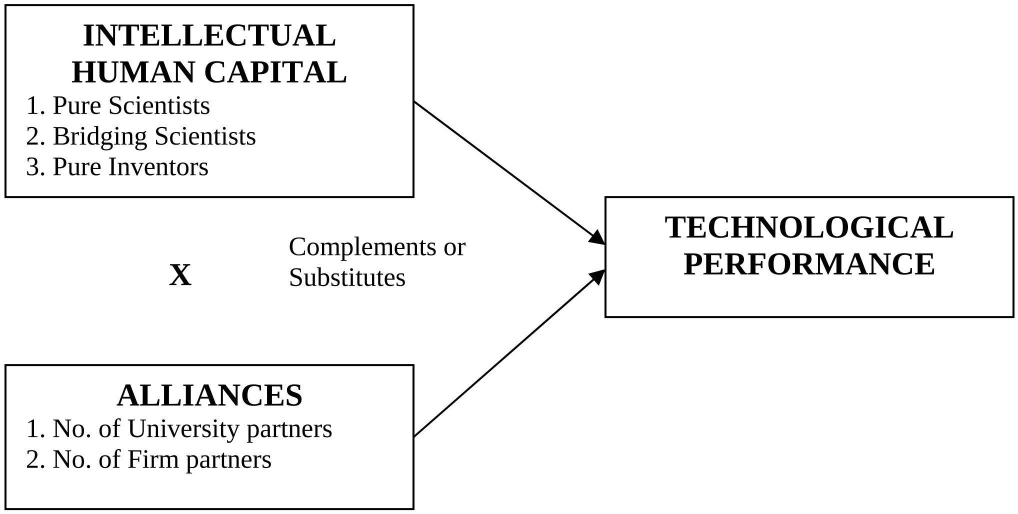


Table 1.1. Summary of the Three Essays

	First Essay (Chapter 2)	Second Essay (Chapter 3)	Third Essay (Chapter 4)
Specific Research Questions	How intellectual human capital such as (a) pure scientists (b) bridging scientists and (c) pure inventors embark on (a) technological (b) geographical and (c) science search in generating valuable technologies? How an alliance portfolio characterized by partners from a (a) diverse technological background (b) diverse geographical background and (c) a greater number of partners from an academic background enhance the value of (a) technological (b) geographical and (c) science search in generating valuable technologies?	How the individual-level mechanism of having (a) bridging scientists and the firm-level mechanism of (b) exploiting science knowledge in the technology domain help a firm in translating the competencies of its scientists into valuable technologies?	Are intellectual human capital such as (a) pure scientists (b) bridging scientists and (c) pure inventors and alliances comprised of (a) firm partners and (b) university partners complements or substitutes of each other in explaining the technological performance of firms?
Research Design	Quantitative analysis of patent, publication and alliance data of 222 biotech firms from Plunkett's biotechnology directory	Quantitative analysis of patent and publication data of 222 biotech firms from Plunkett's biotechnology directory	Quantitative analysis of patent, publication and alliance data of 222 biotech firms from Plunkett's biotechnology directory
Findings	Bridging scientists and pure inventors assist the technological and geographical searches. Pure scientists facilitate the technological and geographical searches of bridging scientists. Technologically and geographically diverse alliance portfolio enhances the contribution of technological and geographical searches.	Firm-level exploitation mechanism moderates the degree of relationship between bridging scientists and technological performance. In the absence of firm-level exploitation mechanisms, the mere presence of bridging scientists need not result in translation of scientific competency into better technologies	Pure scientists and bridging scientists substitute university alliances Pure scientists, bridging scientists, and pure inventors complement firm alliances
Contributions	(1) Differentiates the value of intellectual human capital and strategic alliances to new knowledge search (2) Illustrates that the contribution of intellectual human capital to technological performance and new knowledge search differ depending on their characteristics. (3) Suggests that strategic advantages derived from alliance partners depend on the partners' attributes and their interaction with the focal firm's characteristics.	(1) Suggests that bridging science-technology domains is not a simple human capital story of having scientists who are involved in both scientific research and technological activities (2) Illustrates that firms have to acknowledge the challenges in making the transition from science domain exploration to technology domain exploitation and attempt to have premeditated mechanisms to bridge the gap	(1) Suggests that intellectual human capital and strategic alliances are both complements and substitutes of each other depending on the characteristics of intellectual human capital and attributes of alliance partners (2) Demonstrates that benefits from a formal partnership depend on whether or not it is an extension of the social relationships of human capital already residing within the firm

CHAPTER TWO

NEW KNOWLEDGE SEARCH: THE ROLE OF INTELLECTUAL HUMAN CAPITAL AND ALLIANCE PORTFOLIO

INTRODUCTION

Organizations innovate by combining new knowledge with existing knowledge (Kogut and Zander, 1992). Thus, the search for new knowledge is an inevitable part of technological innovation. There are two types of search behaviors exhibited by firms. First is to look for new ideas in the neighborhood of research and development (R&D) activities residing within the firm. Although the process of 'local search' is cheap and this knowledge is easy to access, the dynamically accelerated marketplace requires firms to consider the second type of search which spans their organizational boundary and look for external knowledge. In this study, firms' endeavors in looking for knowledge residing outside their organizational boundary are termed as a 'new knowledge search'. Several studies belonging to the evolutionary search literature have shown that the ability of organizations to generate high impact technologies is closely tied to their new knowledge search (Rosenkopf and Nerkar, 2001; Ahuja and Lampert, 2001; Rosenkopf and Almeida, 2003; Ahuja and Katila, 2004).

Though new knowledge search helps a firm in generating valuable innovations, organizations find it difficult to reach out for distant knowledge (Jaffe, Trajtenberg and Henderson, 1993; Stuart and Podolny, 1996). In particular, a firm's search for new knowledge is shown to be geographically and technologically bounded. Recent research has shown that firms search for and acquire distant knowledge with the help of their employees and strategic alliances (Rosenkopf and Almeida, 2003). However, more remains to be understood about the precise contribution of these factors to new knowledge search. For instance, the finer aspect of how organizations utilize intellectual human capital and alliances for new knowledge search remains unconnected with the different stages of new knowledge search.

A firm's search for new knowledge to generate better technologies can be described as consisting of two stages (Zahra and George, 2002; Tripas, 1997). The first stage involves searching for new knowledge. Organizations engage their intellectual human capital in search of new knowledge because the knowledge residing in intellectual human capital helps in screening and identifying valuable external knowledge. Though intellectual human capital engages in search of new knowledge, literature has acknowledged that it is not very easy to absorb and exploit knowledge residing outside a firm’s environment. This can be due to reasons such as relative absorptive capacity, the type of knowledge that is searched, etc. (Lane and Lubatkin, 1998; Gambardella, 1995; Phene, Fladmoe-Lindquist and Marsh, 2006). In the absence of an appropriate mechanism to enable the transfer and exploitation of the searched knowledge, it is difficult to convert new knowledge search into better technologies. Hence, the second stage of new knowledge search is to establish collaborative arrangements, such as alliances, that facilitate this process.

Since the search for new knowledge also incurs huge costs, it is critical to investigate the strategic importance of intellectual human capital and alliances for new knowledge search, as outlined above. This study has two objectives to demonstrate the differential effect of these two factors in the process of searching and acquiring new knowledge for creating valuable technologies.

The first objective is in showing that intellectual human capital endowed within a firm undertakes new knowledge search, thereby contributing to better technological performance. There are several examples in the medical industry that underline the significance of intellectual human capital. Their role in search of knowledge related to coronary artery disease, genetic research, and AIDS are exemplary examples (Mina, Ramlogan, Tampubolon and Metcalfe, 2007)[4].

I explore the importance of intellectual human capital for three types of new knowledge search: (a) technological search (the degree to which a firm searches a wide array of technologies), (b) geographical search (the degree to which a firm searches diverse geographic locations) (c) science search (the degree to which a firm searches the science knowledge base). While literature on evolutionary search traditionally concentrates on the 'technological' and 'geographical' dimensions of search, I follow Ahuja and Katila (2004) in including the third dimension 'science search'. This additional dimension has been shown to have a significant contribution to technological performance in the high-tech industries.

I also categorize intellectual human capital into three types. This is done in order to examine their differential effect on the three different dimensions of new knowledge search. Innovations in high-technology industries are determined by the advancement of both scientific and technological knowledge (Nelson, 2003) and the characteristics of intellectual human capital in such industries differ based on the domain in which they carry out research activities (science/technology/both) (Gittelman and Kogut, 2003).

[4] http://www.lifesciencesworld.com/news/view/37908
http://query.nytimes.com/gst/fullpage.html?res=9903E2D61731F934A15751C0A9649C8B63

Hence, I classify intellectual human capital into (a) pure scientists, (b) pure inventors and (c) bridging scientists based on the domain in which they specialize.

The first objective intends to contribute to two streams of research. The first contribution is to the literature on evolutionary search in showing the significance of different types of intellectual human capital for different dimensions of new knowledge search. The second contribution is to the stream of research on intellectual human capital-technological performance link in showing that intellectual human capital contributes to technological performance by engaging in new knowledge search.

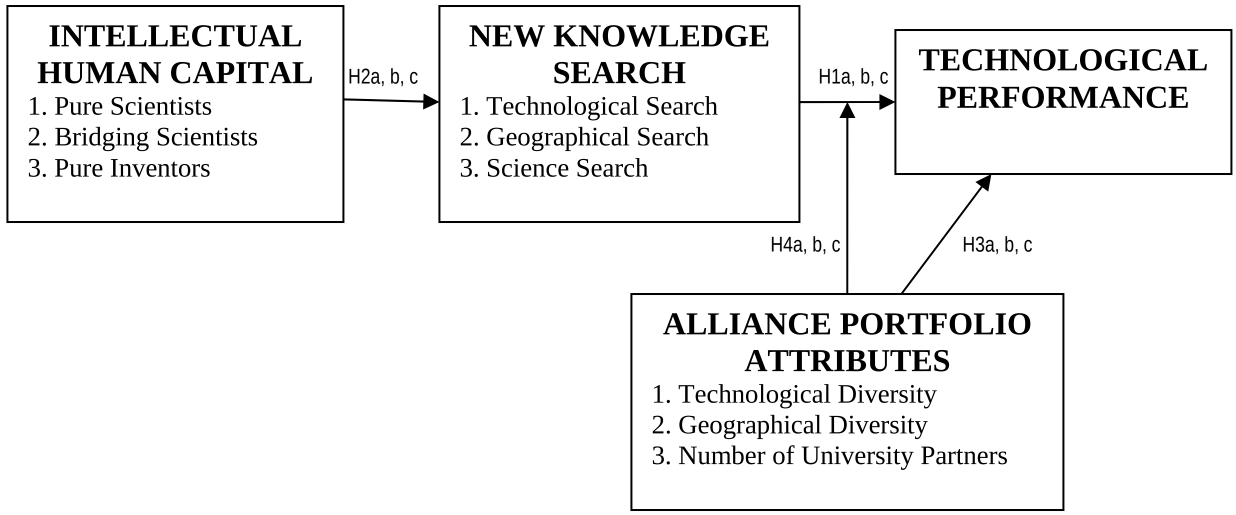
Literature identifies strategic alliances, especially those on research and development (R&D), to be an important mechanism for acquiring and exploiting external knowledge (Mowery, Oxley and Silverman, 1996; Grant and Baden-Fuller, 2004). Hence, the second objective of this research is to show that strategic alliances help a firm in translating its new knowledge search into better technologies. Specifically, I show that strategic alliances moderate the relationship between new knowledge search and technological performance. One might argue that alliances can also be a direct input to new knowledge search. However, I support my claim that the value of strategic alliance is to the second stage of new knowledge search in the following way. According to the absorptive capacity literature, the first and foremost step in forming an alliance is identifying potential partners and evaluating the value of their knowledge. Therefore, a firm’s internal resources, such as intellectual human capital, lay the foundation for new knowledge search by identifying potential partners. It is with these new partners whom the firm then establishes formal relationships such as alliances. Thus, the role of alliances is in facilitating the process of acquiring and exploiting the searched knowledge.

The benefits from cooperative strategy are known to depend on the characteristics of the alliance network (Stuart, 2000). Therefore, the second objective is to specifically investigate the kind of alliance portfolio that best fits the three dimensions of new knowledge search. I propose that an alliance portfolio characterized by partners from diverse technological and geographical background positively moderates the relationship of technological, geographical search with technological performance, respectively. Similarly, I argue that an alliance portfolio characterized by a higher number of partners from the academe enhances the value of science search.

The second objective also intends to contribute to two streams of research. The first contribution is to the evolutionary search literature. I intend to identify the kind of alliance portfolio that best fits with the different dimensions of new knowledge search, thereby enhancing the contribution of new knowledge search to technological performance. The next contribution is to the literature on strategic alliances. I suggest that a holistic understanding of the benefits derived from an alliance portfolio depends on the attributes of the alliance portfolio as well as their interactions with the focal firm's characteristics.

The research framework developed in this study is tested using patent, publication and alliance data of biotechnology firms. This chapter is organized as follows. In the next section I elaborate on each of the linkages shown in Figure 2.1 and develop the hypotheses. This research intends to examine the correlation among the variables shown in Figure 2.1 and not to test their causal relationship. In the subsequent sections I present the research method and results. In the last section I discuss the implications of the findings and the limitations of the study.

Figure 2. 1. Research Model



THEORY AND HYPOTHESES DEVELOPMENT

New Knowledge Search

Search is an inevitable part of the organizational learning process (Huber, 1991). Organizations engage in different types of searches. They are known to search for the best manufacturing routine (Jaikumar and Bohn, 1992), superior organizational design (Bruderer and Singh, 1996), the best means of implementing new technologies (von Hippel and Tyre, 1995), and the like. In this study, I focus on firms' endeavors in searching external knowledge with the anticipation that the knowledge can be recombined into valuable technologies. My study refers to this type of search as 'new knowledge search'.

New knowledge search is categorized into three types: (a) technological search, (b) geographical search and (c) science search, depending on the knowledge that is searched. All three dimensions of new knowledge search are critical for technological performance. For instance, the importance of technological search is explained by

Rosenkopf and Nerkar (2001) using the optical disk drive industry. They show that in the optical disk drive industry the breakthrough discovery of DVD was made possible by integrating ideas from laser technologies. Databases like MedTRACK that incorporate advanced tools in searching geographically dispersed knowledge underline the significance of geographical search. The importance of science search for technological performance can be easily appreciated from the basic definition of technology - "incorporating scientific knowledge into physical artifact that benefits users" (Nelson and Winter, 1982).

There are various means through which firms can search and acquire new knowledge. Firstly, as people are known as knowledge holders and movers of knowledge across boundaries, intellectual human capital assists a firm in its new knowledge search (Almeida and Kogut, 1999). Organizations achieve this by engaging their intellectual human capital in research activities, professional communities, etc. Secondly, firms engage in formal arrangements such as alliances to acquire and access new knowledge.

It should also be acknowledged that many of the organization level factors such as organizational design, R&D structure, firm size and technological strength also play an important role in directing the new knowledge search (Argyres and Silverman, 2004; Siggelkow and Rivkin, 2005; Rivkin and Siggelkow, 2003; Colombo, Grilli and Piva, 2006). The above studies illustrate that decentralized organizations and organizations that are large and highly innovative attempt to search widely for new knowledge. As intellectual human capital and alliances are two mechanisms that are directly engaged in searching and acquiring new knowledge, my research concentrates on these two factors.

Nevertheless, I use some of the firm level variables such as size and technological strength as control variables.

The following sections examine the details of the three dimensions of new knowledge search and their contribution to technological performance.

Technological Search and Technological Performance

Technological search refers to the search for diverse technological areas in the anticipation of recombining them into novel technologies (Rosenkopf and Nerkar, 2001). Technological search can enhance the technological performance of firms by the following means. First, technological search can positively influence the technological performance by increasing the number of elements available for recombination. Innovation has been conceptualized as a process of recombination and, according to this perspective, important innovations arise out of combining technological components in a novel manner (Nelson and Winter, 1982; Henderson and Clark, 1990; Weitzman, 1996). When a firm attempts to move beyond existing technological landscapes and search broadly for technological elements, it enriches the knowledge pool available. The enriched knowledge pool creates opportunities for the cross-fertilization and cross-application of ideas across technological domains for generating high-impact technologies. Indeed, most modern innovations are fusions of ideas searched across different technological landscapes. For instance, the discovery of inkjet printers by Hewlett Packard as well as the birth of genetic engineering[5] are examples of how search

[5] "In a conference held in 1972, Stanley Cohen of Stanford University elaborated on the technique of introducing DNA (the double-stranded helical molecule chain found in the nucleus of each cell that carries the genetic information) into Escherichia Coli, which is the main species of the lower intestine of mammals. In the same meeting, Herbert Boyer from the University of San Francisco shared his work on a revolutionary enzyme called EcoRI, which could cleave the double-stranded DNA molecule to produce single-stranded ends with identical termini. The two scientists saw the potential of combining the two discoveries into what is currently known as genetic engineering. Subsequently, the biotechnology industry

of new technological landscapes can increase the possibility of recombination, thereby resulting in valuable innovation.

Second, broad technological search provides a basis for breakthrough technologies by helping firms overcome familiarity traps. When firms experiment with the technological elements they are familiar with, their experience in those elements increases. Greater experience will foster greater usage of the same technological elements. This path dependency increases the risk of firms falling into the familiarity trap, and this can impair firms' capability to develop valuable technologies (Ahuja and Lampert, 2001). A broad technological search can help to overcome this problem in the following ways. Technological search exposes firms to new technological elements that challenge the stability of the existing cognitive structure (Lei, Hitt and Bettis, 1996). In understanding the new and unfamiliar technological elements, firms develop additional insights and profundity. Exposure to diverse technological areas also helps in building a heterogeneous repertoire of knowledge. The broad knowledge base provides the benefit of heterogeneity in solving problems (Amabile, 1988) rather than solving in a paradigmatic way. On both these accounts, broad technological search can circumvent the familiarity trap, providing a basis for creating valuable technologies. The above arguments suggest that the search for knowledge from diverse technological domains is capable of generating valuable technologies.

Though technological search has the above-mentioned advantages, it is also associated with certain disadvantages. The search of wide technological areas is a costly and tedious task. In addition, recombining ideas from different technological domains is

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has become increasingly richer, involving knowledge from different disciplines such as molecular biology, chemistry, computer science, and the like" (Christensen, 2003; DeCarolis and Deeds, 1999).

not straightforward and has inherent uncertainties (Fleming and Sorenson, 2004). Identifying one fruitful combination amid the potential number of technological recombination is time consuming. Hence, beyond a point, searching across diverse technological areas will result in diminishing returns. The above arguments lead to the following hypothesis:

Hypothesis 1a: The breadth of a firm's technological search is curvilinearly (inverted U) related to its technological performance.

Geographical Search and Technological Performance

Geographical search refers to the search for geographically distant knowledge in the prospect of locating valuable ideas (Song, Almeida and Wu, 2001). There are three explanations to support the argument that geographical search leads to better technological performance. First, geographical search can increase a firm's awareness of diverse knowledge domains, thereby increasing the likelihood of generating valuable technologies. It has been shown that technological trajectories differ across nations (Freeman and Soete, 1997). Owing to the knowledge differences across boundaries, any attempt to span geographical boundaries can give access to diverse knowledge with the potential to be recombined into valuable technologies. As people from different contexts are capable of viewing the same thing differently, geographical search can lead to novel combinations of existing ideas. Geographical search can also expose firms to specialized local knowledge of diverse geographical boundaries that can beget valuable innovation. An excellent example of this is the knowledge gained by the American chemical company W.R. Grace in developing a commercial drug using neem, a herb traditionally used in India for medicinal purposes (Phene et al., 2006).

Second, geographical search can positively influence technological performance by exposing firms to rich information and knowledge networks. In developing valuable technologies, firms have to constantly rely on external sources of information and knowledge. The globalized technological arena has increased the need for firms to stretch their regional boundaries in search for external knowledge. Though knowledge is an intangible asset, it is considered extremely difficult to transfer knowledge across geographical boundaries. With knowledge flow being geographically localized, firms have to rely on network connections in order to access knowledge. Research has suggested that the extent to which a recipient seeks information from a source depends on the extent to which the recipient is aware of the source (Borgotti and Cross, 2003). Therefore, searching or scanning for new knowledge is the first step involved in exposing firms to valuable sources of knowledge. Thus, a firm's geographical search will promote awareness of different regional networks, thereby providing an opportunity to tap into knowledge embedded in these networks for generating valuable technologies. The above arguments suggest that the search for knowledge from diverse geographical regions is capable of generating valuable technologies.

However, scanning wide geographic locations can also be dysfunctional (Ahuja and Katila, 2004). Acquiring and integrating knowledge obtained from different geography is a difficult job. Distance and cultural differences further exasperate the problem of utilizing the searched knowledge to develop technologies. Hence, beyond an extent, scanning diverse geographic locations can result in decreased technological performance. The above arguments lead to the following hypothesis:

Hypothesis 1b: The breadth of a firm's geographical search is curvilinearly (inverted U) related to its technological performance.

Science Search and Technological Performance

Science search refers to the intensity of scientific knowledge search with the expectation that the knowledge will assist in finding novel technologies (Ahuja and Katila, 2004). Unlike technological and geographical search, science search refers to intensity but not breadth. This is because the purpose of using scientific knowledge is to achieve a deeper understanding of why some phenomena occur during the technology development process (Fleming and Sorenson, 2004).

Science search can positively influence the technological performance of firms through the following means. First, science search has a positive influence on technological performance by acting as a direct source of new ideas. Though important innovations are seen as a combination of technological ideas, the set of elements available for recombination is finite. As a result, the recombination search space will decrease over time, ultimately resulting in technological exhaustion (Hargadan and Sutton, 1997). In the event of the exhaustion of ideas firms must embark on alternative search trajectories, and science is a natural choice. Science search helps in generating new theories which, consequently, increases the availability of new ideas. The new ideas generated by science subsequently become key ingredients for technology activities.

Second, science search can reduce the combinatorial search pace, thereby positively influencing technological performance. For instance, scanning scientific knowledge can improve the understanding of the cause-effect relationship between technological elements. Scientific knowledge also helps in assessing technology and in foreseeing technological risk (Brooks, 1973). Consequently, science search can assist firms in exploring productive research avenues and inventing technologies with greater reliability.

Apart from being a direct input to technological innovation, science search is observed to provide some indirect benefits in generating valuable technologies. These benefits include enhancing the skills and capabilities of human resources, fine-tuning the engineering design and tool and the like. For example, scientific knowledge exploration is shown to impart the necessary research skills required for carrying out technology development activities. Much of the technical knowledge used in designing and in evaluating engineering designs is also shown to be developed from the scientific knowledge base (Brooks, 1994). The above arguments suggest that the search for knowledge from science base is capable of generating valuable technologies.

Though searching the science knowledge base is helpful, excessive amounts of science search can be detrimental to technological performance for the following reasons. Engaging in scientific exploration can lead to random drift and frequent alterations of a firm's knowledge base. The difficulty associated with adjusting to such random drift can obstruct a firm from concentrating on technology development. Time spent on scientific exploration can also reduce the availability of time for actively integrating and exploiting knowledge, thereby reducing the technological performance. Hence, I hypothesize that:

Hypothesis 1c: The intensity of a firm's science search is curvilinearly (inverted U) related to its technological performance.

Intellectual Human Capital and New Knowledge Search

Knowledge is considered to be the core of a firm, and much of an organization's knowledge resides in its human capital. Consequently, human capital is one of the important resources that contribute to knowledge-intensive activities such as new knowledge search. This is one reason why highly-skilled and talented employees are considered to be valuable resources for successfully adapting to technological changes (Siegel, 1999; Siegel, Waldman and Youngdahl, 1997). There are three explanations to support the positive association between intellectual human capital and new knowledge search.

First, the absorptive capacity literature identifies pre-existing knowledge to be an important factor in screening and identifying valuable external knowledge (Cohen and Levinthal, 1990). The knowledge and skills residing in intellectual human capital enables them to actively engage in research activities, thereby playing a key role in new knowledge search. Especially in biotechnology industries requiring specialized skill sets, intellectual human capital has a significant role in the pursuit of searching knowledge (Zuker, Darby and Brewer, 1998). The genetic engineering, AIDS, and polymerization chain reaction examples illustrated earlier also underline the contribution of intellectual human capital to new knowledge search.

Second, propensity to transform knowledge is an essential step for embarking on new knowledge search. Rather than relying on preserved knowledge, engaging in knowledge transformation activities requires questioning of prevailing norms. Intellectual human capital plays a vital role in questioning prevailing norms within the organization and in imparting new ways of thinking (Tushman and Anderson, 1986). Thus, by acting as a predominant source for knowledge transformation, intellectual human capital has a positive influence on search for new knowledge.

Third, engaging in new knowledge search requires awareness of valuable sources of knowledge. By actively plugging itself in external professional communities, intellectual human capital acts as a channel for the flow of information about valuable sources of knowledge. Thus, intellectual human capital plays the vital role of carrying meta-knowledge, thereby having a positive influence on new knowledge search. Meta-knowledge is defined as knowledge about sources of knowledge (Majchrzak, Cooper and Neece, 2004). While the above arguments suggest a positive influence of intellectual human capital on new knowledge search, the following section categorizes intellectual human capital into three types and exemplifies their individual contribution to search.

Traditionally, studies on professional careers concentrated on two tracks. The first track focused on academic researchers and their scientific activities (Keith and Babchuk, 1998), and the second track on industrial engineers and their technological activities (Allen and Katz, 1992). But, with the birth of science intensive industries such as biotechnology and the introduction of the Bayh-Dole Act, we observe an increasing number of scientists from academe actively contributing to technological activities in the industry. Firms are also known to attract scientists into their organizations and encourage them to publish their findings (Stern, 2004). Consequently, we notice three different types of intellectual human capital within an organization. The first one, pure scientists, are exclusively involved in scientific research. The second type, pure inventors, predominantly focus on technological activities. The third type of intellectual human capital, called bridging scientists, are involved in both scientific and technological activities.

The three classifications of intellectual human capital contribute to new knowledge search in varied ways. For instance, involvement of pure scientists in scientific research and scientific community enable them to contribute to science search. The open scientific community comprised of scientists from different geographic locations allows pure scientists to search geographically wide knowledge (Furukawa and Goto, 2006). Since basic scientific knowledge can also help in technology assessment, pure scientists have a significant role in technological search. The nature of scientific research is to question basic assumptions. This means pure scientists play a vital role in knowledge transformation activities of a firm, thereby contributing to new knowledge search.

In parallel, the pure inventors who are engaged in technological activities and connected to technical communities facilitate the technological and geographical search of a firm. They can also direct the attention of search to useful scientific knowledge that has applications in technology development, thereby helping the science search.

Bridging scientists have a role in both scientific research and technological activities, and therefore contribute to new knowledge search in all the above-mentioned ways. In addition, their bridging role aids the flow of information about valuable sources of knowledge across these two groups. Hence, I hypothesize that:

Hypothesis 2a: The number of intellectual human capital (Pure Scientists, Bridging Scientists, Pure Inventors) within a firm is positively related to its technological search.

Hypothesis 2b: The number of intellectual human capital (Pure Scientists, Bridging Scientists, Pure Inventors) within a firm is positively related to its geographical search.

Hypothesis 2c: The number of intellectual human capital (Pure Scientists, Bridging Scientists, Pure Inventors) within a firm is positively related to its science search.

New knowledge search is just one of several avenues through which intellectual human capital can affect technological performance. They can also influence the technological performance by increasing the reputation of the firm. For example, technology emerging from a firm endowed with important intellectual human capital can gain the attention of industry better than technology from a firm lacking in rich intellectual human capital. This effect can also be compared to Merton's Mathew effect in sociology of science literature. A firm's valuable intellectual human capital can also attract investments from corporate venture capitalists, thereby contributing to technological performance. Hence, I do not expect new knowledge search to fully mediate the relationship between intellectual human capital and technological performance. Though mediation is not a part of the research model, the methodology section encompasses the test for mediation.

Alliance Portfolio Attributes and Technological Performance

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). A number of studies have shown that alliances influence the technological performance of firms. In particular, strategic alliances are shown to be beneficial for patent and new product development rates (Deeds and Hill, 1996; Shan, Walker, and Kogut, 1994). There are various means through which firms benefit from the alliances in developing better technologies. For instance, alliance is considered to be an important means for sourcing external knowledge and leveraging external resources that are crucial for better technological performance (Dyer and Singh, 1998). Firms especially rely on alliance partners for gaining the technical, social and commercial capital that are valuable to their innovation performance (Ahuja, 2000). Alliances also influence the technological performance of firms by granting access to complementary assets (Pisano, 1990). Other benefits of alliances for better technological performance include: (1) imparting social status and recognition (Stuart, 2000), (2) defraying cost and sharing risk (Hagedoorn, 1993) and the like. These benefits have an effect on the technological performance of firms in the following ways. Social status and recognition might enhance the opportunities available to a firm for engaging in more R&D alliances, thereby having a spiraling effect on technological performance. The advantage of sharing risk and investment with its partners can encourage a firm to embark on pioneering research avenues that are capable of rendering breakthrough innovations. The above arguments suggest that a firm's alliance network is positively associated with its technological performance.

Though alliances are generally known to be beneficial, the structural holes perspective demonstrates that not all alliance partners are equally beneficial (Burt, 1992). Similarly, an increase in the number of alliances is not necessarily considered to bring in additional benefits. There is a high chance that the attributes of a new partner overlap with existing alliance partners, providing access to redundant information and competency. As engaging in an alliance and managing the relationship entails a huge investment from the focal firm, such redundancies can be very costly. Hence, it is essential to consider the attributes of alliance partners in assessing their contributions (Stuart, 2000). It is also vital to understand the synergetic effect of the whole alliance portfolio rather than viewing them as independent events (George, Zahra, Wheatley and Khan, 2001; Baum et al., 2000). An efficient alliance portfolio comprising of partners with diverse attributes is known to help firms in overcoming redundancy issues and gaining enhanced benefits from the alliance. An efficient alliance network characterized by diverse partners is also recognized to help firms in lowering their failure rate (Baum and Silverman, 1998) and in improving their performance (Baum et al., 2000).

Diversity can be attributed to different sources. The importance of concentrating on the diverse technological and geographical attributes of an alliance network has been recently demonstrated by a study that explored the different dimensions of social capital (Koka and Precott, 2002). Similarly, the significance of relationships with public research organizations, such as universities, has been underlined in a study by Powell and Smith-Doerr (1996) in which they highlight that the development of an animal model for Alzheimer's disease is affiliated with a diverse range of knowledge sources including universities and nonprofit research institutes. Hence, in this study I concentrate on diversity pertaining to the three attributes of an alliance portfolio: (1) technological, (2) geographical and (3) number of partners with a university background. The three alliance attributes under study also correspond to the three types of new knowledge search. Based on the above arguments, I hypothesize that:

Hypothesis 3a: The alliance portfolio of a firm characterized by partners with diverse technological attributes is positively related to its technological performance.

