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Explorative Innovation through Convergence between Science and Technology

- Focusing on the Characteristics of Knowledge and Organization -

과학과 기술의 융합을 통한 조직의 탐색적 혁신 연구
: 지식 및 조직의 특성을 중심으로

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Abstract

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Recently, the development of technology has become more advanced while the life cycle of technology has been shortened. Despite the considerable resources invested in accomplishing innovation, the uncertainty of the research and development (R&D) process as well as the risks inherent in investments into R&D are increasing. Hence, intensified competition lowers the possibility of commercially successful R&D outputs. Therefore, organizations such as industrial firms tend to focus on exploitative innovation activities to avoid the inherent risks of R&D. However, the outcomes of exploitative innovation focus only on short-term performance and incremental improvement, which makes it difficult to maintain a competitive advantage in competitive environments, where discontinuous changes in technology are frequent. Therefore, recent literature

emphasizes the importance of explorative innovation that allows to change paradigms by exploring new knowledge in various fields for the organization's long-term survival. Also, it also elucidates the importance of increasing the proportion of explorative R&D among organizations' R&D activities.

As the importance of explorative R&D activities increases, several studies have been conducted that explorative R&D, aiming at new technology development and knowledge acquisition, has a positive effect on technological innovation. Among these studies, research that emphasize exploration of science knowledge, which can help researchers to understand the basic principles of natural phenomena, have recently attracted increasing attention. In order for R&D organizations to accomplish successful innovation, they must depart from the boundaries of applying applied knowledge like technology, and start with fundamental ideas that can help them understand the principles of phenomena. In this respect, basic scientific knowledge enables anticipation of the outcomes of innovation, thereby reducing the uncertainty of R&D as well as reducing the trial and error of the R&D process. Consequently, industrial firms are trying to strengthen their cooperation with scientific organizations such as universities and research institutes in order to actively incorporate scientific knowledge into their industrial innovation.

Both academics and practitioners emphasize the importance of explorative R&D based on both science and technology. Nonetheless, research on explorative R&D activities focusing on the convergence of science and technology is still lacking. First, from the viewpoint of knowledge, the effect of convergence between science and technology on innovation has not yet been clarified. Also, in terms of organizational behavior, there is a lack of understanding of internal organizational factors that affect the organization's strategy for conducting explorative R&D. Last, even if industrial firms intend to conduct explorative R&D through cooperation with external scientific partners, they need to understand the factors that can enhance the innovation performance gained through the collaboration.

Therefore, this dissertation identifies the determinants of explorative R&D based on science and their effects on the innovations. Specifically, this study tries to provide an integrated view by analyzing it from three different perspectives: knowledge, internal organization, and external organizational aspects. First, this thesis verifies the effects of convergence between science and technology on innovation at the knowledge level. Second, this study suggests the top management team (TMT) within the R&D organization as a key factor influencing the strategy for expanding explorative R&D activities in the organization. Last, this dissertation analyzes the factors that should be considered when industrial firms are collaborating with external scientific partners such as universities and government-funded research institutes to access external scientific knowledge.

Chapter 3 analyzes the effects of the convergence between science and technology on innovation from the viewpoint of knowledge. Scientific knowledge not only allows to move away from a fragmentary perspective on phenomena, but also enables to understand more fundamental principles and to find solutions that are closest to the optimal solution. Empirical results show a positive curvilinear relationship between an increasing proportion of science in innovation and innovation impact. Chapter 3 also introduces empirical evidences that shows that the scientific capacity of the R&D organization, regional scientific knowledge spillover, and the maturity of scientific knowledge positively moderate the relationship between the convergence of science and technology and innovation impact. These results not only demonstrate the importance of applying scientific knowledge in industrial R&D, but also reveal the factors that can enhance the innovation performance of convergence.

Chapter 4 examines the relationship between organization's R&D activities and its top management team (TMT) by employing upper-echelon theory, which argues that the organizational behavior is influenced by the characteristics and perceptions of the TMT. When TMT members have previous functional experience in R&D, or have been educated in science or engineering, they are perceived to pursue innovation, which ultimately influences the organization's R&D strategy. The empirical analysis shows that the higher the percentage of top executives who have innovative experiences, the higher the proportion of explorative R&D activities in the organization. Furthermore, the longer an individual has experience as a top manager, the more the firm conducts explorative R&D activities. In order to actively conduct explorative R&D activities on science and technology, it can be inferred that decision-makers in organization must be willing to innovate and support the continuation of explorative activities. This is because explorative innovations are accomplished after a long period of time and explorative R&D that incorporates scientific knowledge is costly and might cause temporary financial shocks to the organization. Nonetheless, Chapter 4 suggests the necessity for R&D organizations to expand the proportion of top managers who have innovative experiences beyond the traditional top executive involvement in finance, accounting, law, and management.