Hypothesis 3b: The alliance portfolio of a firm characterized by partners with diverse geographical attributes is positively related to its technological performance.

Hypothesis 3c: The alliance portfolio of a firm characterized by a greater number of partners with a university background is positively related to its technological performance.

Alliance Portfolio Attributes Moderating the Effect of New Knowledge Search

Although internal resources such as intellectual human capital engage in search of new knowledge, acquiring external knowledge is not simple. The knowledge and experience residing in the intellectual human capital can help them, to an extent, in absorbing external knowledge. However, in the absence of a facilitating mechanism, certain knowledge, especially knowledge characterized as tacit and complex is difficult to absorb from the external environment. Prior studies have also recognized the difficulty in absorbing knowledge from the three types of new knowledge search. For instance, technology related capabilities are often based on tacit knowledge and are subject to considerable uncertainty concerning their quality and performance. Transferring such knowledge and exploiting them are subject to high risk failures (Mowery, 1983). Studies on national innovation systems suggest that countries have distinct patterns of specialization, and that the difference has increased over time (Archibugi and Pianta, 1992). The geographical distance of the knowledge that makes it valuable also creates difficulty in acquiring and absorbing the knowledge (Phene et al., 2006). Similarly, the difficulty in absorbing science knowledge that is easily available in the form of public good has also been recognized in the past (Gambardella, 1995).

Inter-firm collaborative mechanisms such as alliances are widely recognized as devices for overcoming the above-mentioned difficulties in acquiring and accessing knowledge (Kogut, 1988; Hamel, 1991). Frequent interactions between alliance partners act as a platform for inter-firm knowledge flows. Consequently, by enhancing the degree to which knowledge is absorbed, alliance helps a firm in translating new knowledge search into better technologies. In particular, an alliance portfolio that best fits with the different dimensions of the new knowledge search will be rendering the above-mentioned benefits of enhancing the value of search.

Even if a firm is capable of absorbing the widely searched knowledge, it is very difficult for the firm to have in-depth expertise in all the knowledge areas it searches. Alliance is a prevalent mechanism used by firms in maintaining a broader and deeper knowledge base for translating knowledge into valuable innovations. Many of the alliances in knowledge-based industries are knowledge accessing alliances. These allow the focal firm to concentrate on a few core knowledge areas while collaborating with other firms in order to access their stronger capabilities in additional areas (Grant and Braden-Fuller, 2004). Alliances between biotech firms and IT firms, alliances between firms and universities and alliances that span national borders are some of the prevalent examples in the biotechnology industry falling under this category. Thus, an efficient alliance portfolio that best fits with the different dimensions of the new knowledge search helps a firm in maintaining knowledge diversity as well as richness, thereby moderating the relationship between new knowledge search and technological performance.

Alliances can also enhance the contribution of new knowledge search to technological performance in the following ways. Firms search for new knowledge in the anticipation of combining them into useful technologies. Though widely searched knowledge has the potential of being recombined into breakthrough innovations, the process of achieving this is a risky task. It is highly likely that a firm will invest money and time on a certain combination for several years, yet it might turn out to be unsuccessful. There are several drug failure cases (Pfizer, Merck) in the biotechnology industry that are exemplary examples of this. As biotech innovations are costly in nature, with a new drug consuming about USD 800 million of R&D, firms in this industry are known to distribute the risk by forming collaborations. With an additional firm to share the cost and risk, firms embark on risky journeys in the pursuit of translating the searched knowledge into breakthrough technologies.

Though the last argument suggests that, in general, alliances moderate the relationship between new knowledge search and technological performance, the former two arguments suggest an efficient alliance portfolio that corresponds to different dimensions of new knowledge search to render the moderating effect. Since an alliance portfolio with technologically and geographically diverse alliance partners and partners from a university background is also comparable with the different dimensions of search, I have the following hypotheses:

Hypothesis 4a: An alliance portfolio characterized by partners with diverse technological attributes positively moderates the relationship between a firm's technological search and its technological performance.

Hypothesis 4b: An alliance portfolio characterized by partners with diverse geographical attributes positively moderates the relationship between a firm's geographical search and its technological performance.

Hypothesis 4c: An alliance portfolio characterized by a high proportion of partners with a university background positively moderates the relationship between a firm's science search and its technological performance.

It should be acknowledged that the tacit knowledge of intellectual human capital also helps a firm in the process of converting new knowledge search into valuable technologies. As the focus of the paper is only on those factors that assist a firm in identifying and absorbing knowledge from its external environment, I did not investigate this relationship. Intellectual human capital also helps a firm in absorbing knowledge from its alliance partners. However, testing this relationship is beyond the scope of this paper.

RESEARCH METHODOLOGY

Data

To test the hypotheses I collected data from biotechnology firms. This industry is recognized to be one of the most innovation-intensive industries (Sorenson and Stuart, 2000). The biotechnology industry was an ideal context for testing the framework because the industry is characterized by technological transformation, a growing number of inter-organizational relationships and the widely recognized importance of intellectual human capital.

The data was drawn from Plunkett's[6] directory that comprises of 437 public-listed biotechnology firms. Biotechnology directories are one of the sources that prior studies have consulted in drawing their sample (Gulati and Singh, 1998; Stuart, Huang and Hybels, 1999). Generally, firms in the directory are based in the United States of

[6] Plunkett's *Biotech and Genetics Industry Almanac 2005:* the only comprehensive guide to biotechnology and genetic companies and trends/editor and publisher: Jack W. Plunkett.

America. However, the headquarters of 70 firms are located in other nations such as Canada, Japan, UK, India, Switzerland, etc. The directory has 3 firms from agriculture, 13 from infotech, 100 from chemical manufacturing and 321 from the health care areas of biotechnology. The directory comprises of firms such as EISAI Co. Ltd., DOW Agrosciences, BASF AG and TRIPOS Inc. that have attained the highest sales revenue in the year 2000 for the health care, agriculture, chemical manufacturing and infotech areas respectively. The directory includes very small firms (with respect to R&D, number of employees and sales) such as VIRAGEN and SPECTRAL DIAGNOSTICS, as well as large firms such as BAYER and NOVARTIS. With respect to age, there are old firms such as PFIZER, as well as new firms formed in the late 90's such as ATHEROGENICS and ARENA PHARMACEUTICAL.

I used the publication, patenting and alliance data of these firms in testing the hypotheses. The patents issued to these firms between 1990-2000 were obtained from the NUS patent database[7]. The database comprises of patents issued to firms by the United States Patent and Trademark Office (USPTO). Publication information of firms between 1980-2000 was obtained from *Web of Science, ISI Science Citation Index (SCI)*. The SCI is an excellent source because it covers a broad range of basic and applied scientific journals (Lim, 2004). As the birth of the biotechnology industry is dated back to the late 70's and my patent data is restricted to 2000, I focused on publication during the period 1980-2000.The Recombinant Capital (Recap) database that provides a comprehensive list of biotechnology companies worldwide along with their alliances, valuations and clinical trials information is used to cross-validate the list of biotechnology firms chosen from the

[7] http://patents.nus.edu.sg/

directory and to obtain alliance-related information between 1990-2000. Compustat Global is used in collecting the financial data of these firms.

The US patent classification system comprises of over 100,000 patent subclasses aggregated to about 400 three-digit patent classes. I used the three-digit patent classes and only included those patents that fall within the U.S. patent classes listed in Table 2.1, which belong to the biotechnology industry. The classes were chosen with reference from the USPTO Technology Profile Reports and from prior research (Lim, 2004). Filtering those firms that did not have patent data in the specified classes between 1990-2000, the final sample size was 222 firms. The list of 222 firms is provided in Table A.2 of the Appendix. Of the listed firms, 215 (437-222) firms were dropped from the directory because they had zero patents. To ensure that the results were still generalizable, I carried out a preliminary assessment of firm level variables. As shown in Table A.3, the average of firm R&D and firm size for 437 firms was not significantly different from the average of these variables in my final sample. However, I found that the average age of my final sample firms was higher than that of the average age for 437 firms. This is possibly because younger firms in the directory might not have patents issued between 1990-2000. Nevertheless, I do believe that the results of my study hold true even for younger firms, because my sample does indeed include younger firms such as Atherogenics and Arena.

The total number of patents and publications under consideration was 10,646 and 100,375. There is huge heterogeneity with respect to patent and publication data. Firms like Anika Therapeutics and Viragen received one patent each, while Abbott and Bayer had about 1000 patents. Patents issued to firms increased from 424 in 1990 to 1722 in 2000. There were 19 firms in my sample with 0 publications, but also about 10 firms with at least a few thousand publications. The publications made by firms increased from 1826 in 1980 to 8181 in 2000. The number of publications, patents and alliances of my sample firms between 1990-2000 is provided in Table A.4 of the Appendix.

Table 2.1. U.S. Patent Classes

Class	Description
424	Drug, bio-affecting and body treating compositions
435	Chemistry: molecular biology and microbiology
436	Chemistry: analytical and immunological testing
514	Drug, bio-affecting and body treating compositions
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

Measures

Technological Performance (Forward Citation): The dependent variable is the cumulative forward citation frequencies accrued to an individual patent. I count all forward citations received by each patent at of the end of 2004. By law, each patent must cite prior patents that relate to its technology. Research demonstrates that the number of forward citations received by a patent correlates highly with its technological importance (Trajtenberg, 1990; Albert, Avery, Narin and McAllister, 1991). Prior studies have observed that the self-citation of a firm to its patents represents the extent to which the firm appropriates the returns from the patents. As a consequence, they find self-citation to reduce the probability of other firms citing the patent (Zhuang, Wong and Lim, 2006). However, in my sample I found the self-citations to be positively related to the overall forward citations, which indicates that overall citations represent the value of knowledge underlying the technology. Hence, instead of removing self-citations, I restricted my attention to overall citations accrued by a patent.

One way to measure technological performance would be to use the number of products introduced by a firm. However, I restricted my focus to a patent-based performance measure because of the following three reasons. First, obtaining data on the number of products introduced by my sample firms was difficult.

Second, the number of products introduced by a firm not only depends on the technological competency of the firm but also other factors such as U.S. Food and Drug Administration (FDA) authorization etc. In order to prevent the results from being confounded by factors that are not of interest to my research, I relied on patent-based performance measure.

Third, the biotechnology industry is characterized by open innovation in which the activities pertaining to the higher end of the value chain are performed by the firms competent in it, while FDA approval and commercialization are taken care of by other firms. Hence, a firm introducing a product into the market may not necessarily be the one responsible for its basic technological development. As the focus of my study is to relate technological competency of a firm with its performance, I believe that a patent would be a more appropriate measure of a firm's capability to generate valuable technologies.

Since patent to product conversion process in the biotechnology industry is time consuming, many of the results that hold true for a patent-based technological performance measure might not hold for a product-based measure. Hence, an interesting future research can be to test my research model with both patent-based and product-based performance measures and compare their results.

Independent Variables

Technological Search (Breadth of Technological Search): Technological search refers to the breadth of technological search conducted by firms. This measure is based on the technology class of patents cited by the focal patent issued to a firm (after removing self-citations). Specifically, the breadth of technological search of patent i is calculated as:

$1-\sum_{j=1}^{n_i} S_{ij}^2$ (One minus the Herfindahl concentration index of the technology classes)

where S_{ij} refers to the proportion of citations made by patent i to the patents in technology class j (after removing self-citations). n_i varies for each patent depending on the number of different technology classes that the focal patent cites. The three-digit technology class is considered in measuring the above. This measure would range between 0 and 1, with a greater value suggesting that the patent has searched for a broad set of technologies. This measure corresponds to the "originality" measure in the work of Jaffe and Trajtenberg (2002).

Geographical Search (Breadth of Geographical Search): One way to measure the geographical search for knowledge would be to use the firm's R&D laboratories and R&D budgets in different locations. Since obtaining data at that level was difficult, I relied on patent data to measure the geographic dispersion of a firm's search for knowledge.

This measure is based on the geographic location of patents cited by the focal patent issued to a firm (after removing self-citations). Specifically, the breadth of geographical search of patent i is calculated as:

$1-\sum_{j=1}^{n_i} S_{ij}^2$ (One minus the Herfindahl concentration index of the geographical locations)

where S_{ij} refers to the proportion of citations made by patent i to the patents in geography j (after removing self-citations). n_i varies for each patent depending on the number of different geographic locations that the focal patent cites. Patent data contains information regarding the geographic location of its inventors. The first inventor's address (as he/she is considered to be a significant contributor for the patent) is taken into consideration in measuring the geographic search (Singh, 2005). The geographical unit is defined at the country level, in which I use the country of the first inventor as the geographic unit for all the patents. In my sample, the majority of the citations are made to patents originating from USA, Japan and Europe. Similar to technological search, this measure would range between 0 and 1, with a greater value suggesting that the patent has searched a broad set of geographic locations.

Science Search: Science search is the number of times a patent issued to a firm references non-patented literature. Every patent is required to cite the prior art that it builds upon. This includes both the patent and non-patent references. Sorenson and Fleming (2004) have observed that 69% of non-patent references are from peer-reviewed scientific journals. The non-patent references cited by a patent are often used as an indicator of the science intensity of the invention, which is in turn found to influence the forward citation of patents (Gittelman and Kogut, 2003; Noyons, van Raan, Grupp and Schmoch, 1994). But the measure does not exclude self-citations to non-patent literature. In this way it is different from the technological and geographical search measures. However, I did examine the extent to which a firm's publications are being cited in its patents. To observe this, I first identified all the publications produced by the focal firm and all the patents citing those publications. For each publication, I checked the first assignee name of the citing patents to see if the patent belongs to the firm that generated the publication or others. I noticed that just 2% of the firms' scientific publications are being cited in their patents. This statistic mitigates the limitation of not removing self-citations.

Intellectual Human Capital (Pure Scientists, Bridging Scientists, and Pure Inventors): The greater the presence of the three types of intellectual human capital, the higher the availability of knowledge, experience and skill for new knowledge search. Traditionally, studies captures the quality of human capital by measuring their qualifications, affiliation, etc. (Hitt, Bierman, Uhlenbruck, and Shimizu, 2001; Hitt, Bierman, Shimizu, and Kochhar, 2006). My study implicitly captures this by looking only at intellectual human capital that possesses high qualifications in order to engage in R&D activities.

I operationalize the three variables in the following manner. The pure scientist measure represents the percentage of scientists within firms whose names are exclusively listed in publications and not in patents. Next, the bridging scientist measure represents the percentage of patent inventors within a firm whose names are listed in both patents and in scientific papers published by the firm. Finally, the pure inventor measure represents the proportion of inventors of each patent who are exclusively involved in patenting but not publishing. In order to obtain these measures, I identified two overlapping sets of individuals for each firm. The first comprises of scientists whose names are listed on at least one publication made by the focal firm, and the second comprises of inventors whose names are listed on at least one patent issued to the focal firm. Based on these two lists, I found the percentage of individuals listed as inventors who are also listed as scientists for each firm. This percentage is termed as bridging scientists. The measure is borrowed from the work of Gittelman and Kogut (2003). Then, I identified the percentage of those scientists whose name appeared only in the publications and not in the patents. These scientists who are exclusively involved in scientific publishing are termed as pure scientists. Then, for each patent, I identified the number of inventors whose names do not appear in the list of scientists. These inventors who are exclusively involved in patenting are termed as pure inventors. On average, my sample firms had about 900 pure scientists, 34 bridging scientists and 47 pure inventors. Firms such as Bayer and Merck had the highest number of pure scientists, bridging scientists, and pure inventors. This shows that the measures are not a complement of each other, with the pure inventors measures being calculated at the patent level while scientist measures are at the firm level.

Apart from qualifications, there are other aspects of quality of intellectual human capital as measured by the extent to which they are active in producing high quality work. This aspect of quality, as measured by the volume and citations of firms' publications and stocks of patents, are captured and controlled in this study. This helps in exploring if firms endowed with a greater proportion of each of the intellectual human capital dimensions (after controlling for quality) are better in their new knowledge search.

Technological Diversity of the Alliance Portfolio: Similar to the work of Baum et al. (2000), I used the Herfindahl index to measure the diversity of the alliance portfolio. By the alliance portfolio, I mean the list of all alliances made by a firm in a year. Specifically, the technology diversity of the alliance portfolio of firm i is defined as:

$$1-\sum_{j=1}^{n_i} S_{ij}^2$$

where S_{ij} refers to the proportion of alliances of firm i that falls under the technology category j (which is nothing but the technology concentration of alliances that is described below). n_i varies depending on the number of different technology category alliances that the focal firm engages in a year.

The Recap database is used in measuring the technological diversity of the alliance portfolio. The Recap database comprises of a list of alliances made by firms in a particular year, along with other information such as the type of alliance (R&D, acquisition, manufacturing, joint venture, licensing, etc.) and technology concentration of the alliance (bioinformatics, DNA probes, combinatorial, gene sequencing, gene expression, microassays, potenomics, etc.). There are 26 types of alliances and 53 types of technology classifications available in the Recap database. The list of alliance types and technology classifications is provided in Table A.5 and A.6 of the Appendix. Since the study pertains to the R&D activities of the value chain, I concentrated on the alliances pertaining to research and development. I then used the classification of partnered technology of all alliance partners in a year in order to arrive at the technological diversity of the alliance portfolio for that year.

Geographical Diversity of the Alliance Portfolio: Similar to the technological diversity of the alliance portfolio, the Herfindahl index was used to measure geographical diversity. I used the nationality of the alliance partners in calculating the Herfindahl index. In my sample, alliance partners are from USA, Europe, Japan and Asia, but the majority of partners are from the USA.

***Number of Alliance Partners with a University Background*:** This measure captures the extent to which the alliance portfolio of a firm in a year is composed of partners from the academe. Hence, I calculated this variable for the focal firm in each year by obtaining the number of alliance partners that are classified as academic institutions. On an average, my sample engaged in 40 alliances during the period of observation, of which 7 are academic institutions.

Control Variables

Publication Volume: This measure is the number of publications produced by the focal firm in the year of observation in which the firm filed a patent. I used the number of publications made by a firm as a proxy for its scientific capability. A number of scholars have used publication count to measure the scientific capability of firms (Lim, 2004; Gittelman and Kogut, 2003; Arora and Gambardella, 1994). A firm with strong scientific capability is able to identify new applications in the technology domain that might give rise to more valuable patents. Prior studies have also shown the significant relationship between publication count and patent performance. It is therefore imperative that I control for it.

Firm's Average Cites to Publications: I use the citations received by the focal firm's publications to represent the relative quality of the firm's stock of scientific knowledge. To compute this measure I first identified all the publications produced by the focal firm between the years 1980-2000 and then obtained the number of citations received by these publications. Based on the citations, I calculated the mean and standard deviation of the citations received by all articles of the sample firms in a publication year. Next, the raw citation counts for each publication of firms are normalized by the mean and standard deviation of the citations received by all articles in its publication year. Normalizing the raw citations by year allows the citations to be summed across years for each firm (Gittelman and Kogut, 2003). I then aggregated the normalized citation count of publications in a year and divided it by the total number of publications made by the firm. The normalized citation count is then aggregated up to the year the observed patent was filed in order to obtain a cumulated amount of publication quality. Because a firm's competency in generating high-quality scientific papers has been observed to impact its capability to produce high-impact innovation, I controlled for it (Gittelman and Kogut, 2003).

Firm's Technological Strength: Since a technologically strong firm is likely to receive more citations, there is a need to control for it. I used the number of patents granted to a firm to measure its technological strength. I take into account the year of the focal patent in calculating the count of patents granted to a firm. For example, if the patent under observation is a patent filed by a firm in year t, I count the number of patents issued to the firm in the year t to account for its technological strength.

***Other Control Variables (Technology Class Dummy Variable, Patent Age, Year Fixed Effects, R&D Expenditure, Firm Size and Firm Age)*:** Forward citations may accrue to patents for other reasons such as technology field characteristics, patent characteristics and firm characteristics. Therefore, I included the patent-level and firm-level control variables to account for the heterogeneity among firms and for age and field effects. Patents belonging to a certain technology class may inherently be more cited than others. Similarly, patents with a higher number of years that elapsed since the patent was filed are capable of attaining higher citations. I used technology-class dummy variables and patent age as patent-level control variables to control for these effects. I also used year-fixed effects to capture the differences in citation probability across different years.

Firms may be highly innovative for different reasons. Larger firms have this capability due to economies of scale and scope, younger firms because they represent the knowledge of the younger vintage and some firms devote significantly more resources to

R&D. Hence, I included firm-level control variables such as R&D expenditure, size of the firm as measured by the number of employees and age of the firm as measured by the number of years since the firm was founded. I included the logarithmic value of the above variables as the control variables.

The summary of the dependent, independent and control variables is presented in Table A.1 of the Appendix. The summary data for the dependent and independent variables and the correlation between the variables at the patent level are reported in Table 2.2.

Table 2.2. Descriptive Statistics and Correlations

N	Variables	Mean	Std. Dev	Min	Max	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	Forward Citation	6.34	11.87	0	233	1															
2	Technological Search	0.35	0.29	0	0.98	0.11*	1														
3	Geographical Search	0.23	0.26	0	0.85	0.05*	0.46*	1													
4	Science Search	18.36	35.14	0	492	0.05*	0.16*	0.10*	1												
5	Pure Scientists	0.77	0.32	0	0.99	0.02	-0.08*	-0.03*	0.12*	1											
6	Bridging Scientists	0.25	0.15	0	0.83	-0.02	0.09*	0.08*	-0.19*	-0.69*	1										
7	Pure Inventors	0.65	1.11	0	17	-0.01	0.11*	0.08*	-0.06*	-0.34*	0.45*	1									
8	Tech.Diversity of Alliance Portfolio	0.30	0.27	0	1	0.19*	0.06*	0.01	0.07*	0.06*	-0.10*	-0.05*	1								
9	Geog. Diversity of Alliance Portfolio	0.10	0.22	0	1	0.04*	0.27*	0.45*	0.02	-0.21*	0.28*	0.49*	0.03*	1							
10	No. of Univ. Partners in Alliance Portfolio	1.61	2.25	0	18	0.27*	-0.03*	0.03*	-0.05*	0.02	0.09*	0.03*	-0.03*	0.04*	1						
11	Publication Volume	136.39	222.74	0	1272	-0.06*	-0.06*	0.01	-0.01	0.31*	-0.18*	-0.10*	-0.15*	-0.05*	-0.01	1					
12	Publication Citation	0.04	0.91	-6.73	9.65	-0.04*	0.03*	0.05*	-0.15*	-0.28*	0.25*	0.08*	-0.10*	0.07*	0.08*	-0.08*	1				
13	Patent Age	10.12	2.80	7	17	0.28*	0.03*	-0.01	-0.15*	-0.09*	0.10*	-0.02	0.17*	-0.02	0.08*	0.11*	0.00	1			
14	R&D	3.04	2.15	-0.55	12	0.17*	0.06*	-0.00	0.05*	0.34*	-0.37*	-0.21*	0.29*	-0.12*	-0.02	-0.30*	0.09*	0.06*	1		
15	Firm Size	6.82	2.32	0	11.69	-0.10*	-0.03*	0.01	-0.06*	-0.63*	0.55*	0.30*	-0.20*	0.18*	0.03*	0.00	-0.04*	0.01	-0.69*	1	
16	Firm Age	3.37	1.21	0	5.01	-0.18*	-0.01*	0.07	-0.23*	-0.47*	0.61*	0.28*	-0.31*	0.18*	0.18*	0.14*	0.29*	0.07*	-0.57*	0.53*	
17	Tech. Strength	62.86	61.33	1	240	-0.16*	0.00	0.01	0.02	-0.37*	0.32*	0.17*	-0.30*	0.09*	-0.02	0.18*	-0.12*	-0.09*	-0.65*	0.62*	0.46*

*p<0.01

Analysis

Since the dependent variable is forward citation count, a count model was more appropriate for this research. The Poisson model is a frequently used count model. As patent citations exhibited over-dispersion, I used a negative binomial model that is best suited for estimating an over-dispersed parameter (Cameron and Trivedi, 1998). The results of negative binomial regression are presented in Table 2.3. All specifications include fixed effects for both technology class and application year of the patents. I used robust standard errors adjusted for clustering of the firm to control for random firm effects. Though my sample had 222 firms and 10,606 patents, due to missing observations, the final regression results are based on 157 firms and 7,648 patents.

Effect of Control Variables

Model 1 of Table 2.3 presents the regression coefficients for the control variables. The publication volume has a significant negative effect ($p<0.01$) on the forward citation of patents. The result pertaining to the negative role of publications on patent citation rate is contrary to the findings of Cockburn and Henderson (1998), Gambardella (1995) and Gittelman and Kogut (2003). These scholars observed publication volume to have either an insignificant or positive influence on patent citations. One possible explanation of my result is that when firms concentrate more on producing scientific publications, their attention towards developing important technologies might deteriorate and result in fewer forward citations for their patents. This explanation is also consistent with the result pertaining to publication citation. The quality of firms' publications as reflected by the average cites to these publications has a negative relationship with the forward citation of patents ($p<0.05$). This shows that when firms engage in the generation of cutting-edge scientific research, their technological performance suffers.

As expected, firm age has a negative impact on the forward citation of patents ($p<0.01$). Firm size and R&D expenditure do not have a significant relationship with the forward citation of patents. A plausible explanation for R&D and firm size being insignificant is that increased R&D spending and economies of scale need not necessarily increase the quality of technologies, as measured by the forward citations. The technological strength of a firm, as measured by the number of patents it generates, is negatively associated with the forward citation of patents ($p<0.01$). This shows that the quality of patents is inversely proportional to the quantity generated. A plausible explanation for the above negative association is that when firms generate more patents, only a small number of these patents are likely to have applications elsewhere, while majority of them remain unexploited. The significant ($p<0.01$) positive effect of patent age shows that older patents receive more citations.

Main Effect of New Knowledge Search

The regression coefficients in testing the main effect of new knowledge search and intellectual human capital are provided in Table 2.3. Models 2, 3, and 4 provide the curvilinear test results for technological search, geographical search, and science search independently. The linear term of technological search is significantly positive ($p<0.01$) and its squared term is insignificant. The linear terms of geographical and science searches are positively significant ($p<0.01$) and their squared terms are negatively significant ($p<0.01$). Model 5 presents the results of curvilinear test for all three search variables. The results of the combined model are consistent with earlier models. Taken together, the results show that technological search has a linear positive effect on technological performance, while geographical and science searches have curvilinear effects. The results reject H1a and support H1b and H1c.

Table 2.3. Negative Binomial Regression in Testing the Impact of New Knowledge Search and Control Variables on Forward Citation

Variables	Model 1	Model 2	Model 3	Model 4	Model 5
Constant	0.1750 [0. 3741]	-0.0605 [0. 3354]	-0.0176 [0.3411]	-0.0779 [0.4005]	-0.2723 [0.3535]
Independent Variables					
Technological Search		0.6253*** [0.2623]			0.4081** [0.2528]
Technological Search Squared		-0.0066 [0.3088]			0.0365 [0.2562]
Geographical Search			1.4510*** [0.4048]		0.7989*** [0.3062]
Geographical Search Squared			-1.5472*** [0.6761]		-0.9095** [0.5480]
Science Search				0.0056*** [0.0015]	0.0043*** [0.0016]
Science Search Squared				-0.0001*** [0.0000]	-0.0000*** [0.0000]
Pure Scientists					
Bridging Scientists					
Pure Inventors					
Firm Level Control Variables					
Publication Volume	-0.0004*** [0.0001]	-0.0003*** [0.0001]	-0.0004*** [0.0001]	-0.0004*** [0.0001]	-0.0004*** [0.0001]
Publication citations	-0.0500** [0.0292]	-0.0429** [0.0265]	-0.0474* [0.0271]	-0.0354 [0.0339]	-0.0331 [0.0300]
Firm age	-0.2277*** [0.0548]	-0.2204*** [0.0493]	-0.2315*** [0.0533]	-0.2020*** [0.0566]	-0.2045*** [0.0518]
Firm size	0.0401 [0.0347]	0.0272 [0.0320]	0.0376 [0.0315]	0.0406 [0.0339]	0.0296 [0.0311]
R&D Expenditure	0.0254 [0.0327]	0.0105 [0.0315]	0.0203 [0.0295]	0.0237 [0.0294]	0.0107 [0.0281]
Technological Strength	-0.0024*** [0.0007]	-0.0022*** [0.0006]	-0.0023*** [0.0006]	-0.0025*** [0.0006]	-0.0022*** [0.0005]
Patent Level Control Variables					
Patent age	0.1718*** [0.0218]	0.1748*** [0.0217]	0.1749*** [0.0214]	0.1790*** [0.0222]	0.1810*** [0.0219]
Log Likelihood	-20551.68	-20480.89	-20501.23	-20517.27	-20449.79
No of	7648	7648	7648	7648	7648

Observations

*p<0.1, **p<0.05, ***p<0.01. Standard error is provided in the parentheses
Technology class dummy variables and year fixed effect were included but not reported

The regression results in testing the main effects of intellectual human capital variables on new knowledge search are presented in Table 2.4 and Table 2.5. Since the technological and geographical search variables are continuous with values restricted between 0 and 1, a Tobit regression model is employed. Models 1, 2 and 3 in Table 2.4 present the Tobit regression with technological search as the dependent variable and the three intellectual human capital variables as independent variables, included one at a time. Model 4 presents the results when all of the three intellectual human capital variables are included together. The results show that both bridging scientists and pure inventors have a significant positive influence on technological search (p<0.01). However, the relationship between pure scientists and technological search is negatively significant (p<0.01). Hence, H2a is supported for bridging scientists and pure inventors, but not for pure scientists. Models 5, 6, 7 and 8 in Table 2.4 present the Tobit regression with geographical search as the dependent variable and the three intellectual human capital variables as the independent variables. Similar to the previous result, I observe both bridging scientists and pure inventors to have a positive impact on geographical search (p<0.01), while pure scientists have a negative influence (p<0.05) on geographical search. Therefore, H2b is also supported for bridging scientists and pure inventors, but not for pure scientists. As science search is a count variable, I ran a negative binomial regression to test the relationship between science search and intellectual human capital. Table 2.5 presents the path coefficients with science search as the dependent variable and the three intellectual human capital variables as the independent variables. The coefficients of all the three intellectual human capital variables are insignificant, thereby rejecting H2c.

Table 2.4. Regression in Testing the Impact of Intellectual Human Capital and Control Variables on the Technological and Geographical Search

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Regression Model	Tobit	Tobit	Tobit	Tobit	Tobit	Tobit	Tobit	Tobit
Dependent Variable	Technological Search	Technological Search	Technological Search	Technological Search	Geographical Search	Geographical Search	Geographical Search	Geographical Search
Constant	0.4109*** [0. 0572]	0.1104** [0. 0454]	0.1173*** [0.0455]	0.2859*** [0.0590]	0.1297** [0.0663]	0.0476 [0.0529]	0.0541* [0.0528]	0.0362 [0.0688]
Independent Variables								
Pure Scientists	-0.2016*** [0.0240]			-0.1196*** [0.0259]	-0.0506** [0.0279]			0.0078 [0.0302]
Bridging Scientists		0.5040*** [0.0482]		0.3318*** [0.0542]		0.2890*** [0.0556]		0.2219*** [0.0625]
Pure Inventors			0.0367*** [0.0045]	0.0250*** [0.0047]			0.0297*** [0.0052]	0.0237*** [0.0055]
Firm-Level Control Variables								
Publication Volume	0.0000* [0.0000]	0.0000 [0.0000]	0.0000** [0.0000]	0.0001*** [0.0000]	0.0001*** [0.0000]	0.0001*** [0.0000]	0.0000*** [0.0000]	0.0001*** [0.0000]
Publication citations	-0.0168*** [0.0063]	-0.0073 [0.0060]	0.0011 [0.0059]	-0.0155*** [0.0063]	-0.0010 [0.0073]	-0.0015 [0.0069]	0.0032 [0.0068]	0.0001 [0.0073]
Firm age	-0.0095** [0.0060]	-0.0278*** [0.0064]	-0.0082* [0.0060]	-0.0275*** [0.0064]	0.0214*** [0.0069]	0.0088 [0.0073]	0.0182*** [0.0069]	0.0085 [0.0073]
Firm size	0.0200*** [0.0038]	0.0245**** [0.0035]	0.0309*** [0.0034]	0.0169*** [0.0038]	0.0067* [0.0044]	0.0047 [0.0041]	0.0075** [0.0040]	-0.0043 [0.0044]
R&D Expenditure	0.0339*** [0.0039]	0.0363*** [0.0038]	0.0350*** [0.0038]	0.0356*** [0.0038]	0.0134*** [0.0045]	0.0148** [0.0045]	0.0141*** [0.0044]	0.0050*** [0.0045]
Technological Strength	-0.0000 [0.0001]	-0.0001 [0.0001]	-0.0001 [0.0001]	-0.0000 [0.0001]	-0.0002** [0.0001]	-0.0001* [0.0000]	-0.0001* [0.0001]	-0.0001** [0.0000]
Patent-Level Control Variables								
Patent age	-0.0082*** [0.0029]	-0.0080*** [0.0029]	-0.0063*** [0.0029]	-0.0075*** [0.0029]	-0.0109*** [0.0034]	-0.0110*** [0.0034]	-0.0098*** [0.0034]	-0.0101*** [0.0034]
Log Likelihood	-4854.14	-4834.94	-4857.24	-4810.36	-5102.80	-5090.97	-5088.70	-5081.77
No. of Observations	7648	7648	7648	7648	7648	7648	7648	7648

*p<0.1, **p<0.05, ***p<0.01. Standard error is provided in the parentheses.
Technology class dummy variables and year fixed effect were included but not reported.

Table 2.5. Negative Binomial Regression in Testing the Impact of Intellectual Human Capital and Control Variables on Science Search

Variables	Model 1	Model 2	Model 3	Model 4
Constant	5.5656***	5.3371***	5.3189***	5.82586***
	[0. 7734]	[0.5228]	[0.5144]	[0.8906]
Independent Variables				
Pure Scientists	-0.1568			-0.3017
	[0.2197]			[0.2999]
Bridging Scientists		-0.4621		-0.7985
		[0.6279]		[0.7321]
Pure Inventors			0.0130	0.0304
			[0.0399]	[0.0350]
Firm-Level Control Variables				
Publication Volume	0.0001	-0.0001	0.0000	0.0000
	[0.0003]	[0.0002]	[0.0003]	[0.0002]
Publication citation	-0.1898***	-0.1684***	-0.1758***	-0.1869***
	[0.0711]	[0.0650]	[0.0718]	[0.0667]
Firm age	-0.4836***	-0.4494***	-0.4781***	-0.4513***
	[0.0932]	[0.0958]	[0.0897]	[0.0949]
Firm size	0.0023	0.0189	0.0122	-0.0007
	[0.0500]	[0.0407]	[0.0414]	[0.0495]
R&D Expenditure	-0.0403	-0.0404	-0.0386	-0.0464
	[0.0627]	[0.0636]	[0.0630]	[0.0630]
Technological Strength	0.0011	0.0012*	0.0012*	0.0011
	[0.0009]	[0.0009]	[0.0008]	[0.0009]
Patent-Level Control Variables				
Patent age	-0.0901***	-0.0868***	-0.0876***	-0.0882***
	[0.0335]	[0.0335]	[0.0341]	[0.0350]
Log Likelihood	-27870.01	-27867.20	-27871.50	-27859.14
No. of Observations	7648	7648	7648	7648

*p<0.1, **p<0.05, ***p<0.01. Standard error is provided in the parentheses.
Technology class dummy variables and year fixed effect were included but not reported.

Main and Moderating Effect of Alliance Portfolio Attributes

The regression coefficients for testing the main effects of alliance portfolio attributes are provided in Table 2.6. Models 1, 2 and 3 present the main effects of the three attributes of alliance portfolio. Model 4 presents the results when all three alliance portfolio attributes are included together. The results show that the technological and geographical diversity of the alliance portfolio and the number of university partners in the alliance portfolio have significant positive effects on the forward citation of patents ($p<0.01$). Hence, H3a, H3b and H3c are accepted.

In order to test if alliance portfolio moderates the relationship between new knowledge search and technological performance, I included the interaction terms. The results of these are presented in Models 5, 6 and 7 in which each of the interaction terms is introduced one by one. Model 8 presents the results when all the interaction terms are included together. As technological search had a linear positive effect on forward citation (from Table 2.3), I included just the linear interaction term for technological search. Since geographical and science search are curvilinearly related to forward citation, I included both the linear and squared interaction terms.

The significant interaction term of technological diversity of the alliance portfolio and technological search in Models 5 and 8 ($p<0.01$) supports H4a. Figure 2.2 is a 3D representation of this interaction effect. The coordinate (L, L) represents low in technological search and low in technological diversity of alliance portfolio, while (L, H) represents low in technological search and high in technological diversity of alliance portfolio. Since technological diversity of alliance portfolio has a positive influence on technological performance, the coordinate (L, H) has a higher technological performance than (L, L). Similarly, the coordinate (H, L) represents high in technological search and low in technological diversity of alliance portfolio, while (H, H) represents high in technological search and high in technological diversity of alliance portfolio. The positive slope from (L, L) to (H, L) and (L, H) to (H, H), clearly shows that there is positive interaction between technological search and technological diversity of alliance portfolio. In testing the interaction effect of geographical diversity of alliance portfolio with geographical search, I looked at the squared term of interaction because it provides a more complete explanation by preventing any misinterpretation of effects due to linearity and additivity in correlated variables (Cortina, 1993). The significant interaction term of geographical diversity of alliance portfolio with geographical search squared ($p<0.01$) supports H4b. However, the interaction between number of universities and science search squared is negatively significant, thereby rejecting H4c.

Table 2.6. Negative Binomial Regression in Testing the Main and Moderating Effect of Alliance Portfolio Attributes

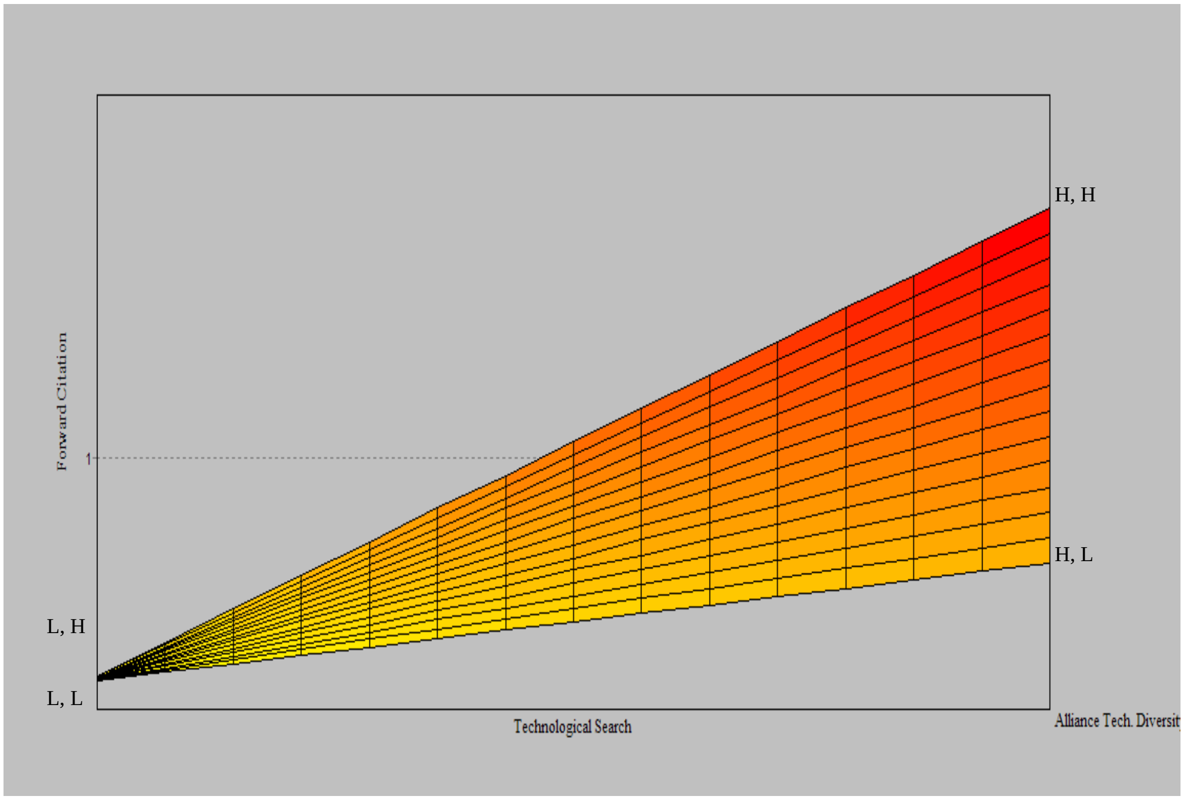
Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model8
Constant	0.0354 [0.3772]	0.1119 [0. 3528]	0.1194 [0.4296]	-0.0408 [0.3774]	-0.0459 [0.3330]	0.0060 [0.3353]	-0.0219 [0.4229]	-0.1439 [0.3742]
Independent Variables								
Technological Diversity of Alliance Portfolio	0.4318*** [0.1649]			0.4409*** [0.1023]	0.0124 [0.1650]			0.1004 [0.1241]
Geographical Diversity of Alliance Portfolio		0.6045*** [0.1503]		0.4579*** [0.1188]		2.0006*** [0.4905]		1.4271*** [0.3611]
No. of University Partners in Alliance Portfolio			0.2233*** [0.0645]	0.2192*** [0.0627]			0.1673*** [0.0673]	0.1598*** [0.0628]
Technological Search					0.3033* [0.2021]			0.1652 [0.1613]
Geographical Search						0.8589*** [0.4035]		0.0819 [0.2711]
Geographical Search Squared						-0.7195 [0.6558]		0.1319 [0.4551]
Science Search							-0.0008 [0.0023]	-0.0021 [0.0023]
Science Search Squared							0.0000 [0.0000]	0.0000 [0.0000]
Technological Diversity of Alliance Portfolio *Technological Search					0.8998*** [0.2931]			0.6161*** [0.2595]
Geographical Diversity of Alliance Portfolio *Geographical Search						-5.6775*** [1.9333]		-4.0277** [1.5151]
Geographical Diversity of Alliance Portfolio *Geographical Search Squared						4.3912*** [2.0497]		2.7745** [1.7033]
No. of Univ. Partners in Alliance portfolio *Science Search							0.0038*** [0.0012]	0.0037*** [0.0011]
No. of Univ. Partners in Alliance portfolio *Science Search Squared							-0.0000*** [0.0000]	-0.0000*** [0.0000]

Table 2.6. Negative Binomial Regression in Testing the Main and Moderating Effect of Alliance Portfolio Attributes (Contd.)

Firm-Level Control Variables								
Publication	-0.0003***	-0.0004***	-0.0004***	-0.0003***	-0.0003***	-0.0003***	-0.0004***	-0.0003***
Volume	[0.0001]	[0.0001]	[0.0001]	[0.0001]	[0.0001]	[0.0001]	[0.0001]	[0.0001]
Firm age	-0.2098***	-0.2404***	-0.2633***	-0.2592***	-0.2125***	-0.2398***	-0.2362***	-0.2373***
	[0.0565]	[0.0528]	[0.0777]	[0.0661]	[0.0520]	[0.0523]	[0.0700]	[0.0572]
Firm size	0.0351	0.0325	0.0460*	0.0359	0.0243	0.0302	0.0446*	0.0273
	[0.0332]	[0.0326]	[0.0349]	[0.0307]	[0.0316]	[0.0317]	[0.0334]	[0.0297]
R&D	0.0235	0.0234	-0.0004	-0.0029	0.0064	0.0177	-0.0018	-0.0162
Expenditure	[0.0335]	[0.0300]	[0.0357]	[0.0337]	[0.0321]	[0.0290]	[0.0324]	[0.0299]
Technological	-0.0018***	-0.0022***	-0.0017**	-0.0011**	-0.0017***	-0.0022***	-0.0016***	-0.0010*
Strength	[0.0017]	[0.0006]	[0.0009]	[0.0008]	[0.0006]	[0.0006]	[0.0008]	[0.0008]
Patent-Level Control Variables								
Patent age	0.1649***	0.1770***	0.1568***	0.1539***	0.1694***	0.1780***	0.1639***	0.1614***
	[0.0215]	[0.0287]	[0.0188]	[0.0188]	[0.0211]	[0.0214]	[0.0185]	[0.0179]
Log Likelihood	-20527.82	-20510.30	-20114.23	-20056.08	-20452.59	-20478.22	-20027.68	-19935.71
No. of Observations	7648	7648	7648	7648	7648	7648	7648	7648

*p<0.1, **p<0.05, ***p<0.01. Standard error is provided in the parentheses.
Technology class dummy variables and year fixed effect were included but not reported.

Figure 2.2. Interaction between Technological Search and Technological Diversity of Alliance Portfolio for Forward Citation



Note: The coordinates are for technological search and technological diversity of alliance portfolio

Mediating Role of New Knowledge Search in Explaining the Relationship between Intellectual Human Capital and Technological Performance

Though mediation is not a part of the research model, I performed this test in order to have a better understanding of the intellectual human capital-new knowledge search-technological performance link. I followed the three-step procedure suggested by Baron and Kenny (1986) to test the mediating effect of new knowledge search. In the first step, I tested if intellectual human capital demonstrates significant association with technological performance. Models 1, 2 and 3 of Table 2.7 present the main effects of the three intellectual human capital variables on the forward citation of patents. Both bridging scientists and pure inventors have a significant positive influence on the forward citation of patents ($p<0.10$, $p<0.01$). On the contrary, pure scientists have a significant negative effect on the forward citation of patents ($p<0.01$). A detailed discussion of these results is provided in the next section.

The second step in testing the meditating effect of new knowledge search is to test the relationship between intellectual human capital and new knowledge search. The results of regressions in Tables 2.4 and 2.5, which investigate this relationship, have been discussed earlier. The regression results suggest the possibility of technological and geographical searches mediating the relationship of bridging scientists and pure inventors with that of technological performance. The results rule out the need for testing the mediation for pure scientists as well as for testing science search as a mediating variable.

Therefore, in testing the last step of Baron and Kenny (1986), I concentrated solely on the mediating roles of technological and geographical searches for bridging scientists and pure inventors. In testing this, I regressed the technological performance variable on bridging scientists, pure inventors and new knowledge search, the results of which are presented in Table 2.8. To establish complete mediation, the effects of intellectual human capital variables on forward citation should become insignificant in the presence of new knowledge search variables. However, in comparing Models 1 and 2 of Table 2.8, I observed that, in the presence of technological search, the effect of bridging scientists decreased from (1.2057, $p<0.01$) to (0.9554, $p<0.05$). Similarly, comparing Models 1 and 3 shows that, in the presence of geographical search, the effect of bridging scientists decreased to (1.1403, $p<0.05$). This shows that geographical search and technological search partially mediate the relationship between bridging scientists and technological performance.

From Models 4, 5 and 6 of Table 2.8, I observed that technological search and geographical search partially mediate the relationship between pure inventors and technological performance. Thus, the results show that technological and geographical search variables partially mediate the relationship of bridging scientists and pure inventors with that of technological performance. Table 2.9 presents the summary of hypotheses and results as to whether the hypotheses are supported or not.

Table 2.7. Negative Binomial Regression in Testing the Impact of Intellectual Human Capital and Control Variables on Forward Citation

Variables	Model 1	Model 2	Model 3
Constant	1.0636*** [0.4602]	0.7882** [0.4360]	0.7702** [0.4320]
Independent Variables			
Pure Scientists	-0.5815*** [0.1637]	-0.4121*** [0.1749]	-0.4074*** [0.1726]
Bridging Scientists		0.8573* [0.5521]	0.6644* [0.5618]
Pure Inventors			0.0633*** [0.0206]
Firm-Level Control Variables			
Publication Volume	-0.0002* [0.0001]	-0.0001 [0.0001]	-0.0001 [0.0001]
Publication citation	-0.1044*** [0.0366]	-0.1021*** [0.0353]	-0.0995*** [0.0358]
Firm age	-0.2451*** [0.0458]	-0.2815*** [0.0576]	-0.2825*** [0.0579]
Firm size	-0.0087 [0.0311]	0.0140 [0.0330]	-0.0158 [0.0330]
R&D Expenditure	0.0202 [0.0256]	0.0247 [0.0267]	0.0251 [0.2270]
Technological Strength	-0.0027*** [0.0006]	-0.0026*** [0.0005]	-0.0025*** [0.0005]
Patent-Level Control Variables			
Patent age	0.1694*** [0.0214]	0.1692*** [0.0208]	0.1721*** [0.0210]
Log Likelihood	-20525.79	-20514.69	-20506.12
No. of Observations	7648	7648	7648

*p<0.1, **p<0.05, ***p<0.01. Standard error is provided in the parentheses.
Technology class dummy variables and year fixed effect were included but not reported.

Table 2.8. Negative Binomial Regression in Testing the Impact of Intellectual Human Capital, New Knowledge Search, and Control Variables on Forward Citation

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Constant	0.1552 [0. 3348]	-0.0603 [0. 3033]	0.0330 [0.3155]	0.1506 [0.3622]	-0.0701 [0.3258]	0.0089 [0.3408]
Independent Variables						
Technological Search		0.5797*** [0.1462]			0.5923*** [0.1560]	
Geographical Search			0.5139*** [0.1230]			0.5196*** [0.1253]
Bridging Scientists	1.2057*** [0.5366]	0.9554** [0.4641]	1.1403** [0.5253]			
Pure Inventors				0.0887*** [0.0263]	0.0702*** [0.0222]	0.0837*** [0.0245]
Firm-Level Control Variables						
Publication Volume	-0.0002** [0.0001]	-0.0002** [0.0001]	-0.0002** [0.0001]	-0.0004*** [0.0001]	-0.0003** [0.0001]	-0.0004* [0.0001]
Publication citation	-0.0691** [0.0362]	-0.0589** [0.0316]	-0.0670** [0.0350]	-0.0513** [0.0287]	-0.0447** [0.0260]	-0.0502** [0.0276]
Firm age	-0.2859*** [0.0583]	-0.2672*** [0.0531]	-0.2899*** [0.0586]	-0.2420*** [0.0529]	-0.2320*** [0.0488]	-0.2480*** [0.0529]
Firm size	0.0128 [0.0326]	0.0065 [0.0311]	0.0145 [0.0307]	0.0312 [0.0351]	0.0208 [0.0329]	0.0318 [0.0328]
R&D Expenditure	0.0295 [0.0320]	0.0144 [0.0314]	0.0270* [0.0282]	0.0268 [0.0325]	0.0124 [0.0317]	0.0247 [0.0291]
Technological Strength	-0.0023*** [0.0006]	-0.0021*** [0.0005]	-0.0022*** [0.0006]	-0.0023*** [0.0006]	-0.0021*** [0.0005]	-0.0022*** [0.0006]
Patent-Level Control Variables						
Patent age	0.1704*** [0.0209]	0.1734*** [0.0211]	0.1720*** [0.0203]	0.1758*** [0.0216]	0.1778*** [0.0216]	0.1772*** [0.0210]
Log Likelihood	-20525.50	-20464.26	-20489.02	-20533.70	-20469.60	-20496.6
No. of Observations	7648	7648	7648	7648	7648	7648

*p<0.1, **p<0.05, ***p<0.01. Standard error is provided in the parentheses.
Technology class dummy variables and year fixed effect were included but not reported.

Table 2.9. Summary of Hypothesis Testing

Hypothesis	Description	Result	Detailed Result
1a	Technological Search $\xrightarrow{\text{Curvilinear}}$ Technological Performance	Not Supported	Linear positive effect
1b	Geographical Search $\xrightarrow{\text{Curvilinear}}$ Technological Performance	Supported	
1c	Science Search $\xrightarrow{\text{Curvilinear}}$ Technological Performance	Supported	
2a	Intellectual Human Capital $\xrightarrow{+}$ Technological Search	Partially Supported	Supported only for bridging scientists and pure inventors, but not for pure scientists
2b	Intellectual Human Capital $\xrightarrow{+}$ Geographical Search	Partially Supported	Supported only for bridging scientists and pure inventors, but not for pure scientists
2c	Intellectual Human Capital $\xrightarrow{+}$ Science Search	Not Supported	
3a	Technological Diversity of Alliance Portfolio $\xrightarrow{+}$ Technological Performance	Supported	
3b	Geographical Diversity of Alliance Portfolio $\xrightarrow{+}$ Technological Performance	Supported	
3c	No. of University Partners in the Alliance Portfolio $\xrightarrow{+}$ Technological Performance	Supported	
4a	Technological Diversity of Alliance Portfolio $\downarrow +$ Technological Search → Technological Performance	Supported	
4b	Geographical Diversity of Alliance Portfolio $\downarrow +$ Geographical Search → Technological Performance	Supported	
4c	No. of University Partners in Alliance Portfolio $\downarrow +$ Science Search → Technological Performance	Not Supported	

DISCUSSION AND CONCLUSION

Organizations search for new knowledge in the anticipation of developing valuable technologies. The first initiative towards "new knowledge search" is to search and identify new knowledge existing outside an organization. Since knowledge residing in intellectual human capital helps a firm in scanning and identifying new knowledge, my research hypothesizes that intellectual human capital contributes to searching new knowledge residing outside the firm boundary. Having identified the knowledge, the next important step is to acquire and exploit the searched knowledge in creating valuable technologies. Though the internal resources of a firm, including intellectual human capital, play an important role in converting new knowledge search into better technologies, my study emphasizes that collaboration with other firms is essential for a firm to acquire and exploit the new knowledge search. Hence, I hypothesize alliances to play an important role in enhancing the capability of a firm to translate its new knowledge search into better technologies. Consequently, my study has two objectives.

The first objective of this study is to understand how internal resources, such as intellectual human capital, contribute to technological performance by engaging in new knowledge search. Specifically, my study explores how the three different types of intellectual human capital (1) pure scientists, (2) bridging scientists and (3) pure inventors, assist the three dimensions of new knowledge search (1) technological, (2) geographical and (3) science, thereby contributing to technological performance. The second objective is to investigate the role of alliances in enhancing the contribution of new knowledge search to technological performance. In particular, the study investigates how an alliance portfolio characterized by (1) technologically diverse partners, (2) geographically diverse partners and (3) partners from academic institutions, moderates the relationship between the three dimensions of new knowledge search and technological performance. When combined, the two objectives help in understanding how intellectual human capital and alliances help a firm in the process of searching new knowledge and translating it into better technologies. The following sections discuss the four hypotheses of my research that encompass the above two objectives.

The first hypothesis tests the curvilinear relationship of the three dimensions of new knowledge search with technological performance. The results show that technological search has a linear positive effect on forward citations, and that the relationship is not curvilinear as hypothesized. This suggests that even though searching a broad array of technologies is time-consuming and associated with high uncertainty, it is helpful in creating valuable technologies. The reason for the results not supporting the curvilinear effect of technological search can also be due to the biotech context that is under study. Biotech innovations are considered to be interdisciplinary in nature. Hence, in creating important innovations, firms inevitably have to search for technologically wide knowledge.

However, I find geographical and science search to have curvilinear relationships with forward citations. This suggests that searching knowledge across a wide geography and from the science base is good but, beyond a point, it is detrimental to technological performance. My results limit me in further discussion about the possible reasons for diminishing returns of geographical search. Nevertheless, some of the results of control variables combined with the curvilinear effect of science search help in better understanding the role of science for technological performance. Two of my control variables, publication volume and publication citation, had significant negative influences on forward citation of patents. The publication volume and publication citation variables, as measured in this study, can be interpreted as the capability of firms to generate high quality scientific knowledge. The science search reflects a firm’s effort in searching scientific knowledge to apply it to technology development. The results corresponding to these variables show that the capability of firms to generate scientific knowledge is not helpful for technological performance. However, a firm's ability to optimally search for knowledge and then apply it to technological development is beneficial to technological performance.

While prior studies have extensively examined the benefits and drawbacks of local search (Karim and Mitchell, 2000; Ahuja and Lampert, 2001), the results from the first hypothesis attempt to follow the recent stream of research in explaining the benefits and drawbacks of search that spans different boundaries (Ahuja and Katila, 2004). The findings highlight the benefits and drawbacks of geographical search and science search. Earlier studies have suggested the importance of scientific findings to technological search and that technological search conducted beyond national boundaries is detrimental to innovation (Fleming and Sorenson, 2004; Phene et al., 2006). My findings suggest that searching a wide array of technologies (after controlling for the geographical and science searches) is always beneficial for innovations, which are characterized to be inter-disciplinary in nature.

The second hypothesis studies the relationship between the three intellectual human capital variables and new knowledge search. Both bridging scientists and pure inventors have a significant role to play in assisting with the technological and geographical search process of a firm. However, pure scientists, who are exclusively involved in scientific research, have a negative impact on technological and geographical searches. It is surprising to find that none of the three intellectual human capital variables are related to science search. Two limitations pertaining to science search can be plausible explanations for the insignificant results. First, count of all non-patent references is taken into consideration in measuring science search. A more appropriate measure would have been to consider only citations to scientific publications. But this limitation is, to some extent, mitigated by the observation of Sorenson and Fleming (2004) that 70% of non-patent references are citations to scientific publications. The second limitation is related to the observation by Noyons et al. (1994). They showed that reference to scientific literature in patents is not an appropriate measure for identifying the science intensity associated with the innovation.

A plausible explanation for the negative influence of pure scientists on new knowledge search is the same as that of negative influences of publication volume and publication citation on technological activities. Pure scientists of an organization represent human capital that engages in pure scientific research. The results pertaining to publication volume and publication citation and evidences from prior research suggests that a firm’s scientific research endeavors are not direct inputs to its technological activities (Gittelman and Kogut, 2003). Indeed firms’ technological activities are shown to suffer when they concentrate on scientific research. This can be one of the reasons why pure scientists have a negative influence on new knowledge search that is targeted toward developing technologies. It is only through the skillful application of scientific research and resources to technological activities that a firm can benefit from its scientific research endeavors (Gittelman and Kogut, 2003). The following section elaborates on how pure scientists can indirectly contribute to technological activities by assisting bridging scientists and pure inventors.

Fleming and Sorenson (2004) observed that scientific knowledge alters technology inventors' search process. According to my conceptualization, bridging scientists and pure inventors are those who are directly involved in developing technologies. Therefore, the above observation by Fleming and Sorenson (2004) guides me to explore if pure scientists' contributions to new knowledge search are through bridging scientists and pure inventors, by providing them with a stylized representation of search. If the role of pure scientists is indirect as speculated above, then the relationship between bridging scientists, pure inventors and new knowledge search would be moderated by pure scientists. In order to test this effect I performed interaction tests, the results of which are presented in Table 2.10.

Model 1 presents the interaction between pure scientists and bridging scientists in explaining the technological search. The interaction term is significant ($p<0.01$), confirming that the contribution of bridging scientists to technological search increased in the presence of pure scientists. Figure 2.3 is a 3D representation of this interaction effect. The coordinate (L, L) represents low in bridging scientists and low in pure scientists, while (L, H) represents low in bridging scientists and high in pure scientists. Since pure scientists have a negative influence on technological performance, the coordinate (L, L) has a higher technological performance than (L, H). Similarly, the coordinate (H, L) represents high in bridging scientists and low in pure scientists, while (H, H) represents high in bridging scientists and high in pure scientists. The positive slope from (L, L) to

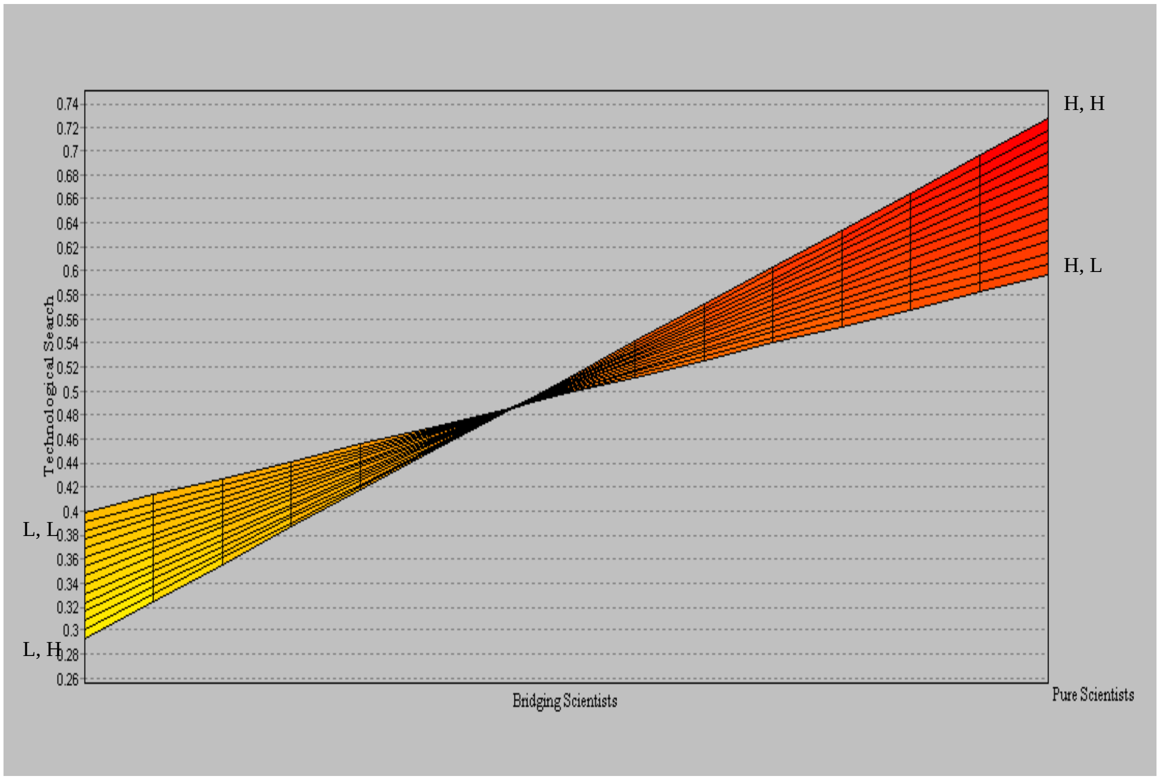
(H, L) and (L, H) to (H, H), clearly shows that there is positive interaction between bridging scientists and pure scientists. On the contrary, Model 2 in Table 2.10 shows that pure scientists do not help pure inventors in their technological search. Models 3 and 4 present the interaction results for geographical search and are similar to that for technological search. The moderating effect of pure scientists in explaining the relationship between bridging scientists and geographical search is further illustrated using a 3D graph in Figure 2.4. The interpretation of Figure 2.4 is similar to that of Figure 2.3.