Chapter 5 analyzes alliances which were formed for the purpose of gaining access to the external scientific knowledge of scientific partners. R&D organizations that pursue industry-focused technology innovation often seek to access scientific knowledge by partnering with scientific research institutes. Due to information asymmetry, however, technology-based firms may have difficulty in selecting appropriate scientific partners. Chapter 5 investigates the knowledge characteristics of the two different organizations, industrial firms and scientific institutes, and identifies the knowledge factors that improve post-alliance innovation performance. Empirical results show that the scientific partner's research capacity, knowledge diversity, and knowledge similarity with the industrial firm are positively influencing post-alliance innovation performance. In particular, the level of the industrial firm's scientific capacity is found to have a positive moderation effect on the above relationships. Overall, Chapter 5 presents knowledge factors to be considered by industrial firms when searching for potential scientific partners.

The results of this dissertation suggest the following implications: First, from the

perspective of convergence, this dissertation analyzed both science and technology simultaneously. In order to increase the influence of innovation, it is necessary to establish a R&D strategy that applies the appropriate scientific knowledge during the initial invention stage. The efficiency of R&D can be improved through the convergence of science and technology, which also results in an increase of innovation quality. Second, this dissertation analyzed various aspects of explorative R&D activities. The analysis from the perspectives of the knowledge and the organizations' internal and external environment increases the understanding of science-based explorative R&D activities. Last, this thesis examined various factors influencing explorative innovation. Together, this study emphasizes the importance of explorative innovation based on scientific disciplines. At the same time, this study identifies and suggests the factors necessary to understand the characteristics of science-based explorative R&D activities.

Keywords: Science, Technology, Explorative R&D, Convergence, Top Management Team, Industry-Science Link

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Chapter 1. Introduction

1.1 Backgrounds

The increasing importance of technology in creating and sustaining a firm's competitiveness is leading firms to increasingly strive for explorative R&D, which is associated with radical change and groundbreaking solutions derived from exploring knowledge in new fields or building new capabilities (March 1991; Rosenkopf and Nerkar 2001; Benner and Tushman 2003). Even conducting explorative R&D has higher risks due to higher resource requirements and a longer lag between investment and results, firms and technology-leading organizations in R&D intensive industries such as pharmaceutical, chemical and electronics, where finding new material or developing new technologies faster than rival organization is important, put a higher priority on exploration-focused R&D strategies (March 1991; Li et al. 2008; Lee et al. 2016). Innovation through exploration often brings about paradigm shifts, which means that the established accumulated knowledge is no longer useful or new knowledge becomes more important (Van de Vrande 2013). Therefore, if researchers and organizations hold onto old knowledge or capabilities, they fail to follow the new change in the environment. Through exploration it is possible to find new solutions for technological problems by employing concepts and ideas from other fields (March 1991; Van de Vrande 2013).

Regarding explorative R&D, previous studies mainly investigated ways of acquiring new knowledge in various technologic fields from the open innovation perspective, such as alliance (Stuart et al. 2007), mergers and acquisitions (M&A) (Makri et al. 2010), licensing (Teece 1986), and investing in new firms through corporate venture capital (CVC) (Dushnitsky and Lenox 2006). Many studies have recognized the above strategies as efficient ways to access explorative knowledge, especially when sourcing from external organizations (Van de Vrande 2013). However, this stream of research leans more towards the methodological aspects of conducting explorative R&D and has paid little attention to the knowledge side. Since innovation can be described as a search activity for finding the best alternative for understanding and solving problems that arise during the R&D process (Nelson and Winter 1982; Storto 2006), it is important to investigate which knowledge can make a large contribution to solve the barriers inherent in an R&D process. In this respect, several studies highlighted the contributions of science in industrial R&D. Scientific discipline helps researchers to understand the fundamental mechanisms of technological operations (Sorenson and Fleming 2004). Explorative search aiming at scientific knowledge could contribute to not only solving fundamental issues occurring in industrial R&D, but also help to design differentiated products.

However, many studies on technology and innovation, as well as the explorative R&D, have so far focused only on technology and overlooked the effects and contributions of science to innovation (Greve 2007; Li et al. 2008; Belderbos et al. 2010).

Consequently, there is still a lack of understanding on how science influences industrial R&D, especially how it affects innovation. Moreover, factors affecting science-based explorative R&D have been barely studied by the existing literature. Since the importance of explorative R&D and the contributions of science to overcoming barriers in R&D are well articulated, a comprehensive understanding of the topic is required.