Table 2.10. Regression in Testing the Moderating Role of Pure Scientists

Variables	Model 1	Model 2	Model 3	Model 4
Regression Model	Tobit	Tobit	Tobit	Tobit
Dependent Variable	Technological Search	Technological Search	Geographical Search	Geographical Search
Constant	0.3752** [0. 1043]	0.2661*** [0.0628]	0.3294*** [0.1104]	0.1016* [0.0669]
Independent Variables				
Pure Scientists	-0.2209** [0.0997]	-0.0541** [0.0291]	-0.3344*** [0.1058]	-0.0347 [0.0309]
Bridging Scientists	0.0565 [0.1994]		-0.3889** [0.2122]	
Pure Inventors		0.0379*** [0.0079]		0.0274*** [0.0084]
Bridging Scientists* Pure Scientists	0.5128*** [0.2237]		0.7986*** [0.2382]	
Pure Inventors * Pure Scientists		0.0037 [0.0121]		0.0029 [0.0128]
Firm-Level Control Variables				
Publication Volume	0.0001*** [0.0000]	0.0001*** [0.0000]	0.0001*** [0.0000]	0.0001*** [0.0000]
Publication citation	-0.0108* [0.0075]	-0.0025 [0.0069]	-0.0114* [0.0079]	0.0001 [0.0073]
Firm age	-0.0286** [0.0070]	-0.0174*** [0.0065]	0.0085 [0.0073]	0.0172*** [0.0069]
Firm size	0.0178*** [0.0042]	0.0167**** [0.0041]	0.0071* [0.0044]	0.0053 [0.0044]
R&D Expenditure	0.0377*** [0.0042]	0.0370*** [0.0042]	0.0145*** [0.0045]	0.0140*** [0.0045]
Technological Strength	-0.0000 [0.0001]	-0.0000 [0.0001]	-0.0001 [0.0001]	-0.0002* [0.0001]
Patent-Level Control Variables				
Patent age	-0.0090*** [0.0031]	-0.0076*** [0.0031]	-0.0109*** [0.0034]	-0.0099*** [0.0034]
Log Likelihood	-5291.4	-5285.23	-5085.35	-5088.04
No. of Observations	7648	7648	7648	7648

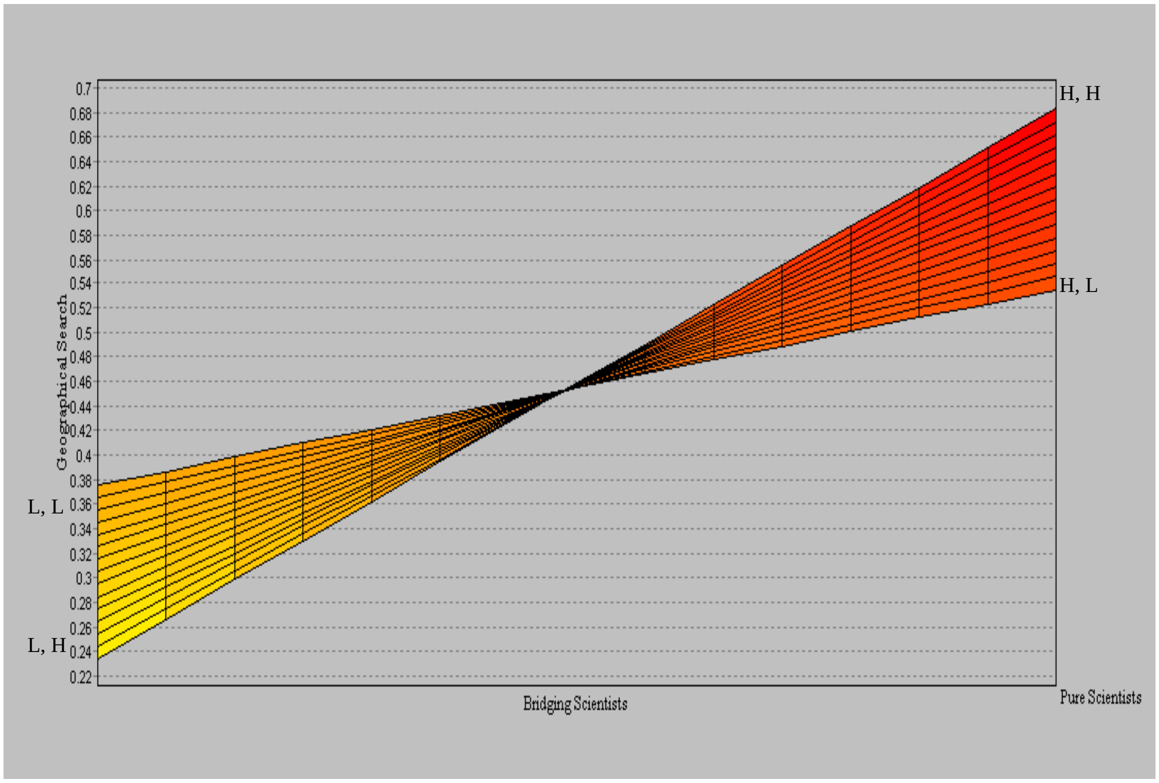
*p<0.1, **p<0.05, ***p<0.01. Standard error is provided in the parentheses.
Technology class dummy variables and year fixed effect were included but not reported.

Figure 2.3. Interaction between Bridging Scientists and Pure Scientists for Technological Search



Note: The coordinates are for bridging scientists and pure scientists

Figure 2.4. Interaction between Bridging Scientists and Pure Scientists for Geographical Search



Note: The coordinates are for bridging scientists and pure scientists

Taken together, the results illustrate that pure scientists facilitate the technological and geographical search processes of bridging scientists, but not of pure inventors. A potential explanation is that bridging scientists, who are involved in both science and technology domains are in a better position to benefit from pure scientists. Because of their dual role, bridging scientists tend to collaborate with pure scientists, thereby benefiting from the pure scientists' scientific understanding (Furukawa and Goto, 2006). This is also evident from my data, as I observed a number of collaborations between pure scientists and bridging scientists in publishing papers. On the other hand, pure inventors have been observed to exhibit different communication behavior from that of pure scientists (Allen, 1977), and can find it difficult to bridge the gap and take advantage of the scientific knowledge possessed by pure scientists. Thus, I follow Gittelman and Kogut’s (2003) assertion that scientists who can play a dual role and successfully bridge the science and technology domains have a positive influence on technological performance. I go one step further in saying that the dual role of bridging scientists can also help in translating the ideas of pure scientists into a language that can be easily interpreted by pure inventors.

Before discussing the results pertaining to alliances, it is worth explaining a few other results related to intellectual human capital that are not part of the research model. First is the findings related to the influence of intellectual human capital on technological performance. The results demonstrate that pure inventors and bridging scientists have positive impacts on the technological performance of firms. On the contrary, pure scientists have a negative impact on the technological performance. The positive effect of pure inventors is trivial because they are solely dedicated to applied research and to developing important innovations. However, it is interesting to note the contingent value of scientists, whose involvement in scientific research detracts them from technology development. Scientists have a positive influence on technological performance only if they are bridging scientists, viz. they are capable of also engaging themselves in technology development. This finding further underlines the importance of bridging scientists to firms (Gittelman and Kogut, 2003)

The next result is corresponding to the mediating role of new knowledge search in explaining the intellectual human capital and technological performance link. As speculated, the results support only partial mediation, suggesting that new knowledge search is one of the means through which intellectual human capital contribute to technological performance. Specifically, the findings reveal that technological and geographical searches partially mediate the path connecting pure inventors and technological performance. Similarly, technological and geographical searches are found to partially mediate the relationship between bridging scientists and technological performance. The mediating role of new knowledge search is not supported for pure scientists. Thus, both pure inventors and bridging scientists, who are directly involved in technology development activities, have a positive impact on technological performance by assisting in the technological and geographical searches. Since pure scientists are not directly involved in the technology development, it is not surprising to notice that the results do not support the role of new knowledge search in mediating the relationship between pure scientists and technological performance. However, I discussed the indirect contribution of pure scientists to new knowledge search in a previous section.

The above findings that pertain to the influence of intellectual human capital on new knowledge search have important theoretical and practical implications. The theoretical implication is to the stream of research that emphasizes the importance of intellectual human capital to technological performance (Subramaniam and Youndt, 2005). Although the basic link between intellectual human capital and the technological performance of firms is persuasive, the finer aspect of how organizations utilize intellectual human capital for new knowledge search, which is capable of explaining the heterogeneity across firms' technological performance, is unexplored. This research gap is surprising given that organizations invest a significant amount of resources in their intellectual human capital, often with the strategic need to develop expertise along new trajectories (Zucker, Darby, and Brewer, 1998). My study addresses this issue by showing that intellectual human capital engages in new knowledge search, thereby contributing to technological performance. Further, it contributes to the literature on evolutionary search by illustrating the importance of intellectual human capital to new knowledge search and how the contribution of human capital differs depending on their domain of expertise. The differences exhibited by the three intellectual human capital variables in influencing the new knowledge search as well as technological performance (elaborated in the following sections) help managers decide how to utilize their varied intellectual human capital in different knowledge-related activities.

Hypothesis 3 pertains to the main effect of alliance portfolio. The results demonstrate that an alliance portfolio characterized by technologically and geographically diverse partners and partners with academic background are beneficial for the technological performance of firms. This finding draws the attention of scholars to concentrate on the alliance portfolio attributes rather than merely look at the size of the portfolio (Stuart, 2000). Further to the main effect of an alliance portfolio, Hypothesis 4 tests the moderating effect of an alliance portfolio in enhancing the contribution of new knowledge search for better technological performance. The results show that a technologically and geographically diverse alliance portfolio enhances the value of a firm's technological and geographical searches, respectively. However, the number of university partners does not enhance the value of science search. There are two possible reasons for this result. The first reason is due to the limitations of the science search measure as described earlier. The second reason is that the difference in institutional affiliation (profit firms/non-profit academic institutions) can prevent firms from fully benefiting from their university partnership. But the latter reasoning cannot be true, at least with respect to my results, because the main effect of the number of university partners on technological performance was positive. While prior studies have shown that alliance helps firms in going beyond local search (Rosenkopf and Almedia, 2003), the above results pertaining to the alliance-knowledge search strategy fit have important implications in framing an effective alliance strategy that best fits the search strategy of a firm. The findings also suggest that a holistic understanding of strategic advantage of alliance partners warrants careful examination of the alliance partners' attributes and their interaction with the focal firm's knowledge requirements. In addition, I contribute to the literature on strategic alliances by illustrating one of the second-order benefits of alliances, viz. enhancing the value of new knowledge search.

This research is subject to a number of limitations, the first pertaining to patent data. Restricting the scope to patent data can be limiting because not all companies have the same propensity to patent and organizations can limit their patents only to most successful innovations. In spite of the above limitations, patent data has been widely used in testing the factors contributing to innovation (Sorenson and Fleming, 2004; Gittelman and Kogut, 2003).

The second limitation is related to the operationalization of new knowledge search. Currently search is restricted to inference from patent documents, which represents successful searches that eventually transformed into patentable innovations. However, an enormous amount of search conducted by firms is unsuccessful or at least not converted into patents. A measure that incorporates all search efforts made by firms will improve my findings and implications.

The third limitation is pertaining to the forward and backward citations of patents. It is noted that 40% of the citations in patents are added by patent examiners (Alacer and Gittelman, 2006). I take into account all the forward and backward citations of patents in calculating my measure, which is a limitation of the study. However, this limitation is mitigated by the way citations are used in my study. With respect to forward citations, whether the citation is made by firms or included by examiners, it represents in general the value of the patent. With respect to search measures, even if some of the citations are included by examiners, it signifies that the focal firm has implicitly made use of the knowledge.

The fourth limitation is pertaining to publications. Not all firms involved in scientific research have the inclination to disclose their findings by publishing. Even among publications, there are articles that can be classified as basic journals and applied journals (Lim, 2004). A fine-grained approach in categorizing publications can strengthen my implications. There are also publications made by firms through collaboration with other firms and universities. My study includes all publications that are affiliated with the sample firms, irrespective of whether the publication is associated with more than one organization or not. However, not considering the information on collaboration is not a major limitation of my study because the publication is still a strong predictor of the knowledge captured by the firm and that the firm has acquired the tacit knowledge of individuals engaged in the research (Zucker, Darby and Armstrong, 2002).

A fifth limitation is related to the intellectual human capital measure. Currently it is operationalized as the proportion of intellectual human capital in science/technology/both domains. In reality there exists huge heterogeneity, even among individuals belonging to each of these categories. Hence, one of the fruitful research extensions can be to develop an intellectual human capital measure that is capable of capturing individuals' breadth and depth of knowledge.

Sixth, it would be helpful if my study could capture the benefits derived from an alliance partner using patents emerging from that specific collaboration, rather than looking at the performance of the whole patent portfolio of a firm. Though this is an important agenda for my future work, I intend to acknowledge this limitation in interpreting the findings of this study.

A seventh and final limitation is that, because my study explores the importance of intellectual human capital, it can only be generalized to other high-technology industries where intellectual human capital is considered a key input for technological innovation.

Despite these limitations, this research explaining the means through which intellectual human capital and alliance influence the technological performance of firms has made several theoretical and practical contributions. In conclusion, this study identifies three types of intellectual human capital and illustrates their contributions to new knowledge search. The study also demonstrates the characteristics of an alliance portfolio that best fits with the different dimensions of new knowledge search, thereby enhancing the value of new knowledge search to technological performance.

Although the current study explains the importance of intellectual human capital, examples in the first chapter reveal that converting their competencies into important discoveries, especially the contributions of scientists, is not straightforward. The next chapter addresses this issue by determining some of the mechanisms through which a firm can benefit from its scientists. Since the results of this chapter identified bridging scientists as a valuable human capital, the focus of the next chapter is restricted to bridging scientists.

CHAPTER THREE

UNDERSTANDING THE MECHANISM OF BRIDGING SCIENCE AND TECHNOLOGY DOMAINS WITHIN FIRMS FOR BETTER TECHNOLOGICAL PERFORMANCE

INTRODUCTION

Scholars have long believed that scientific input and R&D effort improve a firm's technological innovation and performance (Henderson and Cockburn, 1994). A study of 66 firms from seven major manufacturing industries estimates that about 11% of new products and 9% of new processes could not have been developed in the absence of scientific research from the academe (Mansfield, 1991). Several explanations have been offered to illustrate the benefits of science for better technological innovation. Scholars have shown that scientific research enhances a firm's absorptive capacity (Cohen and Levinthal, 1990; Gambardella, 1992; Lim, 2004) and serves as guideposts for the process of technological investigation (Dasgupta and David, 1994), management of research activities (Owen-Smith, 2001), technological search (Fleming and Sorenson, 2004) and firm entry into new technologies (Zucker, Darby and Brewer, 1998).

While these studies illustrate the benefits of scientific knowledge for technology innovation, the process of converting competencies of scientists into better technological performance is actually not simple or straightforward (Gittelman and Kogut, 2003). In spite of the difficulty in benefiting from scientific competency, firms in high technology industries continue to spend heavily on scientific research through research programs organized internally and externally (Rosenberg, 1990). Firms also provide lucrative research funds and opportunities in order to attract star scientists into their organizations.

With these huge investments emerges an important question: How do firms make use of the competencies of scientists and translate them into better technology innovations?

The difficulty of converting the competencies of scientists into better technological performance has not been well investigated with a few exceptions such as Gittelman and Kogut (2003). Their study demonstrates that innovation builds on knowledge made in science, but science that is good for innovation is propelled by a logic different from that employed by the scientific community in determining valuable science. Using the patenting and publishing data in the biotechnology industry, they generated evidence to show that the logic of scientific discovery does not adhere to the same logic that governs the development of new technologies. Their findings suggest that by possessing the so-called bridging scientists, who are engaged in both scientific and technology domains, firms are in a better position to exploit the competencies of their scientists. Thus, their study suggests the importance of the individual-level mechanism of possessing bridging scientists in managing the two evolutionary logics.

While Gittelman and Kogut (2003) suggest the importance of bridging scientists, it is not feasible to expect all scientists in a firm to be bridging scientists. According to the learning style inventory model proposed by Kolb, Osland and Rubin (1995), different individuals are inclined to different styles of learning and knowledge generation. The two learning styles pertaining to knowledge residing in science and technology domains are 1) conceptualization and 2) experimentation. Conceptualization means designing an abstract concept— a theory —in order to explain events, which is similar to producing scientific publications. The process of trying out theories in practice is called experimentation, and this is equivalent to applying scientific knowledge in practice to the technology innovation process. Every person is inclined to either one learning style or, at maximum, two learning styles (Kolb et al. 1995; Raelin, 1997). Hence, it is not reasonable to expect every scientist who conducts fundamental research within an organization to also focus on downstream innovation activities requiring scientific knowledge.

While the learning style inventory model questions the viability of expecting all scientists to be involved in scientific research and technological innovation, March’s (1991) explorative/exploitative learning framework provides a remedial solution. Scientists' attempts to investigate new phenomena so as to provide a basic understanding of why phenomena occur can be termed as exploration. In contrast, inventors' attempts to test and apply the scientific knowledge for developing new technologies can be termed as exploitation. A recent study that builds on March’s (1991) framework has emphasized the importance of delineating the different domains of experiential learning and advancing the notion of maintaining exploration/exploitation balance within and across the domains (Lavie and Rosenkopf, 2006). Extending the lessons from this branch of study, I distinguish between the science and technology domains within organizations and advance the argument that, apart from relying on bridging scientists, firms have to encourage inventors involved in technology development to exploit the knowledge produced by their scientists. Organizations should have the necessary mechanisms in place to ensure that the scientific knowledge discovered by scientists is independently exploited by the inventors.

The importance of such firm-level mechanism in benefiting from scientists has also been established in the past. A study by Furukawa and Goto (2006) has shown that heavily-publishing scientists are not known to directly contribute to the technology development process. However, these scientists are known to help the firm indirectly by increasing the patenting activities of other inventors who collaborate with them. This emphasizes that firm-level knowledge sharing and integration are necessary mechanisms for translating scientists' competencies into better technological performance.

To further underscore the importance of firm-level mechanism over individual-level mechanism in bridging science-technology domains, I study the interaction effect between the two mechanisms. Specifically, I use the absorptive capacity literature to propose that, in the presence of firm-level exploitation mechanism, the contribution of bridging scientists to technological performance increases. Thus, the major tenet of this paper is to show how March's exploration/exploitation framework complements the lessons drawn by Gittelman and Kogut (2003) from the sociology and economics of science literature in explaining the mechanisms through which science-technology domains can be bridged within a firm. I use the publication and patenting behavior of biotechnology firms to test my hypotheses.

This chapter is organized as follows. The next section provides an overview of prior studies pertaining to science-technology relationship and discusses the need for bridging the science and technology domains within the firm. In the subsequent sections I develop hypotheses pertaining to the two mechanisms through which the science-technology domains can be bridged, present the research method and results. The last section discusses the implications of my findings and the limitations of the study.

THE NEED FOR BRIDGING SCIENCE AND TECHNOLOGY DOMAINS WITHIN FIRMS

The notion that scientific research stimulates technological performance and economic growth has long been established (Mansfield, 1972; Adams, 1990; Henderson and Cockburn, 1994; Jaffe and Trajtenberg, 1996). Both scientific research and scientists are known to have a significant positive effect on firms' performances, especially that of firms in high-tech industries (Zucker and Darby, 2001; Zucker, Darby and Armstrong, 1998).

Although research has reiterated the benefits of science and scientists for technology innovation, there is difficulty associated with the process of converting competencies of scientists into tangible benefits that a corporate firm demands. The reason[8] is driven by the open norm of the scientific community and the general conflict involved in the adaptation of professionals, such as scientists, to organizational goals. Scientific endeavors were cloaked in secrecy until sixteenth century, but today scientific investigation receives a substantial amount of attention for its norm of openness. The institutionalization of science has encouraged the validation and diffusion of scientific ideas as open to public scrutiny (David, 1998; Gittelman and Kogut, 2003; Merton, 1973). The nature of the scientific community reinforces norms of rapid disclosure and wider dissemination of new discoveries to account for rapid validation of findings, reducing excess duplication of efforts, and enlarging the domain of complementarities.

[8] While certain areas of scientific research cannot be translated into practical applications (an example pertaining to the biotech context includes gene-sequencing. Identifying a gene-sequence potentially has no direct application. But the gene-sequencing research aids the process of relating a disease with a distortion in a gene-structure, which can subsequently be corrected by a chemical compound), in discussing the above, I focus on that scientific research that has practical applications.

Consequently, the success of scientists and their professional reputation is tied to priority based publication in prestigious journals.

While firms have a lower incentive to let potentially valuable information spillover to the public domain, in order to attract and retain very good scientists, firms realign the incentive structure and allow scientists to publish their research findings (Stern, 1999; Zucker and Darby, 2001). In addition to giving scientists autonomy and letting them operate in a community that values communism, firms must also become more adept at utilizing their scientific skills for better technological performance. The difficulty in achieving the above has been highlighted by Merton (1949) wherein he mentions that professional scientists differ from 'technicians' (or technical inventors) who believe that their primary obligation is to make their technical skills available to the organization. Kornhauser (1962, p:9) has termed this phenomenon as 'professions limit organizations', whereby professionals are constrained to act according to the requirements set by their profession rather than their corporate firms.

Thus, utilizing the competencies of scientists and translating them into better technological performance is not simple or straightforward. However, the question of how firms bridge science and technology domains has not attained enough attention in the literature. Such an understanding is essential because, in the absence of mechanisms to translate the competencies of scientists into better technological performance, firms might not be able to directly benefit from their scientific investments. In the following section, I develop hypotheses pertaining to two important mechanisms in bridging the science and technology domains within firms.

THEORY AND HYPOTHESES DEVELOPMENT

Bridging Science-Technology Domains: Individual Level

The work of Arrow (1962) exhibits science to be associated with features of public good and hence the need for academia and non-profit research to be involved in the production and dissemination of basic research findings. In subsequent research on the science and technology relationship, scholars started recognizing the importance of in-house scientific research for firms to even absorb scientific knowledge from the public domain (Allen, 1991; Gambardella, 1995). The development of pharmaceutical and biotechnology industries has also singled out the scientific competency of firms and the presence of star scientists as critical factors for successful and productive firms (Zucker, Darby and Brewer, 1998; Cockburn and Henderson, 1998; Zucker, Darby and Armstrong, 2002).

Although scientists represent a vital resource for firms in high-tech industries, managing scientists who conduct fundamental research in industrial organizations creates friction. The friction is due to the conflicting nature of organizational demands and the identity of scientists being embedded in a collegiate reputation-based reward system of open science. Scientists are more inclined to utilize their competency in producing scientific publications so as to gain a reputation in the community of scientists, whereas the competitive advantage of science-based organizations depends on the ability of the scientists to exploit their scientific competency in innovation.

Though scientific research programs can be tailored to be useful inputs for furthering scientific investigation as well as technological innovation, one major challenge for firms with industrial R&D function is to define the roles of scientists, identify and evaluate the competencies of individual scientists, and provide appropriate incentive schemes to align their interests accordingly. The ability of the firm to find a way to manage the two contradictory logics of science and innovation will be crucial for innovation performance (Cockburn, Henderson and Stern, 1999). However, ineffective human resource policy may also result in some scientists being trapped between the two evolutionary logics.

As implied in the study by Gittelman and Kogut (2003), when scientists are properly motivated, they can be involved in generating both scientific findings as well as developing technologies. This will enable them to establish links between the science and technology domains, thereby creating valuable innovations. A feasible incentive structure is to induce scientists to play a dual role as both scientists and inventors, encouraging them to contribute to both knowledge domains, while inhabiting a single epistemic community. Their primary role as scientists in the community will facilitate firms to benefit from their networks and social interactions (Salter and Martin, 2001), generating a perpetual flow of external knowledge into the firm (Allen, 1991; Furukawa and Goto, 2006). Meanwhile, by making the scientists indulge in technology innovation, a firm can utilize their tacit knowledge specific to internal scientific research to create technological innovation that no other firms can duplicate (Nonaka, 1994; Leonard-Barton, 1995). Thus, their secondary role as inventors aids in utilizing their scientific competencies in the technology innovation process, the consequence of which is found to have positive influence on the innovation performance of the firm (Gittelman and Kogut, 2003). The dual role of scientists also enables them to be gatekeepers of knowledge to bring in new, related and complementary knowledge that is beneficial for technological innovation (Allen, 1991; Gittelman and Kogut, 2003; Tushman, 1977).

The importance of pushing scientists into marketable innovations has also been explained in a study on the Japanese and German biotechnology industries (Lehrer and Asakawa, 2004). The study found that the biotech firms in these countries, unlike the American and British counterparts, had failed to capitalize on the competencies of their scientists for better technological performance because of the lack of science entrepreneurship in the broader industrial context. The inability of these countries to excel in the biotechnology field was said to be a consequence of their scientists' over-inclination toward scientific publishing instead of patenting through commercially driven innovation (Lehrer and Asakawa, 2004).

Following the above arguments and research findings, I posit that by defining the dual role of scientists in both scientific and technology innovation activities, firms can effectively bridge the science-technology domains. With the growing importance of individuals as movers of knowledge between organizational boundaries (Almeida and Kogut, 1999), using scientists as the level of analysis facilitates an 'inside the box' view of how firms bridge the two domains. In this paper, "dual role" means the extent to which scientists are engaged in both publishing and patenting activities organized within the firm. The above arguments suggest that:

Hypothesis 1: The number of scientists within a firm who are directly involved in both scientific publications and technology patenting is positively associated with the technological performance of the firm

Bridging Science-Technology Domains: Firm Level

Building on March's (1991) exploration/exploitation framework, a recent study that delineates distinct domains of exploration and exploitation provides some useful insights through which a firm can benefit from the competencies of its scientists (Lavie and Rosenkopf, 2006).Exploitation is defined as 'refinement and extension of existing competencies', and exploration as 'embarking on new alternatives'. Exploration and exploitation differ on the type and amount of learning rather than presence and absence of learning. Recent studies on exploration/exploitation have shown that the delineation of exploration and exploitation in different domains enable firms to simultaneously embark on both, thereby maintaining the balance (Gupta, Smith and Shalley, 2006; Lavie and Rosenkopf, 2006). The capability of maintaining the exploration/exploitation balance by concurrently engaging in both types of knowledge searches is termed as ambidexterity.

Scientific efforts in producing abstract theories for understanding basic phenomena and causal relationships between technological components can be termed as exploration. The effort in applying the knowledge gained from scientific theories to the technology development process can be termed as exploitation. Though Gittelman and Kogut’s (2003) suggestion that having bridging scientists enables the generation and application of scientific knowledge in technology, there are practical limitations associated with this approach. Exploration and exploitation require radically different mindsets and routines, and it is not reasonable to expect every scientist within firm to also be competent in technology development. Consequently, though engaging scientists in both exploration and exploitation can lead to bridging of science and technology domains, a firm cannot solely rely on this mechanism to exploit the knowledge possessed by its scientists.

The organization learning literature that emphasizes the need for carrying out exploration/exploitation in different domains and maintaining a balance both within and between them provides useful insights in overcoming the above-mentioned limitation (Lavie and Rosenkopf, 2006). Extending lessons from this branch of study, I distinguish the science and technology domains within an organization and advance the notion of letting scientists explore scientific areas and facilitating inventors in the technology domain to actively exploit the knowledge generated by the science domain. The main role of scientists in the science domain will be to specialize in their expertise areas and generate important findings that are valuable to technology development. In addition to the scientific role, scientists who are competent in technology development should be permitted to play a dual role by engaging themselves in technological innovation.

But in bridging the science and technology domains, firms should not wholly rely on the scientists playing the dual role. Instead, the capability of firms in bridging science and technology domains relies on how well the firm has organizing principles to exploit the knowledge produced by the science domain in its technology domain. The organizing principles underlying firm level exploitation mechanism encompasses (a) the extent to which a firm has lateral communication across functional domains (Demsetz, 1991) (b) how work is coordinated within the organization and information disseminated across groups (Grant, 1996) (c) the collective experiences of members of firms that enable even tacit knowledge of scientists to be transformed into comprehensible code that can be exploited by technology inventors (Teeni, 2001) (d) the introduction of an appropriate incentive structure to encourage employees to exploit the knowledge produced by colleagues (Subramanian and Soh, 2009) etc. The mechanisms stated above will facilitate the inventors in the technology domain to actively test and apply the internally-generated scientific findings in developing technologies, thereby bridging the science and technology domains.

The firm-level mechanism of exploiting scientific knowledge in the technology domain results in better technological performance in the following ways. Firstly, firm-level exploitation mechanism provides inventors with quick and easy access to internally-generated scientific findings before being published, thereby enabling the inventors to introduce better products earlier than other firms. Secondly, the firm level exploitation mechanisms help firms readily apply scientific knowledge to resolve many technical problems related to technological breakthrough development. Thirdly, firm-level exploitation mechanism increases a firm's capability in realizing the benefits of its investment in internal basic research.

Following the above arguments, I posit that firms that are capable of exploiting internally-generated scientific knowledge in their technology domain are in a better position to bridge the science and technology domains. The above arguments lead to my second hypothesis:

Hypothesis 2: The degree to which a firm exploits the knowledge produced by its scientists in the technology domain is positively associated with the technological performance of the firm.

It is to be noted that Hypotheses 1 and 2 are not mutually exclusive. The first hypothesis explains the importance of nurturing bridging scientists, whose competence is invaluable to producing better technological innovation. The second hypothesis puts emphasis on a broader firm-level exploitation mechanism. In other words, enabling inventors to access and apply the internally generated scientific knowledge as well as developing absorptive capacity for external sources of innovation would be the routines to establish inside a firm. Therefore, it is feasible for a firm to have both bridging scientists and the exploitation mechanism which utilizes the internally-generated scientific knowledge in the firm's technology domain. For example, consider a firm with two scientists (A&B) in the science domain. Scientist A may be competent in both the science and technology domains, and hence becomes a bridging scientist, whereas scientist B may be a pure scientist exclusively involved in generating scientific knowledge. In order to fully translate the competencies of both scientists into better innovation performance, the firm has to facilitate the process of exploiting both the scientists' knowledge in the technology domain, rather than just relying on scientist A to do the job.

The following section develops my third hypothesis which underscores the importance of firm-level exploitation mechanism. I argue that, in the presence of exploitation mechanism, the contribution of bridging scientists to technological performance increases.

Bridging Science-Technology Domains: Firm Level Moderating Individual Level

According to the absorptive capacity literature (Cohen and Levinthal, 1990), a strong positive interaction exists between individual-level and firm-level mechanisms of capability building. It has been observed that the benefits derived from individual-level capabilities are significantly influenced by firm-level mechanisms such as knowledge transfer, integration, and exploitation across units. For example, more conducive organizational mechanisms are found to increase the effectiveness of intellectual human capital (Hitt, Hoskisson, Ireland and Harrison, 1991). In particular, a study by

Grosysberg, Nanda and Nohria (2004) showed that when star financial analysts switched firms their short-term variations in performance were determined by organizational aspects of the new firm. Following this perspective, I hypothesize that the firm-level exploitation mechanism moderates the positive influence of bridging scientists on the technological performance. In order words, the degree of influence of bridging scientists on technological performance is higher for firms that are good at exploiting the scientific knowledge in their technology innovation. Two explanations support the moderating effect.

First, scientific knowledge exploitation in the technology domain widens the scope of application of bridging scientists' knowledge, thereby enhancing their contribution to technological performance. As emphasized by Brooks (1994), scientific knowledge can help technology development in sundry ways. Science generates new knowledge that can function as inputs to technology development across wide areas. For example, advancement in basic physics led to the discovery of the transistor, which was subsequently found to be useful in developing medical equipment such as hearing aids. Scientific knowledge can be used in designing engineering tool and techniques. In addition, science helps in evaluating technological areas.

Though the presence of bridging scientists can help in exploiting scientific knowledge, it is undue to expect bridging scientists to be involved in every application area to exploit the knowledge. Bridging scientists can help firms in translating abstract scientific theories into working ideas for technology development. Despite the surface level similarities, scientists and engineers are observed to exhibit different communication behavior (Allen, 1991). Bridging scientists can act as a channel to translate the ideas of other core scientist within the firm into a language that can be easily interpreted by inventors. In the presence of such bridging scientists, when a firm encourages its inventors in the technology domain to exploit the knowledge, the translated ideas of bridging scientists can span a broader set of technology domains. Thus, by widening the application of bridging scientists' knowledge, firm-level exploitation mechanism can positively moderate the relationship between bridging scientists and the technological performance of firms.

Second, firm-level exploitation mechanisms enhance the value of bridging scientists by providing them with novel scientific challenges. The application of science knowledge to the technology innovation process is a rich source of novel scientific challenges. Exploration of these scientifically challenging questions would bring forth important findings that are in turn valuable to technological innovation. For example, the use of basic physics to understand some of the material processes and properties in semiconductor devices has led to the birth of a new scientific discipline called Materials Sciences (Brooks, 1994). This discipline now has an extensive use in the technology innovation process, including innovations related to nutrition and dietetics. Firm-level mechanisms that encourage the exploitation of scientific knowledge in technology domain would make inventors from diverse background experiment with the knowledge generated by scientists. Since bridging scientists are involved in science and technology domains, the firm-level exploitation mechanism would expose these scientists to new application areas. Novel questions arising from these diverse areas can be easily picked up by bridging scientists for further exploration, thereby enhancing the value of bridging scientists for technology development. The above arguments lead to my third hypothesis:

Hypothesis 3: The degree of relationship between the dual role of scientists and the technological performance of a firm is moderated by the extent to which the firm exploits its scientists' knowledge in the technology domain.

Even in the presence of bridging scientists, certain circumstances might prevent firms from translating the competencies of scientists into better technologies. For instance, since scientific ideas serve as inputs for scientific research as well as technology development, it is vital that bridging scientists make use of the important scientific knowledge to generate valuable technologies rather than merely investing their time and effort in furthering the scientific understanding. But, as the professional reputation of scientists is tied to their important discoveries in the scientific discipline, even bridging scientists might intend to use the knowledge for scientific advancement. Besides, as publishing scientists in firms receive lower wages than other scientists and inventors who are not allowed to publish, they have less incentive to exploit the important scientific findings for the benefit of the firm. Therefore, the professional orientation of bridging scientists can prevent a firm from translating their scientific competency into better technological innovation. Active collaboration between inventors and scientists can facilitate inventors to exploit important scientific findings in the technology development process. This can enable firms to overcome the incentive issues and to fully benefit from the competencies of bridging scientists. Further to the moderation effect of exploitation mechanism in enhancing the value of bridging scientists, the above argument emphasizes that, in the absence of firm-level exploitation mechanisms, the presence of bridging scientists alone may not help in bridging science and technology domains.

RESEARCH METHODOLOGY

Data

To test the hypotheses I collected data from the biotechnology industry. Biotechnology is recognized to be one of the most innovation-intensive industries (Sorenson and Stuart, 2000). The biotechnology industry was an ideal context in testing the framework because the industry is characterized by technological transformation and the widely-recognized importance of scientific research and intellectual human capital.

The data was drawn from Plunkett's[9] directory that comprises of 437 public-listed biotechnology firms. Biotechnology directories are one of the sources that prior studies have consulted in drawing their samples (Gulati and Singh, 1998; Stuart, Hoang and Hybels, 1999). Generally, firms in the directory are based in the United States of America. However, the headquarters of 70 firms are located in other nations such as Canada, Japan, UK, India, Switzerland, etc. The directory has 3 firms from agriculture, 13 from infotech, 100 from chemical manufacturing and 321 from the health care areas of biotechnology. The directory comprises of firms such as EISAI Co. Ltd., DOW Agrosciences, BASF AG and TRIPOS Inc. that have attained the highest sales revenue in the year 2000 for the health care, agriculture, chemical, and infotech areas respectively. The directory includes very small firms (with respect to R&D, number of employees, and sales) such as VIRAGEN and SPECTRAL DIAGNOSTICS, as well as large firms such as BAYER and NOVARTIS. With respect to age, there are old firms such as PFIZER as well as new firms formed in late 90's such as ATHEROGENICS and ARENA PHARMACEUTICAL.

[9] Plunkett's *Biotech and Genetics Industry Almanac 2005:* the only comprehensive guide to biotechnology and genetic companies and trends/editor and publisher: Jack W. Plunkett.

I used the publication and patenting activities of these firms in testing the hypotheses. The patents issued to these firms between 1990-2000 were obtained from the NUS patent database[10].The database comprises of patents issued to firms by the United States Patent and Trademark Office (USPTO). Publication information of firms between 1980-2000 was obtained from *Web of Science*, *ISI Science Citation Index (SCI)*. The SCI is an excellent source because it covers a broad range of basic and applied scientific journals (Lim, 2004). As the birth of the biotechnology industry is dated back to the late 70's and my patent data is restricted to 2000, I focused on publication during the period 1980-2000.Compustat Global is used in collecting the financial data of these firms.

The US patent classification system comprises of over 100,000 patent subclasses aggregated to about 400 three-digit patent classes. I used the three-digit patent classes and only included those patents that fall within the U.S. patent classes listed in Table 3.1, which belong to the biotechnology industry. The classes were chosen with reference from the USPTO Technology Profile Reports and from prior research (Lim, 2004). Filtering those firms that did not have patent data in the specified classes between 1990-2000, the final sample size was 222 firms. The list of 222 firms is provided in Table A.2 of the Appendix. Of the listed firms, 215 (437-222) firms were dropped from the directory because they had zero patents. To ensure that the results were still generalizable, I carried out a preliminary assessment of firm level variables. As shown in Table A.3, the average of firm R&D and firm size for 437 firms was not significantly different from the average of these variables in my final sample. However, I found that the average age of my final sample firms was higher than that of average age for 437 firms. This is possibly because younger firms in the directory might not have patents issued between 1990-2000.

[10]http://patents.nus.edu.sg/

Nevertheless, I do believe that the results of my study hold true even for younger firms, because my sample does indeed include younger firms such as Atherogenics and Arena.

The total number of patents and publications under consideration was 10,646 and 100,375. There is huge heterogeneity with respect to patent and publication data. Firms like Anika Therapeutics and Viragen received one patent each, while Abbott and Bayer had about 1000 patents. Patents issued to firms increased from 424 in 1990 to 1722 in 2000. There were 19 firms in my sample with 0 publications, but also about 10 firms with at least a few thousand publications. The publications made by firms increased from 1826 in 1980 to 8181 in 2000. The number of publications and number of patents of my sample firms between 1990-2000 is provided in Table A.4 of the Appendix.

Table 3.1. U.S. Patent Classes

Class	Description
424	Drug, bio-affecting and body treating compositions
435	Chemistry: molecular biology and microbiology
436	Chemistry: analytical and immunological testing
514	Drug, bio-affecting and body treating compositions
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

Measures

Dependent Variable

Technological Performance (Forward Citation) : The dependent variable is the cumulative forward citation frequencies accrued to an individual patent. I count all forward citations received by each patent at of the end of 2004. By law, each patent must cite prior patents that relate to its technology. Research demonstrates that the number of forward citations received by a patent correlates highly with the technological importance (Trajtenberg, 1990; Albert, Avery, Narin and McAllister, 1991). On average, each patent in my sample received about 6 forward citations. Prior studies have observed that the self-citation of a firm to its patents represents the extent to which the firm appropriates the returns from the patents. As a consequence, they find self-citation to reduce the probability of other firms citing the patent (Zhuang, Wong and Lim, 2006). However, in my sample I found the self-citations to be positively related to the overall forward citations, which indicates that overall citations represent the value of knowledge underlying the technology. Hence, instead of removing self-citations, I restricted my attention to overall citations accrued by a patent.

Independent Variables

Bridging scientists or Joint Patent-Publishers: This measure represents the percentage of patent inventors within a firm whose names are also listed on scientific papers published by the firm. In order to obtain this measure I identified two overlapping sets of individuals for each firm. The first comprises of those scientists listed on at least one publication made by the focal firm, and the second list comprises of inventors involved in at least one patent issued to the focal firm. Based on these two lists, I calculated the percentage of individuals listed as inventors who are also listed as scientists for each firm. The measure is borrowed from Gittelman and Kogut (2003).

Exploitation of science domain knowledge in technology domain or Relative use of a firm's publications in patents: Since measuring the exploitation mechanisms through secondary data was difficult, I take into account the outcome of exploitation mechanism in my measure, which the extent to which a firm uses internally-generated scientific knowledge in technology. For this, I measured the proportion of the focal firm's patents over all patents citing the focal firm's scientific publications. To compute this measure, I first identified all the publications produced by the focal firm and then all the patents citing those publications. For each publication, I checked the first assignee name of the citing patents to obtain a count of patents by focal firm and by other firms. Next, I computed the proportion of publication citations by focal firm over the total citations received by each publication. I then averaged this out for all the publications made by the focal firm. For each firm the value of this measure ranges from 0 to 1. The value 0 is assigned when focal firm's publications are cited only by other firms and 1 when the publications are cited only by the focal firm.

Control Variables

Publication Volume: This measure is the number of publications produced by the focal firm in the year of observation in which the firm filed a patent. I used the number of publications made by a firm as a proxy for its scientific capability. A number of scholars have used publication count to measure the scientific capability of firms (Lim, 2004; Gittelman and Kogut, 2003; Arora and Gambardella, 1994). A firm with strong scientific capability is able to identify new applications in the technology domain that might give rise to more valuable patents. Prior studies have also shown the significant relationship between publication count and patent performance. It is therefore imperative that I control for it.

Non-patent Reference: Non-patent reference is the count of the number of times a patent issued to a firm references non-patented literature. Every patent is required to cite the prior art that it builds upon, and this includes both the patent and non-patent references. It has been observed by Fleming and Sorenson (2004) that 69% of the non-patent references are from peer-reviewed scientific journals. Non-patent references cited by a patent are often used as an indicator of the science intensity of the invention that is found to be influencing the forward citation of patents (Gittelman and Kogut, 2003; Noyons, van Raan, Grupp and Schmoch, 1994). Hence, I controlled for it. The average number of non-patent references cited by the patents under study is about 18.

Firm's Average Cites to Publications: I use the citations received by the focal firm's publications to represent the relative quality of the firm's stock of scientific knowledge. To compute this measure, I first identified all the publications produced by the focal firm between the years 1980-2000, and then obtained the number of citations received by these publications. Based on the citations, I calculated the mean and standard deviation of the citations received by all articles of the sample firms in a publication year. Next, the raw citation counts for each publication of firms are normalized by the mean and standard deviation of the citations received by all articles in its publication year. Normalizing the raw citations by year allows the citations to be summed across years for each firm (Gittelman and Kogut, 2003). I then aggregated the normalized citation count of publications in a year and divided it by the total number of publications made by the firm. The normalized citation count is then aggregated up to the year the observed patent was filed in order to obtain a cumulated amount of publication quality. Because a firm's competency in generating high-quality scientific papers has been observed to impact its capability to produce high-impact innovation, I controlled for it (Gittelman and Kogut, 2003).

Number of Pure Inventors: This measure is the number of inventors listed in a patent who are exclusively involved in patenting. Since the number of inventors listed in a patent represents the research effort and resources invested in coming up with the patent, I controlled for it.

***Other Control Variables (Technology class dummy variable, Patent age, Year fixed effects, R&D expenditure, Firm size, and Firm age)*:** Forward citations may accrue to patents for other reasons such as technology field characteristics, patent characteristics and firm characteristics. Therefore, I included the patent-level and firm-level control variables to account for the heterogeneity among firms and for age and field effects. Patents belonging to a certain technology class may inherently be more cited than others. Similarly, patents with a higher number of years that elapsed since the patent was filed are capable of attaining higher citations. I used technology-class dummy variables and patent age as patent-level control variables to control for these effects. I also used year-fixed effects to capture the differences in citation probability across different years.

Firms may be highly innovative for different reasons. Larger firms have this capability due to economies of scale and scope, younger firms because they represent the knowledge of the younger vintage, and some firms devote more resources to R&D. Hence, I included firm-level control variables such as R&D expenditure, size of the firm as measured by the number of employees, and age of the firm as measured by the number of years since the firm was founded.

The summary of the dependent, independent and control variables is presented in Table A.1 of the Appendix. The summary data for the dependent and independent variables and the correlation between the variables at the patent level are reported in Table 3.2. As the numbers show, the patents and publications exhibit a lot of variance.

Table 3.2. Descriptive Statistics and Correlations

S.No	Variables	Mean	Std. Dev	Min	Max	1	2	3	4	5	6	7	8	9	10	11
1	Forward Citation	6.34	11.87	0	233	1										
2	Bridging Scientists	0.25	0.15	0	0.83	-0.02	1									
2	Exploitation of Science Knowledge	0.29	0.28	0	1	0.05*	-0.38*	1								
3	Publication Volume	136.39	222.74	0	1272	-0.06*	-0.18*	0.04*	1							
4	Publication Citation	0.04	0.91	-6.73	9.65	-0.04*	0.25*	0.23*	-0.08*	1						
5	Patent Age	10.12	2.80	7	17	0.28*	0.10*	-0.15*	0.11*	-0.01	1					
6	R&D	3.04	2.15	-0.55	12	0.17*	-0.37*	0.28*	-0.30*	0.09*	0.06*	1				
7	Firm Size	6.82	2.32	0	11.69	-0.10*	0.55*	-0.45*	0.00	-0.04*	0.01	-0.69*	1			
8	Firm Age	3.37	1.21	0	5.01	-0.18*	0.61*	-0.29*	0.14*	0.29*	0.07*	-0.57*	0.53*	1		
9	Tech. Strength	53.22	56.29	1	240	0.31*	0.32*	-0.34*	0.18*	-0.12*	-0.09*	-0.65*	0.62*	0.46*	1	
10	Non-patent reference	18.36	35.14	0	492	0.05*	-0.19*	0.07*	-0.01	-0.15*	-0.15*	0.05*	-0.06*	-0.23*	0.02	
11	No of Pure Inventors	0.65	1.11	0	17	-0.01	0.45*	-0.20*	-0.10*	0.08*	-0.02	-0.21*	0.30*	0.28*	0.17*	-0.06*

*p<0.01

Analysis

Since the dependent variable is forward citation count, the count model was more appropriate for my study. The Poisson model is a frequently used count model. As patent citations exhibited over-dispersion, I used the negative binomial model that is best suited for estimating an over-dispersed parameter (Cameron and Trivedi, 1998). The results of negative binomial regression are presented in Table 3.3.

Table 3.3. Negative Binomial Regression in Testing the Impact of Bridging Scientists, Exploitation of Science Domain Knowledge, and Control Variables on Forward Citation

Variables	Model 1	Model 2	Model 3	Model 4	Model 5
Constant	-0.0465	-0.0739	-0.3861	-0.4773*	-0.4741*
	[0. 3830]	[0.3479]	[0.3831]	[0.3559]	[0.3522]
Independent Variables					
Bridging scientists		1.1610***		1.3101***	1.4573***
		[0.5504]		[0.5830]	[0.5591]
Exploitation of science domain knowledge			0.3722*	0.4323**	0.5603**
			[0.2553]	[0.2568]	[0.3002]
Bridging Scientists* Exploitation of science domain knowledge					-0.6558
					[1.0979]
Firm-Level Control Variables					
Publication Volume	-0.0003***	-0.0002**	-0.0004***	-0.0002***	-0.0002**
	[0.0001]	[0.0001]	[0.0001]	[0.0001]	[0.0001]
Publication citation	-0.0415*	-0.0582*	-0.0731**	-0.0975**	-0.0894**
	[0.0305]	[0.0368]	[0.0456]	[0.0508]	[0.0552]
Firm age	-0.2230***	-0.2725***	-0.2060***	-0.2587***	-0.2575***
	[0.0545]	[0.0613]	[0.0499]	[0.0554]	[0.0559]
Firm size	0.0321	0.0081	-0.0501*	0.0261	0.0217
	[0.0346]	[0.0324]	[0.0340]	[0.0292]	[0.0292]
R&D Expenditure	0.0257	0.0288	0.0320	0.0369	0.0345
	[0.0298]	[0.0291]	[0.0303]	[0.0295]	[0.0293]
Technological Strength	-0.0024***	-0.0024***	-0.0022***	-0.0021***	-0.0022***
	[0.0006]	[0.0006]	[0.0006]	[0.0006]	[0.0005]
No. of Pure Inventors	0.0878***	0.0593***	0.0933***	0.0617***	0.0607***
	[0.0258]	[0.0184]	[0.0279]	[0.0189]	[0.0187]
Patent-Level Control Variables					
Patent age	0.1812***	0.1792***	0.1846***	0.1828***	0.1828***
	[0.0219]	[0.0212]	[0.0212]	[0.0204]	[0.0205]
Non patent reference	0.0033***	0.0036***	0.0031***	0.0035***	0.0035***
	[0.0012]	[0.0011]	[0.0011]	[0.0011]	[0.0011]
Log Likelihood	-20506.10	-20483.69	-20488.22	-20459.97	-20458.76
No. of Observations	7648	7648	7648	7648	7648

*p<0.1, **p<0.05, ***p<0.01. Standard error is provided in the parentheses.
Technology class dummy variables and year fixed effect were included but not reported.

All specifications include fixed effects for both technology class and application year from 1985-2000. I used robust standard errors adjusted for clustering of firm to control for random firm effects.

Results pertaining to Control Variables: Model 1 in Table 3.3 presents the results for all the control variables. The publication volume has a negative influence on the forward citation of patents ($p<0.01$). On the contrary, the non-patent reference has a significant positive influence ($p<0.01$) on the forward citation of patents. One possible explanation of my result is that when firms concentrate more on producing scientific publications, their attention towards developing important technologies might deteriorate and result in fewer forward citations for their patents. This explanation is also consistent with the result pertaining to the publication citation. The quality of firms' publications, as reflected by the average cites to publications, has a negative relationship with the forward citation of patents ($p<0.10$). This shows that when firms engage in the generation of cutting-edge scientific research, their technological performance suffers. As expected, the firm age and number of pure inventors have, respectively, a negative and positive impact on the forward citation of patents ($p<0.01$, $p<0.01$). Firm size and R&D expenditure do not have a significant relationship with the forward citation of patents. A plausible explanation for R&D and firm size being insignificant is that increased R&D spending and economies of scale need not necessarily increase the quality of innovation, as measured by the forward citations. The technological strength of a firm, as measured by the number of patents generated by the firm, is negatively associated with forward citation of patents ($p<0.01$). This shows that quality of patents is inversely proportional to the quantity generated. A plausible explanation is that for a given amount of R&D

investment and firm size, firms producing more number of patents receive fewer citations for their patents. The significant ($p<0.01$) positive effect of patent age shows that older patents receive more citations.

Results pertaining to the independent variables: Model 2 presents the results after including the first independent variable, bridging scientists. The coefficient of bridging scientists is positively significant ($p<0.01$) suggesting that the presence of bridging scientists confirms the translation of scientific competency into valuable patents for firms. Thus, hypothesis 1 is accepted.

Model 3 includes the second independent variable, which is the extent to which organizations exploit their scientific publications in their technology domain. The positive significant coefficient ($p<0.10$) supports hypothesis 2 that firms' endeavors toward the exploitation of their scientific knowledge in technology innovation will increase the forward citation rates of their patents. Model 4 includes both the independent variables. The significant coefficients of both 'bridging scientists' and 'exploitation of science domain knowledge' confirm the acceptance of hypotheses 1 and 2.Model 5 introduces the interaction term of the two independent variables under study. Since hypothesis 3 pertains to degree moderation, an insignificant interaction term need not mean that the hypothesis is rejected. The following section elaborates on the methodology in testing the degree moderation.

Results pertaining to the moderation effect: The moderation effect is usually tested by observing the interaction term of regression analysis. However, such a test will only verify the moderating effect of the form of relationship, not the degree of relationship. The degree of relationship between a dependent variable Y and an independent variable

X indicates the percentage of Y variance accounted for by X. The form of relationship denotes the amount of score difference in Y associated with a unit change in X. As argued by Arnold (1982), the form of relationship between two variables is indicated by the coefficients of the regression equation, whereas the degree of relationship is measured by the magnitude of the correlation coefficient. Since my third hypothesis is regarding the moderation of degree, I observed the correlation coefficient to test the effect.

In testing the moderating effect of the degree of relationship between bridging scientists and technology performance, I performed a mean split on the variable 'exploitation of science domain knowledge', resulting in two groups. In other words, I broke the sample into two groups based on the extent to which the firms exploited their scientific knowledge in the technology domain. With the mean of scientific knowledge exploitation in technology being 0.29, I had the high exploitation group comprising of 47% of the sample firms. The low exploitation group had about 53% of the sample firms. The technique of splitting the sample is also consistent with Baron and Kenny's (1986) third case of moderation, wherein it is suggested that, at some value of 'exploitation of science domain knowledge', the 'bridging scientists' become more effective in increasing the technological performance of firms. Their study also suggests the approach of dichotomizing the moderating variable to evaluate a variable's moderating effect. Thus, in testing the degree of moderation using the above technique, I observe the correlation between bridging scientists and forward citation for both the groups. According to Arnold (1982), the following formulae are used in testing the difference in correlation between the two groups to confirm the significance of moderation effect:

$$\text{Fisher } Z = (Z_1 - Z_2)/\text{SQRT}\,[1/ (n_1\text{-}k\text{-}2) + (1/n_2\text{-}k\text{-}2)]$$

where k is the number of independent variables and n is the size of the group.

Z_1 and Z_2 are obtained by the Fisher Z transformation of the partial correlations between bridging scientists and forward citation obtained for the two subgroups, given by

$$Z_i=0.5 * LN [(1+r_i)/ (1-r_i)]$$

where LN is the natural log and r_i is the partial correlation coefficient.

Table 3.4 reports the result of correlation analysis for testing the moderating effect of bridging scientists. The significance of the Z value shows that, in the presence of exploitation of scientists' knowledge in the technology domain, bridging scientists account for much higher variance in the forward citation of patents. This confirms that exploitation of science domain knowledge moderates the degree of relationship between bridging scientists and technology innovation performance, thus supporting hypothesis 3.

Table 3.4. Analysis of Correlation Differences

Variables	Group 1: High Exploitation of science domain knowledge (Z_1)	Group 2: Low Exploitation of science domain knowledge (Z_2)	Z Value	Significance
Bridging Scientists and Forward Citation relationship	0.0726	-0.0195	4.03	The difference is significant ($p<0.01$). Moderation Supported

Apart from testing the correlation differences, I also estimated the regression coefficients of bridging scientists for the two subgroups. This was done to understand the extent to which the relationship between bridging scientists and forward citation of patents is moderated by the exploitation mechanism. It is evident from Table 3.5 that the regression coefficient of bridging scientists in explaining the forward citation of patents for high exploitation group is significant at the 5% level of significance. On the contrary, the coefficient is insignificant for the low exploitation group. Taken together, the results show that, when the exploitation of science domain knowledge in technology domain is low, the mere presence of bridging scientists is not capable of generating valuable technological innovation. Thus, the results strongly confirm the moderating effect of ‘exploitation of science domain knowledge in technology domain’ in explaining the relationship between ‘bridging scientists’ and ‘forward citation of patents’.

One might suspect that the story behind such a relationship is that the firm-level mechanism of exploitation is actually capturing the bridging scientists’ efforts in exploiting science knowledge in the technology domain. Nevertheless, this reason appears to be unlikely because, in my data, very few inventors (2.5% of the inventors) referenced their own publication materials. While Sorenson and Fleming (2004) observed about 3% of the inventors in their sample to reference their own publications, in my data I found the percentage to be much smaller. Hence, it is highly unlikely that the result pertaining to firm-level bridging mechanism is confounded because of bridging scientists. In addition, it is important to note that, in the presence of firm-level exploitation mechanisms, the main effect of bridging scientists on forward citation rate of patents is positively significant (Table 3.3). If the firm-level mechanism is capturing the effect of exploitation of knowledge by bridging scientists, then the main effect of bridging scientists should have become insignificant in Table 3.3.

Table 3.5. Analysis of Regression Coefficient

Variables	Group 1: High Exploitation of science domain knowledge	Group 2: Low Exploitation of science domain knowledge
Independent Variable		
Bridging Scientists	1.2338*	0.7086
	[0.9244]	[0.8351]
Firm-Level Control Variables		
Publication Volume	-0.0001	-0.0007**
	[0.0001]	[0.0004]
Publication citation	-0.0578*	-0.1713*
	[0.0419]	[0.1282]
Firm age	-0.3478***	-0.2342***
	[0.1452]	[0.0550]
Firm size	-0.0155	-0.0204
	[0.0425]	[0.0398]
R&D Expenditure	0.0345	-0.0050
	[0.0525]	[0.0423]
Technological	-0.0026***	-0.0026***
Strength	[0.0011]	[0.0006]
No. of Pure Inventors	0.1062***	0.0434***
	[0.0330]	[0.0136]
Patent-Level Control Variables		
Patent age	0.1594***	0.1935***
	[0.0373]	[0.0202]
Non-patent reference	0.0042***	0.0021**
	[0.0013]	[0.0010]
No. of Observations	3595	4053

*p<0.1, **p<0.05, ***p<0.01. Standard error is provided in the parentheses.
Technology class dummy variables and year fixed effect were included but not reported.

DISCUSSION AND CONCLUSION

While many studies explore the benefits of science to technology development, this study focuses on the means through which firms are able to make use of the competencies of scientists and translate them into better technological innovations. My study investigates two important mechanisms of bridging science-technology domains, one at the individual level and the other at the firm level, and has several important findings to enrich this branch of literature.

The first mechanism explored in my study is the extent to which a firm has bridging scientists, who are involved in both scientific research and technological innovation. In other words, these scientists publish as well as patent. My results are consistent with Gittelman and Kogut's (2003) assertion that bridging scientists improve the technological performance of firms. Further to bridging scientists, in my second mechanism I show that it is also important for firms to have an exploitation mechanism in place so as to ensure that the knowledge generated by their scientists is exploited by the inventors in technology domain. One of the main contributions of my study is to show that the degree to which bridging scientists enhance the technological performance is much higher in the presence of a firm-level exploitation mechanism. In the absence of calculated exploitation of scientific knowledge in the technology domain, bridging scientists do not play a significant role in explaining the technological performance. Therefore, the mere presence of bridging scientists in an organization does not ensure a smooth transfer of knowledge between science and technology domains.

Consequently, my research demonstrates that March's exploration/exploitation framework complements the sociology and economics of science literature in understanding the mechanisms of transforming competencies of scientists into better technological innovation. Science and technology are two distinct domains within a firm. Apart from maintaining exploration/exploitation balance within each domain, it is also important that knowledge exploration of the science domain is complemented by the exploitation of such knowledge in the technology domain. This underlines Lavie and Rosenkopf's (2006) suggestion that firms ought to be ambidextrous in maintaining an exploration/exploitation balance, both within and across domains. Bridging science-technology domains is not a simple human capital story of having scientists who are involved in both patenting and publishing. Firms have to acknowledge the challenges in making the transition from science domain exploration to technology domain exploitation, and attempt to have premeditated mechanisms to bridge the gap. Inventors involved in developing technologies should be encouraged to actively experiment and make use of the knowledge generated by the scientists. Similarly, scientists should be encouraged to coordinate with inventors in solving basic problems encountered in the technology development process. This underscores active communication, coordination and knowledge sharing within an organization to let individuals specialize in their expertise area, yet not to let them work solo.