As March (1991) stated, conducting explorative activities in R&D requires an enormous amount of resources. Further, difficulties in predicting outcomes from explorative R&D make it harder for industrial firms to focus on explorative innovation. These inherent high risks and uncertainties of explorative R&D often prevent R&D organizations from deploying their resources for explorative R&D projects. Conducting explorative R&D by applying scientific knowledge requires even more resources and entails higher risks than relying on technological knowledge only. However, the influence of science on innovation is still being uncovered that there is a lack of evidence to support a decision of industrial firms to focus more on explorative activities in order to increase their long-term performance.

Meanwhile, individual firms decide on different R&D strategies even though they belong to the same industry and thus face the same technological environment and competitive pressures. Some firms set their strategies to conduct their R&D activities with the goal of accomplishing radical innovation, while others aim for only minor improvements. It is much more difficult for industrial firms to pursue explorative innovations, as explorative R&D requires more resources, especially when applying scientific knowledge. Thus, it is necessary to investigate which internal factors of R&D organizations allow them to establish R&D strategies favoring explorative activities.

In order for industrial firms to conduct explorative R&D using scientific knowledge, firms have to conduct science-related R&D projects internally or source scientific knowledge from external organizations. But scientific research conducted by industrial firms requires large amount of resources while the scientific knowledge is seldom directly reflected in the final products. To lower the risks of conducting internal scientific research, a significant number of industrial firms is looking for cooperation with scientific institutions, but their familiarity of dealing with technology rather than science prevents them from properly evaluating potential scientific partners. Therefore, choosing suitable scientific partners is of great importance to industrial firms when they need to source external scientific knowledge to conduct explorative R&D.

1.2 Research purpose

Aiming at improving the understanding of the mechanisms that allow applying science in the industrial R&D process to lead to successful innovation, this dissertation provides a comprehensive approach of explorative R&D based on the convergence of science and technology from knowledge and organizational aspects and identifies the effects of this mechanism on innovation.

Specifically, the objective of this dissertation is to uncover the mechanisms of how

R&D organizations could increase their innovation performance through explorative R&D that focuses on the role of science. To provide a comprehensive analysis, this dissertation investigates the effects of science on industrial R&D from three different perspectives: First, it aims to uncover how science contributes to innovation as well as investigating environmental determinants of this relationship. From the knowledge perspective, this thesis also investigated the moderation effects of the scientific capacity of R&D organizations and the accessibility of scientific knowledge such as regional spillovers and maturity of the knowledge. Second, it aims to investigate which internal factors of R&D organizations influence the proportion of explorative activities in their R&D. Especially, this dissertation focused on how the cognitive base of top managers in R&D organizations, reflected in their observable characteristics such as their functional experiences or academic degrees, influences their decision making towards explorative R&D projects. Last, this thesis examines the determinants and effects of sourcing scientific knowledge from external scientific partners through upstream alliances. Overall, this dissertation increases the understanding of scientific aspects in technological innovation as well as explorative R&D and provides implications and recommendations for R&D organizations to improve their innovation quality.

1.3 Research outline

This dissertation consists of the following sections: the research background, three different empirical studies on the effects of the convergence between science and technology on innovation, the effects of top managers in R&D organization for conducting science-based explorative R&D, and the firm's strategy for sourcing external scientific knowledge through alliances, as well as the overall conclusions.

Chapter 2 explains the research background of this dissertation. Specifically, this chapter introduces the extant studies on the characteristics and effects of scientific knowledge on innovation, the directions of an organization's R&D strategies, and the sourcing of external scientific knowledge through alliance. The arguments highlighted in this section provide the basis for the subsequent empirical studies and key assertions of this thesis.