There are a few other results worth explaining to understand the science-technology relationship. First, the non-patent reference also termed as the science intensity of patents was found to be a significant predictor of patents' values. This result, together with the negative relationship of publication volume with patent performance, suggests that a firm's ability to generate scientific knowledge does not result in the firm generating better technological innovation. On the contrary, a firm's capability to apply scientific knowledge in technology development guarantees generation of valuable technological innovation. This result is consistent with the findings of Gittelman and Kogut (2003). I follow their contention in saying that it is only through the skillful application of science to the innovation process that firms can transform their scientific capability into valuable innovation. This has important implications for firms with low R&D budgets. These firms can encourage their inventors to effectively utilize scientific findings in their technology innovation process, so as to benefit from the scientific community's knowledge spillover.

Second, the publication citation has a negative influence on the forward citation of patents. This shows that a firm's capability to generate cutting-edge science is not helpful for its technological innovation. Rather, the extra attention paid in creating cutting-edge science diverts the firm's attention from working on valuable technologies. As explained above, another plausible reason could be that the cutting-edge science represents an embryonic stage of research which the firms' are unable to translate into patentable innovations within a short span. Thus, indulging in breakthrough science is detrimental to firms' technological performance if they fail to exploit the breakthrough results in developing valuable patents.

This research is subject to a number of limitations. The first one is pertaining to patent data. Restricting the scope to patent data has several limitations because not all companies have the same propensity to patent and firms can limit their patents only to their most successful innovations. In spite of the above limitations, patent data has been widely used in testing the factors contributing to innovation (Sorenson and Fleming, 2004; Gittelman and Kogut, 2003). Secondly, a count of all non-patent references is considered when measuring a firm's capability to apply science to technology development. A more appropriate measure would have been to consider only citations to scientific publications. However, this limitation is to some extent mitigated by the observation of Fleming and Sorenson (2004) that the majority of the non-patent references are citations to scientific publications. My research interprets the citations of publications in patents as the usage of scientific knowledge in technology. However, practitioners such as Narin, Hamilton, and Olivastro (1997) have acknowledged that such linear science-push perspective is simplistic and inaccurate.

Third is a limitation is pertaining to publications. Not all firms involved in scientific research have the inclination to disclose their findings by publishing. Even among publications, there are articles that can be classified as basic journals and applied journals (Lim, 2004). A fine-grained approach in categorizing publications can strengthen my implications. There are also publications made by firms through collaboration with other firms and universities. My study includes all publications that are affiliated with the sample firms, irrespective of whether the publication is associated with more than one organization or not. However, not considering the information on collaboration is not a major limitation of my study because the publication is still a strong predictor of the knowledge captured by the firm and that the firm has acquired the tacit knowledge of individuals engaged in the research (Zucker, Darby and Armstrong, 2002).

Fourth, my study exploring the relationship between science and technology can be generalized to only those industries where scientific findings are important inputs for technological innovation.

Despite the above limitations, the study has enhanced the understanding of bridging the science and technology domains. In summary, the research has made an important theoretical contribution by showing that the degree to which bridging scientists enhance the technological performance of a firm depends on the extent to which the firm exploits its scientific findings in technology development.

While the first two essays emphasize the importance of intellectual human capital and alliances, it is important to analyze the interdependency across these two factors to better understand their contribution to technological performance. The next essay attempts to investigate this issue. Specifically, the next essay explores if intellectual human capital and alliances are substitutes or complements of each other in explaining firms' technological performance.

CHAPTER FOUR

INTELLECTUAL HUMAN CAPITAL AND STRATEGIC ALLIANCES: ARE THEY SUBSTITUTES OR COMPLEMENTS

INTRODUCTION

Organizations are perceived as biological organisms that struggle and compete in a hostile environment (Nelson and Winter, 1982). Since the survival of firms in such an environment depends on their innovativeness, a number of scholars investigate factors related to firms' capability to generate high-impact technologies. Studies exploring this issue can be classified into two levels: firm level and network level.

Scholars exploring the firm level determinants of innovation attribute technological performance differences across firms to the variance in firms' resources. Resources are defined as those attributes of physical and knowledge-based assets that enable firms to conceive and implement strategies that lead to a variance in performance (Wernerfelt, 1984). Among the organizational resources, the human element has gained greater importance because the knowledge they hold is considered a critical ingredient for a competitive advantage (Grant, 1996). It is especially true that an organization's capability to produce valuable technologies is closely tied to its intellectual human capital (Subramaniam and Venkataraman, 2001). In this study, intellectual human capital refers to "highly skilled and talented employees who hold advanced degrees".

Scholars investigating the network level determinants of innovation attribute performance differences across firms to the variance in the extent to which firms leverage external resources. Among the various means of leveraging external resources, resources leveraged through strategic alliance are known to significantly alter a firm's competitive position (Kogut, 1988). Specifically, a number of studies have conceived of alliances as instruments used by firms to acquire know-how and to learn new skills vital for developing technologies (Hamel, 1991; Powell and Smith-Doerr, 1996; Hagedoorn, 1993).

Recently, scholars have begun to explore the interdependency between determinants of technological performance that lie across multiple levels (Rothaermel and Hess, 2007; Cassiman and Veugelers, 2006). Two different perspectives exist regarding the interdependency of the firm level determinant: Intellectual human capital, and the network level determinant: Strategic alliances. The first perspective argues that intellectual human capital and strategic alliances are complements (i.e. marginal return to one factor increases in the presence of another) (Liebeskind, Oliver, Zucker and Brewer, 1996). On the contrary, the second perspective argues that intellectual human capital and alliances are substitutes (i.e. marginal return to one factor decreases in the presence of another) (Rothaermel and Hess, 2007). Nevertheless, neither perspective has paid attention to the characteristics of these two factors that might alter the nature of their interdependency. Considering that scholars have established that the kind of information and knowledge flowing through intellectual human capital and alliances differs depending on their attributes, this research gap is especially surprising (Owen-Smith and Powell, 2004; Corolleur, Carrere and Mangematin, 2004). Since the contribution of intellectual human capital and alliances to technological performance depends on the nature of the information and knowledge that flows through them, their characteristics are vital in studying the interdependency.

The objective of this study is to use the economics and sociology of science literature in showing that the nature of interdependency (whether substitutes or complements) between intellectual human capital and strategic alliance is contingent on their characteristics. I synthesize insights from prior studies and classify intellectual human capital into three types. Innovations in high-technology industry are determined by the advancement of both scientific and technological knowledge (Nelson, 2003). The characteristics of intellectual human capital in such industries differ based on the domain in which they carry out research activities (science/technology/both) (Gittelman and Kogut, 2003). Hence, I classify intellectual human capital into (a) pure scientists, (b) pure inventors or (c) bridging scientists, based on the domain in which they specialize. Similarly, I categorize alliance partners into two types. As information flow from network partners is known to depend on their institutional regimes (Owen-Smith and Powell, 2004), I classify them into (1) firm partners and (2) university partners.

I begin with the consideration that intellectual human capital and strategic alliances are both substitutive and complementary in nature, depending on their respective attributes. For instance, I argue that pure scientists and bridging scientists substitute university partners. The institutional underpinning of university partners encourages them to be transparent in sharing their knowledge. Through their publications, the pure scientists and bridging scientists of a firm are potentially connected to a scientific network rich in spillover of knowledge from the academe (Furukawa and Goto, 2006). Therefore, I posit that pure scientists and bridging scientists act as boundary spanners in facilitating free flow of knowledge from universities, thereby substituting them. On the contrary, firm partners are committed to proprietary uses of knowledge and require formal arrangement such as alliances in sharing knowledge. The knowledge residing in a firm’s intellectual human capital helps the firm in identifying potential firm partners, evaluating their knowledge quality, and in absorbing knowledge from the partnership (Murray, 2004). Hence, I propose that intellectual human capital complements firm partners. The hypotheses concerning the substitutive and complementary nature of determinants of technological performance across different levels are tested using patent, publication, and alliance data drawn from biotech firms.

This chapter is organized as follows. The next section develops hypotheses regarding the interdependency between the firm-level and network-level determinants of technological performance. In the subsequent sections I present the research method and results. In the last section I discuss the implications of my findings and the limitations of the study.

THEORY AND HYPOTHSES DEVELOPMENT

Intellectual Human Capital and Technological Performance

Knowledge is considered as the core of the theory of firms, and much of the organization’s knowledge resides in its human capital. Consequently, human capital is considered to be one of a firm's most important resources (Pfeffer, 1994). Although human capital is considered a valuable resource, firms in high-technology industries consider highly-skilled and talented employees to be critical determinants of technological performance (Subramaniam and Venkataraman, 2001). Several studies have provided evidence that intellectual human capital is a key input for technological performance (Zucker, Darby and Brewer, 1998; Zucker and Darby, 2001).

Intellectual human capital has a positive influence on the technological performance through the following means. First, intellectual human capital renders a positive impact on the technological performance by actively engaging in technology development. The rigorous training acquired by intellectual human capital during the course of education and tacit knowledge resulting from their research activities help firms to embark on important application areas, consequently having a positive influence on the technological performance.

Second, external resource is an indispensable element of a firm's technology development process. By actively engaging themselves in external professional communities, intellectual human capital acts as a channel for continuous flow of external knowledge, thereby having a positive influence on the technological performance (Corolleur, Carrere and Mangematin, 2004).

Third, intellectual human capital positively influences the technological performance by enhancing the absorptive capacity of firms (Cohen and Levinthal, 1990). By participating in external communities, intellectual human capital facilitates acquiring and assimilating external knowledge and information, thereby improving the potential absorptive capacity of firms. The tacit knowledge and experience of intellectual human capital helps in combining existing knowledge with newly acquired knowledge and in exploiting the knowledge for competitive advantage, thereby enhancing the realized absorptive capacity of firms. The above arguments suggest that firms endowed with intellectual human capital have a greater capability for engaging in knowledge intensive activities, and this is helpful in generating valuable technologies.

Numerous studies have pointed out that not all intellectual human capital is equally competent, creating the notion that there exists heterogeneity even within specialized human capital (Rothaermel and Hess, 2007). Traditionally, studies on professional careers concentrated on two tracks. The first track focused on academic researchers and their scientific activities (Keith and Babchuk, 1998), and the second on industrial engineers and their technological activities (Allen and Katz, 1992). But with the birth of science intensive industries such as biotechnology and the introduction of the Bayh-Dole act, we observe increasing number of scientists from academe actively contributing to technological activities in the industry. Firms are also known to attract scientists into their organization and encourage them to publish their findings (Stern, 2004). Consequently, we notice three different types of intellectual human capital within an organization depending on their domain of specialization: (1) pure scientists, (2) pure inventors and (3) bridging scientists. The first type called 'pure scientists' are exclusively involved in scientific research. The second type called 'pure inventors' predominantly focus on technological activities. The third type of intellectual human capital is called 'bridging scientists', and they are involved in both scientific and technological activities.

All the three types of intellectual human capital are known to fetch the above-mentioned benefits of engaging in R&D activities and acting as gatekeepers of knowledge. Pure scientists contribute to technological performance by engaging in basic research and helping the inflow of scientific knowledge from external environments. On the other hand, pure inventors contribute to technological performance by getting involved in applied research and the inflow of technological knowledge from external environments. Bridging scientists contribute in both these ways as well as helping to bridge pure scientists and pure inventors, thereby enhancing technological performance. Based on the above arguments, I hypothesize:

Hypothesis 1a: The proportion of pure scientists within a firm is positively related to the firm's technological performance.

Hypothesis 1b: The proportion of bridging scientists within a firm is positively related to the firm's technological performance.

Hypothesis 1c: The proportion of pure inventors within a firm is positively related to the firm's technological performance.

Alliance Portfolio Attributes and Technological Performance

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). A number of studies have shown that alliances influence the technological performance of firms. In particular, strategic alliances are shown to be beneficial for patent and new product development rates (Deeds and Hill, 1996; Shan, Walker and Kogut, 1994). There are various means through which firms benefit from alliances in developing better technologies. For instance, alliance is considered to be an important means for sourcing external knowledge and leveraging external resources that are crucial for better technological performance (Dyer and Singh, 1998). Firms especially rely on alliance partners in gaining technical, social and commercial capital that are valuable to their innovation performance (Ahuja, 2000). Alliances also influence the technological performance of firms by giving access to complementary assets (Pisano, 1990). Other benefits of alliances for better technological performance include: (1) imparting social status and recognition (Stuart, 2000), (2) defraying cost and sharing risk (Hagedoorn, 1993), etc. These benefits have an effect on the technological performance of firms in the following ways. Social status and recognition might enhance the opportunities available to a firm to engage in a greater number of R&D alliances, thereby having a spiraling effect on the technological performance. The advantage of sharing risk and investment with its partners can encourage a firm to embark on pioneering research avenues that are capable of rendering breakthrough innovations. The above arguments suggest that a firm's alliance network is positively associated with its technological performance.

Though alliances are generally known to be beneficial, the advantages which a focal firm derives from its alliance partners have been shown to depend on the attributes of the partners (Stuart, 2000). With respect to biotechnology, it is shown that the strength and robustness of the industry depend on contributions from both public and private research entities (Owen-Smith, Riccaboni, Pammoli, and Powell, 2002). Prior studies have also shown that profit and non-profit organizations differ in their flow of information (Owen-Smith and Powell, 2004). Hence, I classify alliances partners into two types: (1) university alliances and (2) firm alliances, depending on their institutional demography. The classification of alliance into the above two types depending on their institutional regime is also consistent with the different types of external professional communities to which the three types of intellectual human capital are connected. Scientists are connected to scientific communities that comprise of other scientists from universities, while inventors are connected to technological communities that comprise of inventors from other firms.

Both university and firm partners are recognized to bring the above benefits to technological performance. University partners are capable of bringing in knowledge and social capital as outlined in the previous section. Apart from knowledge and social capital, firm partners can also bring in commercial capital, thereby contributing to the focal firm's technological performance. Based on the above arguments, I hypothesize:

Hypothesis 2a: The number of university alliances of a firm is positively related to its technological performance.

Hypothesis 2b: The number of firm alliances of a firm is positively related to its technological performance.

Intellectual Human Capital and Alliances: Complements or Substitutes?

Two different perspectives exist regarding the interdependency of intellectual human capital and strategic alliances. According to the first perspective, intellectual human capital complements strategic alliance. Two activities are said to be complements of each other if the marginal effect of an activity increases in the presence of the other activity. Intellectual human capital and strategic alliances are proposed to be complements due to the following reasons. The presence of intellectual human capital is known to help organizations in identifying and incorporating pertinent research from external networks (Liebeskind et al., 1996). Intellectual human capital can act as a gatekeeper, thereby facilitating knowledge flow from alliance partners (Tushman and Katz, 1980). The knowledge residing in intellectual human capital also helps in absorbing knowledge from alliance partners (Cohen and Levinthal, 1990).

On the contrary, the second perspective argues that intellectual human capital and strategic alliance are substitutes of each other. Two activities are said to be substitutes if the marginal benefit of each activity decreases in the presence of the other. According to this perspective, different technology strategies of a firm compete for a finite resource. Hence, a firm's attempt to simultaneously venture in pursuit of innovation across multiple levels (firm and network) would result in decreased innovation output at the margin. It is also recognized that firms use one innovation mechanism repeatedly, learn by experience, and build competency in that specific mechanism, rather than switching across different innovation mechanisms (Levitt and March, 1988). For example, the pharmaceutical firm Merck is known to develop its research capability by developing its intellectual human capital, whereas Eli Lily is known to engage in alliances for innovation (Rothaermel and Hess, 2007).

While both perspectives offer important insights about the interdependency of intellectual human capital and alliances, neither approach has paid attention to the characteristics of intellectual human capital and attributes of alliances that are vital to understanding their interrelationship. For instance, the interdependency of intellectual human capital and alliances can be both complementary and substitutive, depending on the characteristics of intellectual human capital and attributes of alliances that are under consideration. The following section elaborates on how such contingent factors might alter the nature of interdependency. As outlined in previous sections, my study concentrates on three different types of intellectual human capital: (1) pure scientists, (2) bridging scientists and (3) pure inventors, and two attributes of alliance: (1) university alliances and (2) firm alliances.

The institutional differences between university and firm stem from: (1) the kind of research being conducted and (2) the nature of information flow and knowledge diffusion. Universities engage in early stages of research activities that are scientifically advanced and valuable for technology development. Scientific research has received a substantial amount of attention for its norm of openness (David, 1998; Gittelman and Kogut, 2003; Merton, 1973). Consequently, public research organizations such as universities differ from research intensive firms in diffusing their knowledge. New knowledge is known to flow out of universities more readily than it does from commercial entities such as firms (Jaffe, Trajtenberg and Henderson, 1993). Universities are also open to sharing knowledge through informal networks (Dasgupta and David, 1994).

With universities following the open norm of knowledge disclosure, I believe corporate scientists to fetch the information and knowledge benefits that university alliance partners can bring forth. Though the primary task of corporate scientists is to conduct R&D to invent new technologies, many of these scientists also publish papers in order to be connected with the academic community. By building a relationship of give-and-take with the scientific community, corporate scientists also establish trust with university scientists (Furukawa and Goto, 2006). This provides opportunities for them to have significant technological discussions and exchanges of ideas with university scientists in academic meetings. As a result of plugging themselves with the scientific community, corporate scientists help in the inflow of knowledge from universities that adhere to the norm of open information disclosure. Corporate scientists also help firms absorb knowledge from articles published by university scholars in the open domain. The above arguments suggest that, through their informal networks, scientists working for firms can assist in the free flow of information and knowledge from the academic community without necessarily having partnership with them. This can also be appreciated from the fact that the leading biotech firm Genetech, founded by a group of scientists, engaged in only 2 university alliances between the years 1980-2007[11]. Hence, I suppose pure scientists and bridging scientists within firms to act as substitutes for

[11] Source: Recap database

university alliances. However, the likelihood of pure inventors being associated with the academic community is much less because they are not involved in scientific research and in publishing. Therefore, I do not expect pure inventors to substitute university alliances. The above arguments suggest that bridging scientists and pure scientists substitute university alliances.

In a similar vein, we also observe that, in the biotechnology industry, firms lacking internal scientific expertise offset this disadvantage by forming partnerships with universities (George, Zahra, Wheatley and Khan, 2001). This suggests that university alliances can substitute scientific capital of a firm, leading to my third hypotheses:

Hypothesis 3a: Pure scientists and university alliances substitute one another in explaining a firm’s technological performance.

Hypothesis 3b: Bridging scientists and university alliances substitute one another in explaining a firm’s technological performance.

Unlike universities, firms are committed to proprietary uses of knowledge and require formal ties in transferring knowledge. Though corporate scientists and inventors are connected to professional communities that involve other firms, such linkages represent closed conduits (Owen-Smith and Powell, 2004). The possibility of knowledge spillover from other firms through informal relationship is negligible and requires contractual arrangements, such as alliances, in transferring knowledge. Hence, I believe that intellectual human capital within a firm cannot substitute firm partners. Nevertheless, I suppose the informal connections of intellectual human capital to transmit information about potential alliance partners and opportunities for technical collaboration (Rosenkopf, Metiu and George, 2001). Pure inventors, who are connected to professional technical communities, especially help a firm in identifying potential firm partners. Intellectual human capital can also help in evaluating the knowledge of potential firm partners. Particularly, scientific knowledge that is used in assessing technological activities enables pure scientists and bridging scientists to evaluate the knowledge of potential firm partners (Brook, 1994). The presence of intellectual human capital also assists in absorbing, assimilating, and exploiting knowledge from alliance partners (Murray, 2004).

While the above arguments suggest that intellectual human capital enhances the contribution of firm alliances to technological performance, it is equally true that alliance partners enhance the contribution of intellectual human capital to technological performance by helping them learn new skills (Hitt, Bierman, Shimizu and Kochhar, 2006). This leads to the fourth hypotheses:

Hypothesis 4a: Pure scientists and firm alliances complement one another in explaining a firm's technological performance.

Hypothesis 4b: Bridging scientists and firm alliances complement one another in explaining a firm's technological performance.

Hypothesis 4c: Pure inventors and firm alliances complement one another in explaining a firm's technological performance.

Table 4.1 provides the summary of hypothesized interaction effects.

Table 4.1. Summary of Interaction Hypotheses

Variables	**Firm Alliances**	**University Alliances**
Pure Scientists	+	-
Bridging Scientists	+	-
Pure Inventors	+	Not Hypothesized

RESEARCH METHODOLOGY

Data

To test the hypotheses, I collected data from the biotechnology industry. Biotechnology is recognized to be one of the most innovation-intensive industries (Sorenson and Stuart, 2000). The biotechnology industry was an ideal context in testing the framework, because the industry is characterized by technological transformation, a growing number of inter-organizational relationships, and the widely recognized importance of intellectual human capital.

The data is drawn from Plunkett's[12] directory that is comprised of 437 public-listed biotechnology firms. Biotechnology directories are one of the sources that prior research works have consulted in drawing their sample (Gulati and Singh, 1998; Stuart, Hoang, and Hybels, 1999). Generally, firms in the directory are based in the United States of America. However, the headquarters of 70 firms are located in other nations such as Canada, Japan, UK, India, Switzerland, etc. The directory has 3 firms from agriculture, 13 from infotech, 100 from chemical manufacturing and 321 from the health care areas of biotechnology. The directory comprises of firms such as EISAI Co. Ltd., DOW Agrosciences, BASF AG and TRIPOS Inc. that have attained the highest sales revenue in the year 2000 for the health care, agriculture, chemical manufacturing and infotech areas respectively. The directory includes very small firms (with respect to R&D, number of employees and sales) such as VIRAGEN and SPECTRAL DIAGNOSTICS, as well as large firms such as BAYER and NOVARTIS. With respect to age, there are old firms such as PFIZER, as well as new firms formed in late 90’s such as ATHEROGENICS and ARENA PHARMACEUTICAL.

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[12] Plunkett's *Biotech and Genetics Industry Almanac 2005:* the only comprehensive guide to biotechnology and genetic companies and trends/editor and publisher: Jack W. Plunkett.

I used the publication, patenting, and alliances of these firms in testing the hypotheses. The patents issued to these firms between 1990-2000 were obtained from the NUS patent database[13]. The database comprises of patents issued to firms by the United States Patent and Trademark Office (USPTO). Publication information of firms between 1980-2000 was obtained from *Web of Science, ISI Science Citation Index (SCI)*. The SCI is an excellent source because it covers a broad range of basic and applied scientific journals (Lim, 2004). As the birth of the biotechnology industry is dated back to the late 70's and my patent data was restricted to 2000, I focused on publication during the period 1980-2000.The Recombinant Capital (Recap) database that provides a comprehensive list of biotechnology companies worldwide along with their alliances, valuations and clinical trials information was used to cross-validate the list of biotechnology firms chosen from the directory and to obtain alliance-related information between 1990-2000. Compustat Global was used in collecting the financial data of these firms.

The US patent classification system comprises of over 100,000 patent subclasses aggregated to about 400 three-digit patent classes. I used the three-digit patent classes and only included those patents that fall within the U.S. patent classes listed in Table 4.2, which belong to the biotechnology industry. The classes were chosen with reference from the USPTO Technology Profile Reports and from prior research (Lim, 2004). Filtering those firms that did not have patent data in the specified classes between 1990-2000, the final sample size was 222 firms. The list of 222 firms is provided in Table A.2 of the Appendix. Of the listed firms, 215 (437-222) firms were dropped from the directory because they had zero patents. To ensure that the results were still generalizable, I carried out a preliminary assessment of firm level variables. As shown in Table A.3, the average

[13] http://patents.nus.edu.sg/

of firm R&D and firm size for 437 firms was not significantly different from the average of these variables in my final sample. However, I found that the average age of my final sample firms was higher than that of average age for 437 firms. This is possibly because younger firms in the directory might not have patents issued between 1990-2000. Nevertheless, I do believe that the results of my study hold true even for younger firms, because my sample does indeed include younger firms such as Atherogenics and Arena.

The total number of patents and publications under consideration was 10,646 and 100,375. There is huge heterogeneity with respect to patent and publication data. Firms like Anika Therapeutics and Viragen received one patent each, while Abbott and Bayer had about 1000 patents. Patents issued to firms increased from 424 in 1990 to 1722 in 2000. There were 19 firms in my sample with 0 publications, but also about 10 firms with at least a few thousand publications. The publications made by firms increased from 1826 in 1980 to 8181 in 2000. The number of publications, patents and alliances of my sample firms between 1990-2000 is provided in Table A.4 of the Appendix.

Table 4.2. U.S. Patent Classes

Class	Description
424	Drug, bio-affecting and body treating compositions
435	Chemistry: molecular biology and microbiology
436	Chemistry: analytical and immunological testing
514	Drug, bio-affecting and body treating compositions
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

Measures

Technological Performance (Forward Citation): The dependent variable is the cumulative forward citation frequencies accrued to an individual patent. I count all forward citations received by each patent at the end of 2004. By law, each patent must cite prior patents that relate to its technology. Research demonstrates that the number of forward citations received by a patent correlates highly with its technological importance (Trajtenberg, 1990; Albert, Avery, Narin and McAllister, 1991). Prior studies have observed that the self-citation of a firm to its patents represents the extent to which the firm appropriates the returns from the patents. As a consequence, they find self-citation to reduce the probability of other firms citing the patent (Zhuang, Wong and Lim, 2006). However, in my sample I found the self-citations to be positively related to the overall forward citations, which indicates that overall citations represent the value of knowledge underlying the technology. Hence, instead of removing self-citations, I restricted my attention to overall citations accrued by a patent.

One way to measure technological performance would be to use the number of products introduced by a firm. However, I restricted my focus to a patent-based performance measure because of the following three reasons. First, obtaining data on the number of products introduced by my sample firms was difficult.

Second, the number of products introduced by a firm not only depends on the technological competency of the firm but also other factors such as U.S. Food and Drug Administration (FDA) authorization etc. In order to prevent the results from being confounded by factors that are not of interest to my research, I relied on patent-based performance measure.

Third, the biotechnology industry is characterized by open innovation in which the activities pertaining to the higher end of the value chain are performed by the firms competent in it, while FDA approval and commercialization are taken care of by other firms. Hence, a firm introducing a product into the market may not necessarily be the one responsible for its basic technological development. As the focus of my study is to relate technological competency of a firm with its performance, I believe that a patent would be a more appropriate measure of a firm's capability to generate valuable technologies.

Since patent to product conversion process in the biotechnology industry is time consuming, many of the results that hold true for a patent-based technological performance measure might not hold for a product-based measure. Hence, an interesting future research can be to test my research model with both patent-based and product-based performance measures and compare their results.

Independent Variables

Intellectual Human Capital (Pure scientists, Bridging Scientists and Pure Inventors): The greater the presence of the three types of intellectual human capital, the higher the availability of knowledge, experience, and skill for new knowledge search. Traditionally, studies capture the quality of human capital by measuring their qualifications, affiliations, etc. (Hitt, Bierman, Uhlenbruck, and Shimizu, 2001; Hitt et al., 2006). My study implicitly captures this by looking only at intellectual human capital that possesses high qualifications in order to engage in R&D activities.

I operationalize the three variables in the following manner. The pure scientist measure represents the percentage of scientists within firms whose names are exclusively listed in publications and not in patents. Then, the bridging scientist measure represents the percentage of patent inventors within a firm whose names are listed in both patents and scientific papers published by the firm. Finally, the pure inventor measure represents the proportion of inventors exclusively involved in patenting but not publishing. In order to obtain these measures, I identified two overlapping sets of individuals for each firm. The first comprises of scientists whose names are listed on at least one publication made by the focal firm, and the second comprises of inventors whose names are listed on at least one patent issued to the focal firm. Based on these two lists, I found the percentage of individuals listed as inventors who are also listed as scientists for each firm. This percentage of scientists is termed as bridging scientists. The measure is borrowed from the work of Gittelman and Kogut (2003). Then, I identified the percentage of those scientists whose name appeared only in the publications and not in the patents. These scientists who are exclusively involved in scientific publishing are termed as pure scientists. Then, for each patent, I identified the number of inventors whose names do not appear on the list of scientists. These inventors exclusively involved in patenting are termed as pure inventors. On average, my sample firms had about 900 pure scientists, 34 bridging scientists and 47 pure inventors. Firms such as Bayer and Merck had the highest number of pure scientists, bridging scientists and pure inventors. This shows that the measures are not a complement of each other, with the pure inventors measure being calculated at the patent level while scientist measures are at the firm level.

Apart from qualifications, there are other aspects of quality of intellectual human capital as measured by the extent to which they are active in producing high-quality work. This aspect of quality, as measured by the volume and citations of firms' publications stocks of patents, are captured and controlled in this study. This helps to explore if firms endowed with greater proportion of each of the intellectual human capital dimensions (after controlling for quality) are better in their new knowledge search.

Alliances (University alliances, Firm alliances): This measure represents the number of partnerships that a firm engages in a year. I tracked each firm's alliances with academic institutions and for-profit organizations, and had the count of academic alliance partners and firm alliance partners separately. I used the Recap database in obtaining this measure. The Recap database comprises of a list of alliances made by firms in a particular year along with other information such as the type of alliance (R&D, acquisition, manufacturing, joint venture, licensing, etc.), type of alliance partners (university/firm), and technology concentration of alliance. There are 26 types of alliances and 53 types of technology classifications available in the Recap database. The list of alliance types and technology classification is provided in Table A.5 and A.6 of the Appendix. Since the study is pertaining to the R&D activities of value chain, I concentrated on alliance pertaining to Research and Development. However, I concentrated on all types of technology classifications. The information pertaining to the type of alliance partner is used in counting the number of university and firm alliances separately. On average, my sample firms engaged in 40 alliances during the period of observation, of which 7 were with academic institutions.

Control Variables

Publication Volume: This measure is a count of the number of publications produced by the focal firm in the year of observation in which a patent was filed by the focal firm. I used the number of publications made by a firm as a proxy for its scientific capability. A number of scholars have used publication count to measure the scientific capability of firms (Lim, 2004; Gittelman and Kogut, 2003; Arora and Gambardella, 1994). A firm with a strong scientific capability is capable of identifying new applications in the technology domain that might give rise to more valuable patents. Prior researchers have also shown the significant relationship between publication count and patent performance. It is therefore imperative that I control for it.

Non-patent Reference: Non-patent reference is the count of the number of times a patent issued to a firm references non-patented literature. Every patent is required to cite the prior art that it builds upon. This includes both the patent and non-patent references. It has been observed by Fleming and Sorenson (2004) that 69% of the non-patent references are from peer-reviewed scientific journals. Non-patent references cited by a patent are often used as an indicator of the science intensity of the invention that is found to be influencing the forward citation of patents (Gittelman and Kogut, 2003; Noyons, van Raan, Grupp and Schmoch, 1994). Hence, I controlled for it. The average number of non-patent references cited by the patents under study is about 18.

Firm's Average Cites to Publications: I use the citations received by the focal firm's publications to represent the relative quality of the firm's stock of scientific knowledge. To compute this measure I first identified all the publications produced by the focal firm between the years 1980-2000, and then obtained the number of citations received by these publications. Based on the citations, I calculated the mean and standard deviation of the citations received by all articles of the sample firms in a publication year. Next, the raw citation counts for each publication of firms are normalized by the mean and standard deviation of the citations received by all articles in its publication year. Normalizing the raw citations by year allows the citations to be summed across years for each firm (Gittelman and Kogut, 2003). I then aggregated the normalized citation count of publications in a year and divided it by the total number of publications made by the firm. The normalized citation count is then aggregated up to the year the observed patent was filed in order to obtain a cumulated amount of publication quality. Because a firm's competency in generating high-quality scientific papers has been observed to impact its capability to produce high-impact innovation, I controlled for it (Gittelman and Kogut, 2003).

Firm's technological strength: Since a technologically strong firm is likely to receive more citations, there is a need to control for it. I used the number of patents granted to a firm to measure the technological strength of the firm. I take into account the year of the focal patent in calculating the number of patents granted to a firm. For example, if the patent under observation is a patent filed by a firm in year t, I count the number of patents issued to the firm in the year t, to account for its technological strength.

***Other Control Variables (Technology class dummy variable, Patent age, Year fixed effects, R&D expenditure, Firm size, and Firm age)*:** Forward citations may accrue to patents for other reasons such as technology field characteristics, patent characteristics and firm characteristics. Therefore, I included the patent-level and firm-level control variables to account for heterogeneity among the firms and for age and field effects.

Patents belonging to certain technology classes may inherently be more cited than others. Similarly, patents with more years having elapsed since the patent was filed are capable of attaining higher citations. I used technology class dummy variables and patent age as patent-level control variables to control for these effects. I also used year fixed effects to capture the differences in citation probability across different years.

At the firm level, larger firms due to economies of scale and scope, younger firms because they represent the knowledge of younger vintage and firms that devote more resources for R&D are capable of being highly innovative. Hence, I included firm-level control variables such as R&D expenditure, size of the firm as measured by the number of employees and age of the firm as measured by the number of years since the firm was founded. I included the logarithmic value of the above variables as the control variables.

The summary of the dependent, independent, and control variables is presented in Table A.1 of the Appendix. The summary data for the dependent and independent variables and the correlation between the variables at the patent level are reported in Table 4.3. As the numbers show, the patents and publications exhibit a lot of variance.

Table 4.3. Descriptive Statistics and Correlations

S.No	Variables	Mean	Std. Dev	Min	Max	1	2	3	4	5	6	7	8	9	10	11	12	13
1	Forward Citation	6.34	11.87	0	233	1												
2	Pure Scientists	0.77	0.32	0	0.99	0.02	1											
3	Bridging Scientists	0.25	0.15	0	0.83	-0.02	-0.69*	1										
4	Pure Inventors	0.65	1.11	0	17	-0.01	-0.34*	0.45*	1									
5	No. of University Alliances	1.61	2.25	0	18	0.26*	0.02	0.09*	0.03*	1								
6	No. of Firm Alliances	10.00	10.99	0	93	0.12*	-0.05*	0.06*	0.05*	0.04*	1							
7	Publication Volume	136.39	222.74	0	1272	-0.06*	0.31*	-0.18*	-0.10*	-0.01	0.08*	1						
8	Publication Citation	0.04	0.91	-6.73	9.65	-0.04*	-0.28*	0.25*	0.08*	0.08*	0.03*	-0.08*	1					
9	Patent Age	10.12	2.80	7	17	0.28*	-0.09*	0.10*	-0.02	0.08*	-0.02	0.11*	-0.01	1				
10	R&D	3.04	2.15	-0.55	12	0.17*	0.34*	-0.37*	-0.21*	-0.02	-0.17*	-0.30*	0.09*	0.06*	1			
11	Firm Size	6.82	2.32	0	11.69	-0.10*	-0.63*	0.55*	0.30*	0.03*	0.11*	0.00	-0.04*	0.01	-0.69*	1		
12	Firm Age	3.37	1.21	0	5.01	-0.18*	-0.47*	0.61*	0.28*	0.18*	0.17*	0.14*	0.29*	0.07*	-0.57*	0.53*	1	
13	Tech. Strength	53.22	56.29	1	240	-0.16*	-0.37*	0.32*	0.17*	-0.02	0.14*	0.18*	-0.12*	-0.09*	-0.65*	0.62*	0.46*	1
14	Non Patent Reference	18.36	35.14	0	492	0.05*	0.12*	-0.19*	-0.06*	-0.05*	-0.01	-0.01	-0.15*	-0.15*	0.05*	-0.06*	-0.23*	0.02

*p<0.01

Analysis

Since the dependent variable is forward citation count, a count model was more appropriate for this research. The Poisson model is a frequently used count model. As patent citations exhibited over-dispersion, I used a negative binomial model that is best suited for estimating an over-dispersed parameter (Cameron and Trivedi, 1998). The results of negative binomial regression are presented in Table 4.4. All specifications include fixed effects for both technology class and application year of the patents. I used robust standard errors adjusted for clustering of firm to control for random firm effects.

Effect of control variables

Model 1 of Table 4.4 presents the regression coefficients for the control variables. The publication volume has a significant negative effect ($p<0.01$) on the forward citation of patents. On the contrary, the non-patent reference has a significant positive influence on forward citations ($p<0.01$). The result pertaining to the negative role of publications on patent citation rate is contrary to the findings of Cockburn and Henderson (1998), Gambardella (1995) and Gittelman and Kogut (2003). These scholars observed publication volume to have either an insignificant or positive influence on patent citations. One possible explanation of my result is that when firms concentrate more on producing scientific publications their attention towards developing important technologies might deteriorate and result in fewer forward citations for their patents. This explanation is also consistent with the result pertaining to the publication citation. The quality of firms' publications, as reflected by the average cites to publications, has a negative relationship with the forward citation of patents ($p<0.10$). This shows that when firms engage in generating cutting-edge scientific research, their technological performance suffers.

As expected, firm age has a negative impact on the forward citation of patents ($p<0.01$). Firm size and R&D expenditure do not have a significant relationship with the forward citation of patents. A plausible explanation for R&D and firm size being insignificant is that increased R&D spending and economies of scale need not necessarily increase the quality of innovation, as measured by the forward citations. The technological strength of a firm, as measured by the number of patents generated, is negatively associated with the forward citation of patents ($p<0.01$). This shows that quality of patents is inversely proportional to the quantity generated. A plausible explanation is that for a given amount of R&D investment and firm size, firms producing more number of patents receive fewer citations for their patents. The significant ($p<0.01$) positive effect of patent age shows that older patents receive more citations.

Main effect of intellectual human capital and alliances

The regression coefficients in testing the main effects of intellectual human capital and alliances are provided in Table 4.4. Models 2, 3 and 4 present the main effects of the three intellectual human capital variables. Both bridging scientists and pure inventors have a significant positive effect ($p<0.05$, $p<0.01$) on the forward citation of patents, supporting H1b and H1c. On the contrary, pure scientists have a significant negative effect on the forward citation of patents ($p<0.01$), thereby rejecting H1a. Models 5 and 6 present the main effect of alliances. As hypothesized in H2a and H2b, both university and firm alliances have a significant positive effect on the forward citation of patents ($p<0.01$, $p<0.01$).

Interaction effects: Complements and Substitutes

The interaction terms of the three intellectual human capital factors with university alliances are presented in Model 7. Model 8 presents the regression coefficients when all the interaction terms are included in the specifications. The results show that pure scientists and bridging scientists substitute university alliances. Hence, H3a and H3b are supported. 3D graphs illustrating this substitution effect are presented in Figure 4.1 and Figure 4.2. In Figure 4.1 the coordinate (L, L) represents low in pure scientists and low in university alliances, while (L, H) represents low in pure scientists and high in university alliances. Similarly, the coordinate (H, L) represents high in pure scientists and low in university alliances, while (H, H) represents high in pure scientists and high in university alliances. The negative slope from (L, L) to (H, L) and (L, H) to (H, H) clearly shows that pure scientists and university alliances are substitutes of each other. Figure 4.2 should be interpreted in the same way as Figure 4.1 in explaining the substitution effect between bridging scientists and university alliances. Though I did not hypothesize the interaction between pure inventors and university alliances, I included their interaction term to explore the relationship. The interaction term is insignificant, which neither supports the complementary or substitutive argument. A plausible explanation is that pure inventors are not connected to scientific networks to substitute for university alliances, nor are they are competent in the scientific domain to complement university partners.

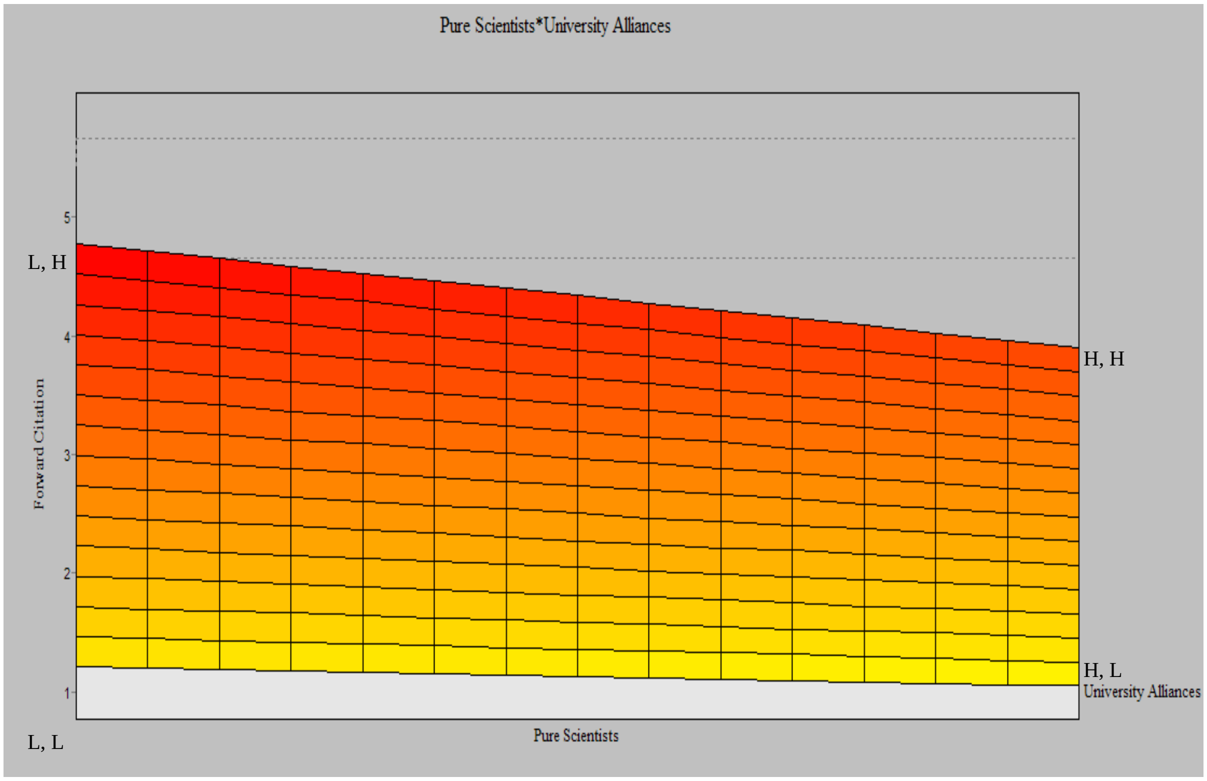
With regard to firm alliances, the results show that all three intellectual human capital variables complement firm alliances. Thus, the results support H4a, H4b, and H4c. Figures 4.3, 4.4 and 4.5 that are 3D plots of complementarity can be interpreted in the same way as that of Figure 4.1. The positive slopes in these figures illustrate the complementarity between pure scientists, bridging scientists, pure inventors and firm alliances.

Table 4.4. Negative Binomial Regression in Testing the Impact of Intellectual Human Capital, Alliances and Control Variables on the Forward Citation

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Constant	-0.0240 [0. 3944]	0.8476** [0.4825]	0.4992 [0.4329]	0.4886 [0.4304]	0.7136** [0.3980]	0.6200** [0.3507]	0.1405 [0.3309]	0.2390 [0.3442]
Independent Variables								
Pure Scientists		-0.5702*** [0.1637]	-0.3660*** [0.1703]	-0.3628*** [0.1682]	-0.5334*** [0.1329]	-0.6050*** [0.1328]	-0.2982*** [0.1815]	-0.3623** [0.2046]
Bridging Scientists			1.0319** [0.5614]	0.8494* [0.5675]	0.4692 [0.4069]	0.5141* [0.5018]	1.7275*** [0.4152]	1.4901*** [0.4591]
Pure Inventors				0.0589*** [0.0186]	0.0568*** [0.0212]	0.0447*** [0.0197]	0.0403*** [0.0206]	0.0081 [0.0216]
University Alliances					0.2207*** [0.0619]	0.1987*** [0.0551]	0.5592*** [0.0696]	0.5694*** [0.0663]
Firm Alliances						0.0231*** [0.0024]	0.0222*** [0.0021]	0.0003 [0.0133]
Pure Scientists* Univ. Alliances							-0.1875*** [0.0708]	-0.1915*** [0.0067]
Brdg. Scientists* Univ. Alliances							-0.7898*** [0.1123]	-0.8072*** [0.1062]
Pure Inventors* Univ. Alliances							0.0010 [0.0062]	-0.0006 [0.0069]
Pure Scientists* Firm Alliances								0.0117* [0.0091]
Brdg. Scientists* Firm Alliances								0.0390** [0.0241]
Pure Inventors* Firm Alliances								0.0031*** [0.0011]
Firm-Level Control Variables								
Publication Volume	-0.0004*** [0.0001]	-0.0001 [0.0001]	-0.0001 [0.0001]	-0.0001 [0.0001]	-0.0001 [0.0001]	-0.0001 [0.0001]	-0.0001 [0.0001]	-0.0001 [0.0001]
Publication citation	-0.0398* [0.0320]	-0.0935*** [0.0394]	-0.0897*** [0.0363]	-0.0878*** [0.0366]	-0.0714*** [0.0316]	-0.0837*** [0.0313]	-0.0765*** [0.0321]	-0.0735*** [0.0331]
Firm age	-0.2088*** [0.0561]	-0.2257*** [0.0483]	-0.2676*** [0.0609]	-0.2688*** [0.0612]	-0.2960*** [0.0607]	-0.3204*** [0.0704]	-0.3280*** [0.0725]	-0.3306*** [0.0723]
Firm size	0.0410 [0.0341]	-0.0069 [0.0309]	0.0134 [0.0328]	-0.0152 [0.0328]	-0.0118 [0.0264]	0.0089 [0.0316]	-0.0022 [0.0303]	0.0018 [0.0297]
R&D Expenditure	0.0242 [0.0300]	0.0194 [0.0238]	0.0244 [0.0243]	0.0249 [0.0247]	-0.0025 [0.0274]	0.0067 [0.0261]	0.0060 [0.0249]	0.0098 [0.0247]
Technological Strength	-0.0025*** [0.0006]	-0.0028*** [0.0005]	-0.0026*** [0.0005]	-0.0026*** [0.0005]	-0.0021*** [0.0007]	-0.0027*** [0.0007]	-0.0027*** [0.0008]	-0.0026*** [0.0008]
Patent-Level Control Variables								
Patent age	0.1774*** [0.0220]	0.1750*** [0.0217]	0.1753*** [0.0210]	0.1779*** [0.0211]	0.1621*** [0.0175]	0.1653*** [0.0007]	0.1626*** [0.0177]	0.1628*** [0.0175]
Non Patent Reference	0.0033*** [0.0012]	0.0032*** [0.0011]	0.0035*** [0.0011]	0.0035*** [0.0011]	0.0030*** [0.0010]	0.0030*** [0.0010]	0.0027*** [0.0009]	0.0028*** [0.0009]
Log Likelihood	-20523.86	-20498.67	-20482.71	-20475.20	-20035.10	-19864.56	-19769.96	-19762.32
No. of Observations	7648	7648	7648	7648	7648	7648	7648	7648

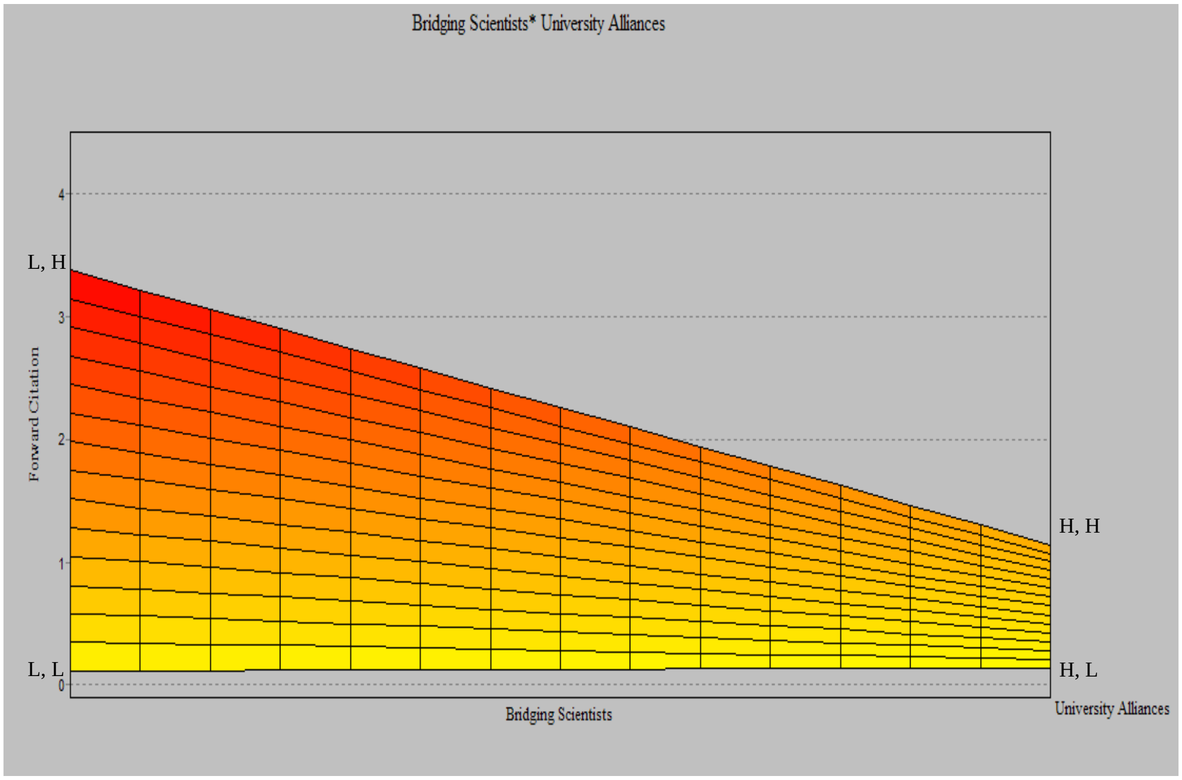
*p<0.1, **p<0.05, ***p<0.01. Standard error is provided in the parentheses.
Technology class dummy variables and year fixed effect were included but not reported.

Figure 4.1. Interaction between Pure Scientists and University Alliances



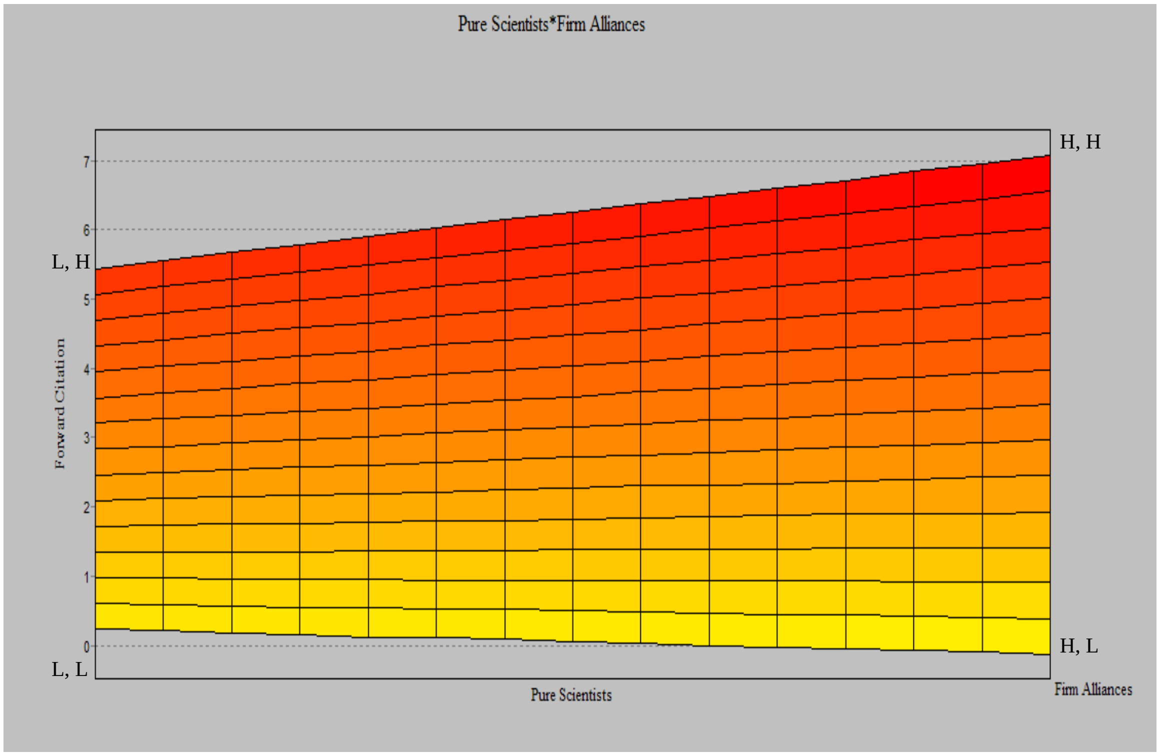
Note: The coordinates are for pure scientists and university alliances

Figure 4.2. Interaction between Bridging Scientists and University Alliances



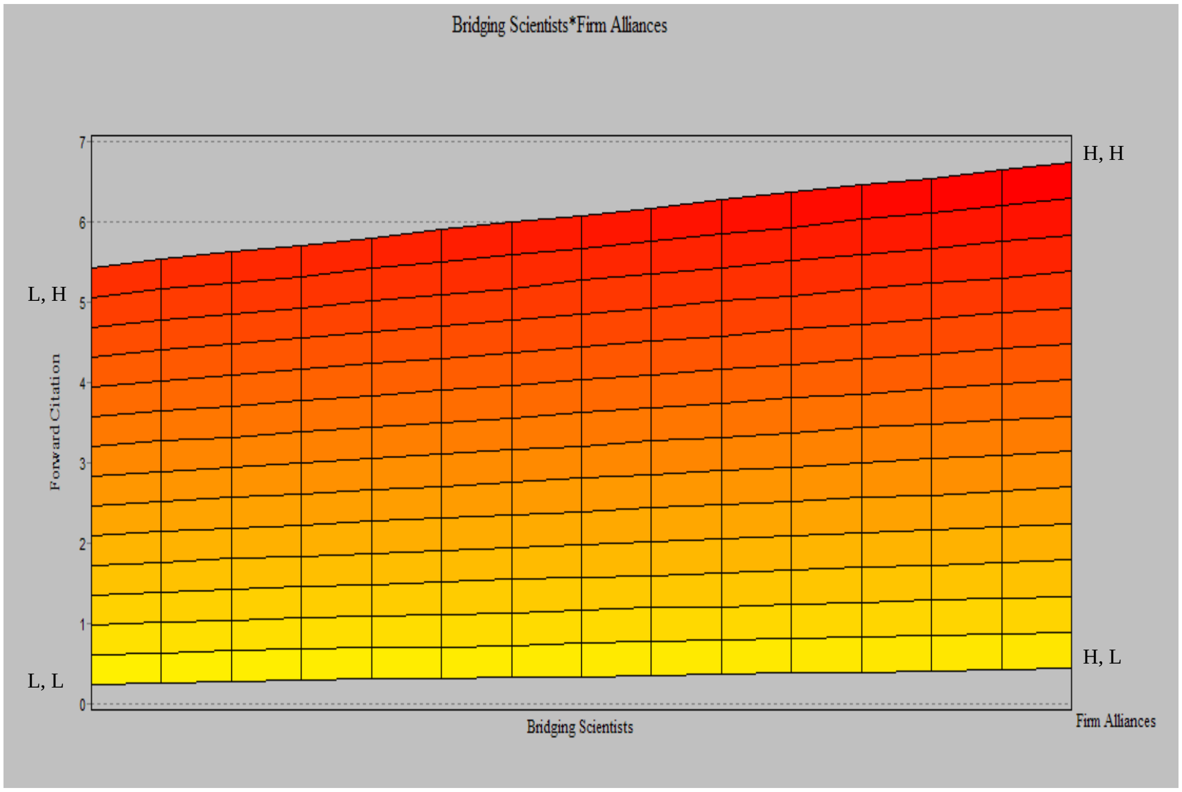
Note: The coordinates are for bridging scientists and university alliances

Figure 4.3. Interaction between Pure Scientists and Firm Alliances



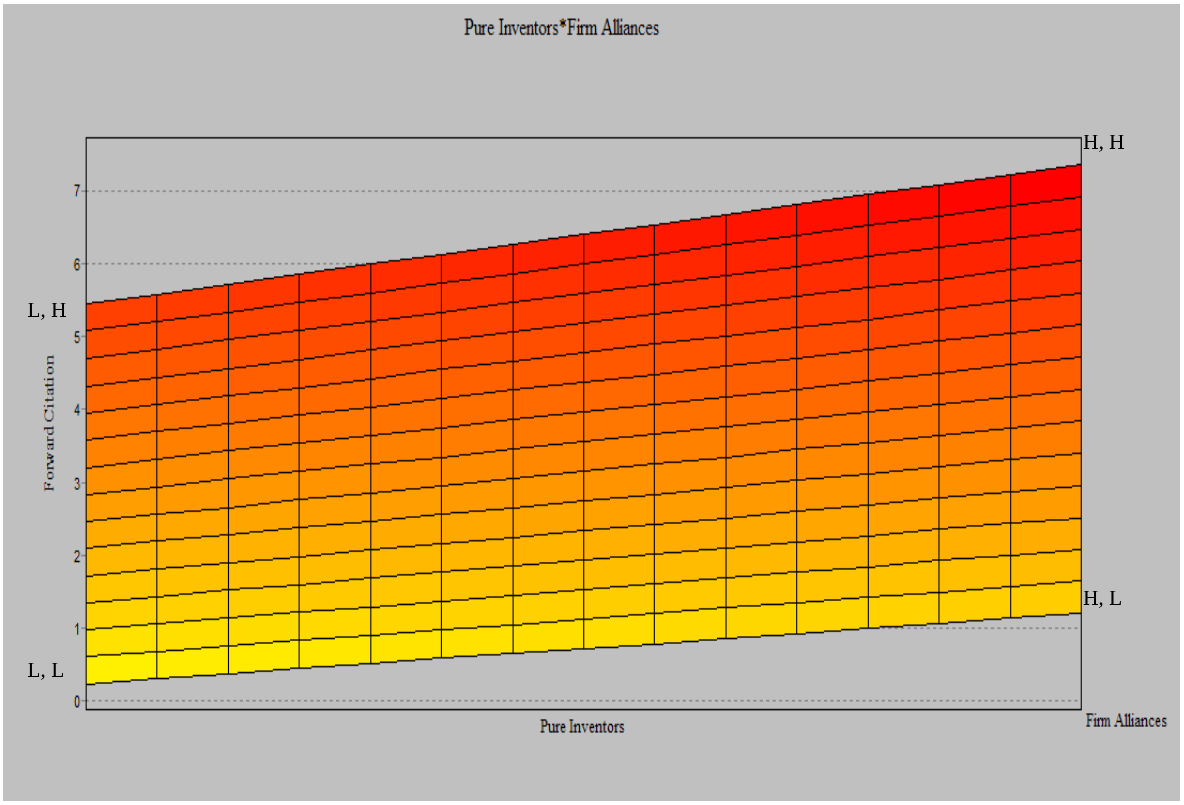
Note: The coordinates are for pure scientists and firm alliances

Figure 4.4. Interaction between Bridging Scientists and Firm Alliances



Note: The coordinates are for bridging scientists and firm alliances

Figure 4.5. Interaction between Pure Inventors and Firm Alliances



Note: The coordinates are for pure inventors and firm alliances

DISCUSSION AND CONCLUSION

Following recent theoretical developments emphasizing that antecedent to technological performance can be found in factors at firm and network level (Eisenhardt and Martin, 2000), this research extends the current understanding of interdependence between factors across these different levels. Intellectual human capital endowed with a firm is the firm level factor under study. Resources leveraged from external relationships such as alliances represent the network level factor under consideration. First, I examined the independent influence of these factors on the technological performance of firms. Second, I investigated if the factors across these two levels are complements or substitutes of each other.

The first hypothesis tested in this study confirms the importance of intellectual human capital for better technological performance. Human capital has been conceptualized in different ways, and recent studies on high-tech industries recognize the importance of intellectual human capital such as scientists (Zucker and Darby, 2001; Zucker, Darby and Brewer, 1998). In order to extend the current understanding of intellectual human capital's contribution to technological performance, this research classifies them into three categories viz. pure scientists, bridging scientists and pure inventors. The results demonstrate that both pure inventors and bridging scientists have a positive impact on the technological performance of firms. On the contrary, pure scientists have a negative impact on technological performance. The positive effect of pure inventors is trivial because they are solely dedicated to applied research and to developing important innovations. However, it is interesting to note the contingent value of scientists, whose involvement in scientific research detracts them from technology development. Scientists have a positive influence on technological performance only if they are bridging scientists, viz. they are capable of engaging themselves in scientific research as well as in technology development. Thus, I follow Gittelman and Kogut’s (2003) assertion that scientists who can play a dual role and successfully bridge the science and technology domains have a positive influence on technological performance.

The second hypothesis tests the importance of alliances for technological performance. I categorize alliances into university alliances and firm alliances, depending on the institutional characteristics of the partners. The results show that both university and firm alliances are helpful for technological performance, but with varied effect sizes. The contribution of university alliances to technological performance was considerably higher than that of firm alliances. This underlines the importance of firms to have partnerships with public research organizations in order to enhance their innovation performance (Powell et al., 1996).

The third and fourth hypotheses of this study examine the interdependency of intellectual human capital and alliance in enhancing a firm's technological performance. While prior studies have shown that intellectual human capital and alliances are either substitutes or complements of each other, my study supports both. Further, I show that the nature of interdependency is contingent on the characteristics of intellectual human capital and attributes of alliance partners. My results show that pure scientists and bridging scientists substitute university alliances, whereas pure scientists, bridging scientists and pure inventors complement firm alliances. Public research organizations, such as universities, tend to shy away from proprietary limitations on the use of their knowledge. Hence, pure scientists and bridging scientists, who are connected to the academic community through their publications, facilitate free inflow of knowledge from the academic arena, thereby making partnerships with universities redundant.

However, firms are reluctant to share their knowledge through informal channels and require formal arrangements such as alliances in benefiting from them. Firms also exercise stringent legal mechanisms to limit spillover of knowledge to alliance partners. With regard to such close conduits of linkages, the presence of intellectual human capital facilitates the transfer and exploitation of knowledge from partners. Hence, intellectual human capital is observed to complement firm alliances. My results show that all three types of intellectual human capital complement firm alliances. The technology development experience of bridging scientists and pure inventors enhances the relative absorptive capacity of firms, thereby facilitating the transfer and exploitation of knowledge from firm alliance partners. Hence, their role in complementing firm alliances is stronger than that of pure scientists. Taken together, the results show that the role played by different intellectual human capital in complementing or substituting the alliance network differs depending on their expertise. In either case, bridging scientists turn out to be an important type of intellectual human capital, and contribute to technological performance in several ways.

While prior studies have widely explored various determinants of technological performance and investigated their interdependency, my findings demonstrate the importance of considering the features of the determinants. I show that the extent to which a focal firm benefits from collaborative strategies depends on the institutional demographics of collaborative partners as well as on the social connections of the intellectual resources of the focal firm. Thus, benefits from a formal partnership depend on whether or not it is an extension of the social relationships of human capital residing within the firm. This explains why firms encourage their corporate scientists to be active in collaborating with star scientists from universities (Zucker, Darby and Armstrong, 2002). This also explains why scholars suggest that informal relationships between individuals residing within a firm should span geographical and technological boundaries (Singh, 2005).

My study also helps in understanding how benefits derived from alliance partners depend on the characteristics of the partners and the kind of resources endowed within the firm. Prior studies have shown the importance of intellectual human capital within a firm for benefiting from alliance partners (Hitt et al., 2006). I go further in saying that the characteristics of intellectual human capital within a firm also help to determine if it is necessary to form partnerships with an entity or not.

This research is subject to a number of limitations, the first of which pertains to patent data. Restricting the scope to patent data has several limitations because not all companies have the same propensity to patent, firms can limit their patents to only the most successful innovations, and the like. In spite of the above limitations, patent data has been widely used in testing the factors contributing to innovation (Sorenson and Fleming, 2004; Gittelman and Kogut, 2003).

The second limitation is related to intellectual human capital measure. Currently it is operationalized as the proportion of intellectual human capital in science/technology/both domains. In reality, there exists huge heterogeneity even among individuals belonging to each of these categories. Hence, one of the fruitful research extensions can be to develop an intellectual human capital measure capable of capturing an individual's breadth and depth of knowledge.

A third limitation pertains to publications. Not all firms involved in scientific research have the inclination to disclose their findings through publishing. Even among publications, there are articles that can be classified as basic journals and applied journals (Lim, 2004). A fine-grained approach in categorizing publications can strengthen my implications. There are also publications made by firms through collaboration with other firms and universities. My study includes all publications that are affiliated with the sample firms, irrespective of whether the publication is associated with more than one organization or not. However, not considering the information on collaboration is not a major limitation of my study. This is because the publication is still a strong predictor of the knowledge captured by the firm and that the firm has acquired the tacit knowledge of individuals engaged in the research (Zucker, Darby and Armstrong, 2002).

Fourth, my study exploring the importance of intellectual human capital can only be generalized to those high-technology industries where intellectual human capital is considered a key input for technological innovation.

Despite the limitations, my research provides important insights about the interdependence of antecedents of innovation across two different levels, one at the firm and other at the network level. With several industries being dominated by an open innovation structure, my study draws the attention of scholars and managers into more pragmatic aspects of evaluating the value of partnerships.

CHAPTER FIVE

DISCUSSION AND CONCLUSION

CONCLUSION

This dissertation comprises of three essays. The central theme underlying the three essays is in exploring the determinants of the technological performance of firms. Specifically, the essays attempt to study the interrelationships between intellectual human capital, strategic alliances and technological performance.

The first essay investigates the means through which intellectual human capital and strategic alliances contribute to technological performance. The findings show that new knowledge search is one process through which intellectual human capital and strategic alliances contribute to the technological performance of firms. Since intellectual human capital differ in their capabilities, I categorized them into pure scientists, pure inventors and bridging scientists, depending on their specialized domains. The results show that the relationship between bridging scientists, pure inventors and technological performance is mediated by technological and geographical searches. The new knowledge search does not mediate the relationship between pure scientists and technological performance. However, pure scientists are observed to help the technological and geographical searches conducted by bridging scientists, thereby contributing to new knowledge search indirectly.

With regard to alliances, the results demonstrate that firms have to rely on external resources, such as those leveraged from alliance partnerships, in order to enhance the value of their new knowledge search to technological performance. A technologically and geographically diverse alliance portfolio is known to increase the contributions of technological and geographical searches to technological performance.

The second essay is about mechanisms that help a firm in converting the competencies of its intellectual human capital, especially scientists, into better technological performance. The essay investigates the importance of two mechanisms for bridging science and technology domains, one at the individual level and the other at the firm level, that help a firm in translating the competencies of its scientists into better technologies. The results suggest that the individual-level mechanism of possessing bridging scientists, who are engaged in both scientific research and technology development, helps an organization to bridge its science and technology domains. Further, the results show that bridging science and technology domains within an organization cannot be achieved by merely engaging individuals in both of the domains. Instead, a firm should have an exploitation mechanism in place for exploiting the knowledge generated by in-house scientists in the technology domain.

The third essay is about the inter-relationship between firm level factors, such as intellectual human capital, and network level factors, such as strategic alliances. The essay examines if intellectual human capital and strategic alliances are substitutes or complements of each other. The findings illustrate that, depending on the characteristics of intellectual human capital and attributes of alliance partners, the factors at these two levels can be either substitutes or complements. Similar to the first essay, three types of intellectual human capital are taken into consideration in testing the interdependency. With respect to alliances, the partners are classified into (1) university alliances and (2) firm alliances, depending on their institutional affiliation. Pure scientists and bridging scientists residing within a firm are observed to be substitutes of university alliances. On the contrary, all of the three intellectual human capital variables are observed to complement firm alliances.

CONTRIBUTIONS

The dissertation contributes to theory and practice in several ways. The first contribution is to the research on knowledge search. This dissertation augments the existing studies that emphasize the importance of technological, geographical and science search for better technological performance (Ahuja and Katila, 2004; Phene et al., 2006; Rosenkopf and Nerkar, 2001). The curvilinear effects of geographical and science searches suggest that, beyond a point, search along these dimensions can result in diminishing returns. The curvilinear effect also highlights the value of identifying the optimum amount of search, suggested by scholars investigating the exploration/exploitation balance. Unlike searching across diverse geographic areas or scientific domains, technological search had a linear positive effect on technological performance. Prior studies have suggested the importance of scientific findings to technological search, and that technological search conducted beyond national boundaries is detrimental to innovation (Fleming and Sorenson, 2004; Phene et al., 2006). However, after controlling for the geographical and science searches, the linear positive effect of technological search suggests that searching a wide array of technologies is always beneficial to biotech innovations, which are characterized to be inter-disciplinary in nature.

A second implication of this dissertation is to the upcoming research on various mechanisms that help the new knowledge search process. Intellectual human capital and strategic alliances are two important mechanisms identified to be helpful in new knowledge search and knowledge brokering (Rosenkopf and Amedia, 2003; Hsu and Lim, 2008). Borrowing insights from absorptive capacity, I show that intellectual human capital helps in searching for new knowledge and that strategic alliances help in translating the new knowledge search into better technological performance. Consequently, I add to the stream of research by distinguishing the value of these two mechanisms to new knowledge search.

Third, in recent times an increasing number of scholars are interested in examining the contributions of human capital, especially the contributions of intellectual human capital to knowledge related activities and technological performance (Zucker et al., 2001; Subramaniam and Venkaratraman, 2001; Rothaermel and Hess, 2006). The results from the first essay suggest that bridging scientists and pure inventors assist in technological and geographical searches. The essay also suggests that pure scientists help the technological and geographical searches conducted by bridging scientists. The results from the third essay suggest that pure scientists and bridging scientists also help in the free flow of knowledge from the open scientific network. Taken together, the results add to the above stream of research in suggesting the kind of knowledge that can be accessed through the different types of intellectual human capital (Rosenkopf and Nerkar, 2001). The findings contribute to the upcoming stream of research that attempts to relate a firm's knowledge exploration process to the kind of employees that the firm hires (Perretti and Negro, 2006). They also support the notion that contributions of pure scientists to technological activities are indirect, by assisting the knowledge related activities of individuals who are directly involved in technological activities (Furukawa and Goto, 2006; Rothaermel and Hess, 2006). In addition, I contribute to the research on the intellectual human capital-technological performance link by showing that new knowledge search is one of the processes through which intellectual human capital contributes to technological performance.

The above findings may also help managers in deciding on the kind of intellectual human capital to hire, depending on their knowledge requirements. If an organization is interested in searching wide arrays of technologies and geographies, the firm should consider hiring bridging scientists and pure inventors. Further, the results show how important it is for organizations to hire bridging scientists. Apart from assisting in the new knowledge search and connecting science-technology domains, bridging scientists also bridge pure scientists and the new knowledge search process, thereby helping firms to indirectly benefit from their pure scientists. Pure scientists might not be of direct help in searching for new knowledge related to technology development. Nevertheless, this thesis identifies a distinct and important role played by pure scientists. Since pure scientists are known to be connected to the open scientific world through publishing, these scientists bring in knowledge and information benefits similar to those that university partners can bring in. As university-firm partnerships are compared to the merging of entities from Mars and Venus, a firm can avoid such difficult partnerships by employing pure scientists within their organization.

Fourth, the findings from the second essay add to the stream of research on science-technology relationship in suggesting that bridging science and technology domains within a firm is not a simple human capital story of having scientists do both. A firm should have an appropriate exploitation mechanism in place to achieve this. The essay also contributes to the research on knowledge exploration/exploitation in the following ways. First, it not reasonable to expect the individuals/domains involved in exploration to be also involved in exploitation. Instead, the exploration/exploitation balance should be balanced across different level/domains (Levie and Rosenkopf, 2006). Second, firm level structures play a vital role in appropriating returns from organizational search (Argyres and Silverman, 2004; Siggelkow and Rivkin, 2006). I also developed a novel measure that uses the patent and publication data to capture the extent to which a firm exploits the scientific knowledge that it produces in its technology development activities. In computing this measure, I first identified all publications produced by the focal firm and then all the patents citing those publications. Based on the assignee name of the patents, I calculated the proportion of the focal firm's patents over all patents citing the focal firm's scientific publications. The measure that lies between 0 and 1 helps in estimating the extent to which the scientific publications produced by a firm are being exploited in its patents. This measure can be used by scholars investigating the science-technology relationship and the exploration/exploitation balance issues.

The above findings have important implications for practice. Managers cannot simply recruit intellectuals such as scientists and expect to see returns. The results suggest the importance of firm-level mechanisms for benefiting from intellectual human capital. I conducted interviews with the CEOs of two biotech firms in order to identify firm-level factors that they think are important for benefiting from intellectual human capital like scientists. Five factors emerged from the interviews. They are (1) frequent inter-departmental meetings that encourage exchange of ideas, (2) deliberate personal meetings with introverted scientists, who are generally silent during meetings, (3) a good project manager- a person with good interpersonal skills, who need not necessarily be a scientist, but is capable of understanding what each scientist in a team is saying at a broader level and attempts to unify the scientists with a single project identity, (4) centralized R&D structure and (5) having at least one star scientist within the firm, or inviting a star scientist from outside onto the firm's advisory board

The fifth implication is to the research on strategic alliances. The importance of strategic alliance to technological performance has been well established in the literature (Powell et al., 1996). Subsequently, scholars have started concentrating on the attributes of alliance partners in order to evaluate their significance (Stuart, 2000). This dissertation proposes that a holistic understanding of the strategic advantage derived from alliance partners warrants a careful examination of the alliance partners' attributes and their interaction with the focal firm's characteristics. A few scholars have started to unravel this effect by studying the technological overlap between alliance partners in investigating the relative benefits (Mowery, Oxley and Silverman, 1998). My first essay contributes to this stream of research in identifying the kind of alliance portfolio that best fits with the different types of searches conducted by the focal firm. Similarly, the finding from the third essay that pure scientists and bridging scientists substitute university partners suggests that the benefits from a formal partnership depend on whether or not it is an extension of the social relationships of human capital residing within the firm. The substitutive/complementary findings from the third essay underline that knowledge spillover from network entities is a function of their institutional commitments and practices of members of the network (Owen-Smith and Powell, 2004). The above result also encourages multi-level scholars who investigate the inter-dependency of factors across different levels to give due attention to the characteristics of factors under study.

In deciding on the alliance strategy, management is required to choose a particular partner from a set of possible choices, often with the objective of minimizing the risk of making the wrong choice. The above findings provide important directions to managers in deciding if a firm will benefit from choosing an entity as an alliance partner or not, in conjunction with the firm’s internal requirements and competencies. The findings suggest that if a firm is interested in searching for new knowledge from a wide array of technologies and geographies, it is vital that the firm deliberately chooses a technologically and geographically diverse alliance portfolio. Nevertheless, it should be acknowledged that absorbing knowledge from such a diverse portfolio is not an easy task. The results supporting the argument that intellectual human capital and firm partners are complements proposes a solution to this absorptive issue. The findings advocate that a firm should have the necessary diversity in their internal expertise in order to ensure that they can absorb the knowledge from a diverse alliance portfolio.

LIMITATIONS AND FUTURE DIRECTIONS

There are number of limitations acknowledged in each of the essays. A few important ones to mention are as follows. The first limitation is pertaining to patent and publication data. Restricting the scope to patent data has several limitations because not all companies have the same propensity to patent and publish. In collecting the patent data, I restricted my attention to 7 technology classes (US 3-digit classification) that represent the biotechnology industry. However, I take into consideration all the publications made by the sample firms rather than restricting my attention to those that concentrate on biotechnology areas. It is possible that a few diversified firms such as Johnson and Johnson and BASF have publications on areas that are beyond the focus of the patent portfolio under consideration. Consequently, an important limitation of my three essays is that the estimates pertaining to publications and scientists can be biased upwards for a few firms.

Second, it is noted that 40% of the citations in patents are added by patent examiners (Alacer and Gittelman, 2006). I take into account all the forward and backward citations of patents in calculating the measures, which is a notable limitation of this dissertation. However, as explained in the first essay, this limitation is mitigated by the way citations are used in my dissertation.

The third limitation is related to the operationalization of measures, such as new knowledge search and exploitation mechanism. Currently, these variables are restricted to inferences from patent and publication documents which represent successful searches and exploitation that eventually were transformed into patentable and publishable innovations. However, not all searches and knowledge exploitation eventually get translated into successful patents and publications. A measure using primary data that completely incorporates the finer aspects of the above variables will improve my findings and implications. Further, in accounting for the geographical search and exploitation mechanism, I consider only the first inventor and first assignee of the patents. A more comprehensive measure encompassing the list of inventors and assignees of patents would make the results and implication robust.

Last but not least, my study exploring the importance of intellectual human capital can only be generalized to high-technology industries where intellectual human capital is considered to be a key input for technological innovation. Further, my sample focuses only on those firms that have patents issued under their name. Hence, the results are applicable only to those firms that have the inclination and competency to apply for patents and get them issued.

There are several avenues of future research. First, I am interested in identifying other factors that might mediate the relationship between intellectual human capital and technological performance. A second opportunity for research is in understanding how intellectual human capital and alliances help firms in a new knowledge search that is both technologically and geographically distant (i.e. interaction of technological and geographical search). Third, I am conducting interviews with biotech firms in order to unravel some of the firm-level factors that facilitate the exploitation of knowledge within organizations. Fourth, while this dissertation uses performance of patents as the dependent variable, a worthwhile area of research is to identify outputs (that are capable of generating economic rents) at different stages of the biotech value chain. This will help in precisely evaluating the contributions of factors that lie across different stages of the value chain. A fifth possibility for research is to identify a method capable of measuring the contributions of alliance partners individually, by looking at the intellectual property rights emerging from each partnership.

To conclude, I believe that the findings from my dissertation will stimulate scholars and practitioners to have a systemic view of managing intellectual human capital and strategic alliances for better technological performance. Scholars and managers should be motivated to delve into the characteristics of intellectual human capital and attributes of alliance partners while they investigate the benefits derived from these factors. In exploring the contribution of intellectual human capital to technological performance, it is equally important that scholars and practitioners give due attention to the organizational structure, as this is what ensures a smooth translation of the competencies of intellectual human capital into better technologies.

APPENDIX

Table A.1. Summary of Dependent, Independent and Control Variables

Variables	Level	Description
Dependent Variable		
Technological Performance	Patent-Year Level	Cumulative forward citation frequencies accrued by the focal patent
Independent Variables		
Technological search	Patent-Year Level	One minus the Herfindahl concentration index of the technology classes of backward cited patents
Geographical search	Patent-Year Level	One minus the Herfindahl concentration index of the geographical origin of backward cited patents
Science search	Patent-Year Level	***N***umber of times a patent refers to non-patented literature
Pure scientists	Firm Level	Proportion scientists within firms whose names are exclusively listed in publications and not in patents
Bridging scientist	Firm Level	Proportion of patent inventors within a firm whose names are also listed in scientific papers published by the firm
Pure inventors	Patent-Year Level	Number of patent inventors for each patent who names are exclusively listed in patents
Technological diversity of alliance portfolio	Firm-Year Level	One minus the Herfindahl concentration index of the technological classification of alliance portfolio (Alliance portfolio comprises of all the entities with whom the focal firm had formed alliance in the year of observation in which a patent was filed by the focal firm)
Geographical diversity of alliance portfolio	Firm-Year Level	One minus the Herfindahl concentration index of the geographical location of alliance portfolio (Alliance portfolio comprises of all the entities with whom the focal firm had formed alliance in the year of observation in which a patent was filed by the focal firm)
No of university partners in the alliance portfolio	Firm-Year Level	Number of alliance partners from academic institutions in the year of observation in which a patent was filed by the focal firm
Exploitation of science knowledge in technology domain	Firm-Year Level	Proportion of focal firm’s patents over all patents citing the focal firm’s scientific publications
University alliances	Firm-Year Level	Number of university partners with whom the focal firm had formed alliance in the year of observation
Firm alliances	Firm-Year Level	Number of firm partners with whom the focal firm had formed alliance in the year of observation
Control Variables		
Publication volume	Firm-Year Level	Cumulated count of the number of publications produced by the focal firm in the year of observation in which a patent was filed by the focal firm
Publication citation	Firm-Year Level	Normalized citation count received by focal firm’s publications
Firm’s technological strength	Firm-Year Level	Number of patents granted to a firm in the year of observation in which a patent was filed by the focal firm
R&D expenditure	Firm-Year Level	R&D expenditure made in the year of observation in which a patent was filed by the focal firm
Firm size	Firm-Year Level	Number of employees in the year of observation in which a patent was filed by the focal firm
Firm age	Firm-Year Level	Number of years since the firm was founded

Patent age	Patent-Year Level	Year elapsed since the patent was filed
Technology class dummy variable	Patent-Year Level	Dummy variable for the technology class of the focal patent
Year fixed effects	Patent-Year Level	Dummy variable for the year in which the focal patent is filed

Table A.2. List of Sample Firms

AASTROM BIOSCIENCES INC	IMMUNOGEN INC
ABAXIS INC	IMMUNOMEDICS INC
ABBOTT LABORATORIES	INSITE VISION INC
ABGENIX INC	INSPIRE PHARMACEUTICALS INC
ACCESS PHARMACEUTICALS	INTRABIOTICS PHARMACEUTICALS
ACLARA BIOSCIENCES INC	ISIS PHARMACEUTICALS INC
ADOLOR CORP	JOHNSON & JOHNSON
ADVANCED BIONICS CORPORATION	KING PHARMACEUTICALS INC
AFFYMETRIX INC	KOS PHARMACEUTICALS INC
AKZO NOBEL NV	KOSAN BIOSCIENCES INC
ALBANY MOLECULAR RESEARCH	LA JOLLA PHARMACEUTICAL
ALCON INC	LARGE SCALE BIOLOGY CORP
ALEXION PHARMACEUTICALS	LEXICON GENETICS INC
ALIZYME PLC	LIFECORE BIOMEDICAL INC
ALKERMES INC	LIGAND PHARMACEUTICALS INC
ALLERGAN INC	LYNX THERAPEUTICS INC
ALLIANCE PHARMACEUTICAL CORP	MARTEK BIOSCIENCES CORP
ALLOS THERAPEUTICS INC	MATRITECH INC
ALPHARMA INC	MAXIM PHARMACEUTICALS
ALTEON INC	MAXYGEN INC
ALZA CORP	MDS INC
AMARILLO BIOSCIENCES INC	MEDAREX INC
AMGEN INC	MEDICIS PHARMACEUTICAL CORP
AMYLIN PHARMACEUTICALS INC	MEDIMMUNE INC
ANDRX CORP	MERCK & CO INC
ANGIOTECH PHARMACEUTICALS	MILLIPORE CORP
ANIKA THERAPEUTICS INC	MOLECULAR DEVICES CORP
APHTON CORP	MONSANTO CO
ARENA PHARMACEUTICALS INC	MYRIAD GENETICS INC
ARIAD PHARMACEUTICALS	NANOGEN INC
ARQULE INC	NASTECH PHARMACEUTICAL CO INC
ASTRAZENECA PLC	NEOPHARM INC
ATHEROGENICS INC	NEOSE TECHNOLOGIES INC
ATRIX LABORATORIES INC	NEUROBIOLOGICAL TECHNOLOGIES INC
AUTOIMMUNE INC	NEUROCRINE BIOSCIENCES INC
AVANIR PHARMACEUTICALS	NEUROGEN CORP
AVANT IMMUNOTHERAPEUTICS	NEXIA BIOTECHNOLOGIES INC
AVI BIOPHARMA INC	NEXMED INC
AVIGEN INC	NORTHFIELD LABORATORIES
BARR LABORATORIES INC	NOVARTIS AG
BASF AG	NOVAVAX INC
BAUSCH & LOMB INC	NOVEN PHARMACEUTICALS
BAXTER INTERNATIONAL INC	NPS PHARMACEUTICALS INC
BAYER CORP	NUTRITION 21 INC
BIOCRYST PHARMACEUTICALS	ONYX PHARMACEUTICALS INC
BIOMET INC	ORCHID BIOSCIENCES INC
BIOMIRA INC	ORGANOGENESIS INC
BIOSITE INC	ORPHAN MEDICAL INC

Table A.2. List of Sample Firms (Contd.)

BIOTECH HOLDINGS LTD	OSI PHARMACEUTICALS INC
BIOTIME INC	OXIGENE INC
BONE CARE INTERNATIONAL	OXIS INTERNATIONAL INC
BOSTON BIOMEDICA INC	PEREGRINE PHARMACEUTICALS INC
BRADLEY PHARMACEUTICALS	PFIZER INC
BRISTOL MYERS SQUIBB CO	PHARMACOPEIA INC
CANGENE CORP	PHARMACYCLICS INC
CARRINGTON LABORATORIES INC	POLYDEX PHARMACEUTICALS
CELGENE CORP	POZEN INC
CELL GENESYS INC	PRAECIS PHARMACEUTICALS
CELL GENESYS INC	PROGENICS PHARMACEUTICALS
CELLEGY PHARMACEUTICALS	PROMEGA CORP
CELSIS INTERNATIONAL PLC	PROTEIN DESIGN LABS INC
CEPHALON INC	PROTEIN DESIGN LABS INC
CHATTEM INC	QLT INC
CHIRON CORP	REGENERON PHARMACEUTICALS INC
CIMA LABS INC	RIGEL PHARMACEUTICALS INC
CIPHERGEN BIOSYSTEMS INC	SALIX PHARMACEUTICALS
COLLAGENEX PHARMACEUTICAL	SANOFI-SYNTHELABO
COLUMBIA LABORATORIES	SCHERING AG
COMMONWEALTH BIOTECHNOLOGIES INC	SCHERING-PLOUGH CORP
CONNETICS CORP	SCICLONE PHARMACEUTICALS
CORTEX PHARMACEUTICALS	SCIOS INC
CSL LIMITED	SENETEK PLC
CUBIST PHARMACEUTICALS	SEPRACOR INC
CV THERAPEUTICS INC	SEQUENOM INC
DEPOMED INC	SICOR INC
DISCOVERY LABORATORIES	SKYEPHARMA PLC
DOW AGROSCIENCES LLC	SONUS PHARMACEUTICALS
DRAXIS HEALTH INC	SPECIALTY LABORATORIES INC
DUSA PHARMACEUTICALS INC	SPECTRAL DIAGNOSTICS INC
DYAX CORP	STRATAGENE CORP
EISAI CO LTD	SUPERGEN INC
ELAN CORP PLC	SYNAPTIC PHARMACEUTICAL
ELI LILLY & CO	SYNBIOTICS CORP
EMBREX INC	TANOX INC
EMISPHERE TECHNOLOGIES	TARGETED GENETICS CORP
ENTREMED INC	TARO PHARMACEUTICAL INDUSTRIES
ENZO BIOCHEM INC	TECHNE CORP
EPIMMUNE INC	TELIK INC
E-Z-EM INC	TEVA PHARMACEUTICAL INDUSTRIES
FORBES MEDI-TECH INC	THIRD WAVE TECHNOLOGIES INC
FOREST LABORATORIES INC	TRANSKARYOTIC THERAPIES
FUJISAWA PHARMACEUTICALS COMPANY LTD	TRIMERIS INC
GENE LOGIC INC	TRIPOS INC
GENELABS TECHNOLOGIES INC	TULARIK INC
GENENCOR INTERNATIONAL INC	UNIGENE LABORATORIES
GENENTECH INC	V.I. TECHNOLOGIES INC
GEN-PROBE INC	VALENTIS INC
GENTA INC	VASOGEN INC

Table A.2. List of Sample Firms (Contd.)

GENVEC INC	VERTEX PHARMACEUTICALS INC
GENZYME BIOSURGERY	VICAL INC
GILEAD SCIENCES INC	VION PHARMACEUTICALS INC
GUILFORD PHARMACEUTICALS INC	VIRAGEN INC
HAUSER INC	VIROLOGIC INC
HEMISPHERX BIOPHARMA INC	VIROPHARMA INC
HESKA CORP	VYSIS INC
HUMAN GENOME SCIENCES INC	WATSON PHARMACEUTICALS INC
HYBRIDON INC	WYETH
HYCOR BIOMEDICAL INC	XECHEM INTERNATIONAL
IDEXX LABORATORIES INC	XOMA LTD
IMCLONE SYSTEMS INC	ZILA INC
IMMTECH INTERNATIONAL	ZYMOGENETICS INC

Table A.3. Comparison of Descriptive Statistics across 437 and 222 firms

Descriptive Statistics for 437 firms				
Variables	**Average**	**Standard Deviation**	**Max**	**Min**
Firm R&D	9.97	15.6	162754.7	0.5
Firm Age	29.6	2.74	149.9	1
Firm Size	8.9	200.3	119372.0	0.1
Descriptive Statistics for 222 firms				
Variables	**Average**	**Standard Deviation**	**Max**	**Min**
Firm R&D	20.9	8.6	162754.7	0.5
Firm Age	29.1	3.35	149.9	1
Firm Size	915.9	10.2	119372.0	1

Table A.4. General Description of 222 Sample Firms between 1990-2000

Year	**No. of Patents**	**No. of Publications**	**No. of Alliances**
1990	424	3863	298
1991	489	3436	455
1992	540	3995	577
1993	584	4573	468
1994	538	4857	643
1995	548	5349	545
1996	901	5297	805
1997	1394	6984	863
1998	1778	7095	847
1999	1728	7943	829
2000	1722	8181	852

Table A.5. Types of Recap Alliances

1	Acquisition	14	License
2	Asset Purchase	15	Loan
3	Assignment	16	Manufacturing
4	Co-Development	17	Marketing
5	Co-Market	18	Merger
6	Collaboration	19	Option
7	Co-Promotion	20	Research
8	Cross-License	21	Security
9	Development	22	Settlement
10	Distribution	23	Sublicense
11	Equity	24	Supply
12	Joint Venture	25	Termination
13	Letter of Intent	26	Warrant

Table A.6. Technology Classification of Recap Alliances

1	Adjuvant	28	Monoclonals - Conjugates
2	Attenuated Virus Production	29	Monoclonals - Humanized Abs
3	Bioinformatics	30	Monoclonals - Transgenic mice
4	Carbohydrates	31	Natural Product
5	Cell Therapy - Stem Cells/Factors	32	Oligonucleotide ligands
6	Collagen matrix	33	Oligonucleotides - Antisense/Triple helix
7	Combinatorial	34	Oligonucleotides - Gene Therapy
8	Device	35	Oligonucleotides - Ribozymes
9	DNA Probes	36	Peptides
10	Drug Delivery - Liposomes	37	PFOB Emulsions
11	Drug Delivery - Oral	38	Pharmacogenomics
12	Drug Delivery - Other	39	Phototherapy
13	Drug Delivery - Sustained Release	40	Polyclonal Antibodies
14	Drug Delivery - Transdermal	41	Polyethylene glycol (PEG) products
15	Gene Expression	42	Proteomics
16	Gene Sequencing	43	Purines & Pyrimidines
17	Generics	44	Rational Drug Design - Computational
18	Hyaluronic acid	45	Rational Drug Design - Synthetics
19	Immunoassay	46	Recombinant DNA
20	Immunoglobulin	47	Resin Polymers
21	Implantable Devices	48	Screening
22	In-licensed Products	49	Separations
23	Microarrays	50	Service Laboratory
24	Micropropagation	51	Synthetics
25	Microspheres	52	Transcription Factors
26	Monoclonals	53	Transgenics
27	Monoclonals - Anti-Idiotypes		

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