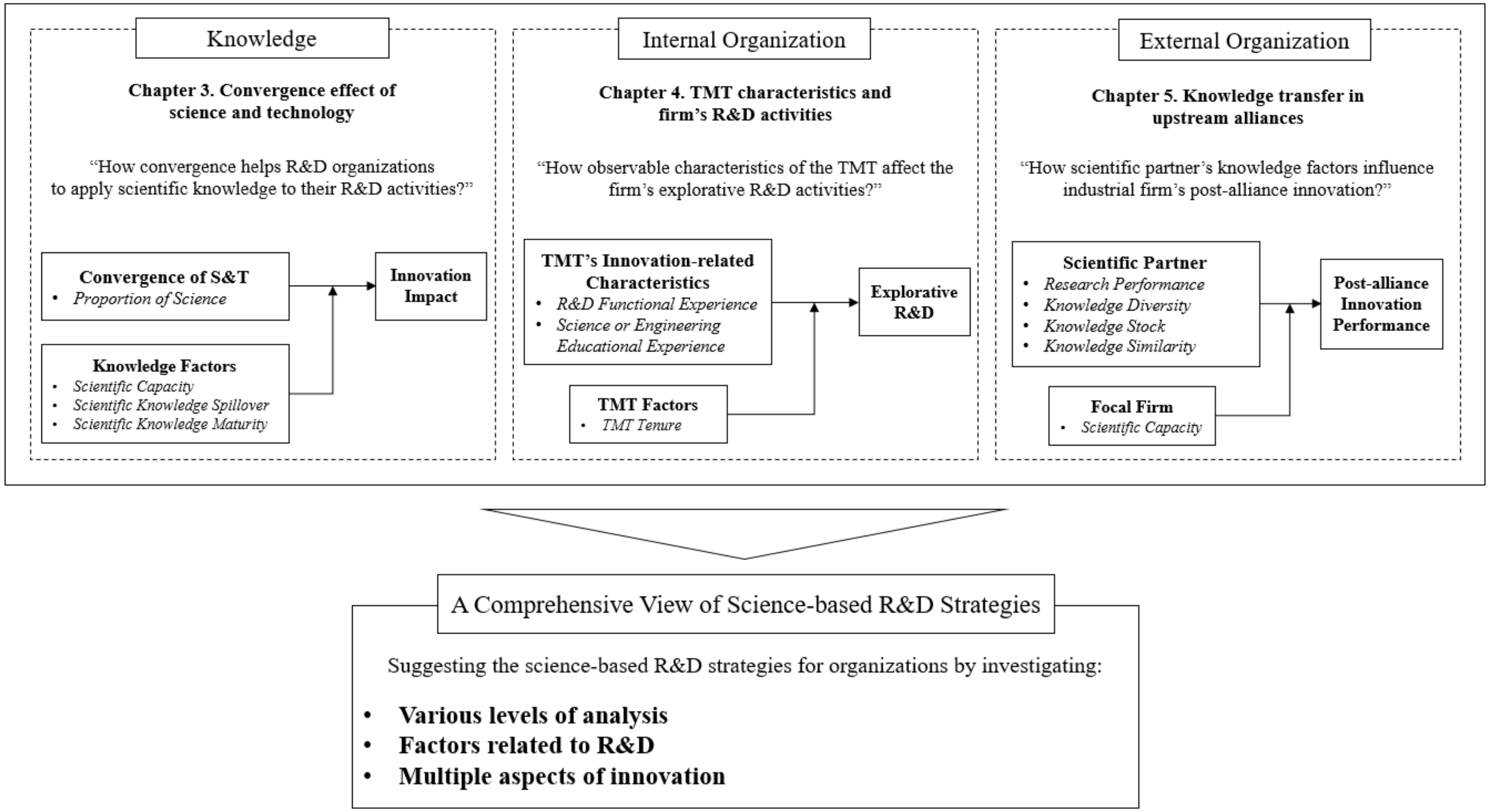

Figure 1-1. Conceptual Model for this dissertation

The three empirical studies are introduced in Chapter 3, Chapter 4, and Chapter 5. Figure 1-1 provides an overview and shows the relationships between the three studies that provide different perspectives of explorative R&D based on science and technology.

Chapter 3 investigates the effects of convergence of science and technology on innovation impact, specifically how convergence helps R&D organizations to apply scientific knowledge to their R&D activities. In addition to direct effects of convergence, this study addresses the moderating effects of scientific capacity, knowledge spillover, and knowledge maturity from the knowledge side. The empirical analysis, which employs a zero-inflated negative binomial regression model uses data on 2,074 patents granted to United States (U.S.) R&D organizations from the pharmaceutical industry. The results show that an increase in the proportion of scientific knowledge in convergence has a positive and curvilinear relationship with innovation impact. Also, Chapter 3 finds that the organization's scientific capacity, regional scientific knowledge spillover, and knowledge maturity positively moderate the relationship between convergence and innovation impact. Findings of this chapter underline the importance of convergence between science and technology as well as provide implications on how to improve the outcome of an organization's research and development process.

Chapter 4 investigates the relationship between characteristics of the firm's top management team (TMT) and its R&D activities. Specifically, Chapter 4 analyzes how observable characteristics of the TMT, such as functional experiences or educational background, and average tenure affect the firm's proportion of explorative R&D activities.

From the perspective of the upper-echelon theory, this study hypothesizes that the TMT's functional experiences with R&D or science or engineering educational backgrounds increase the firm's tendency towards explorative R&D. Moreover, this study proposes that the average tenure of TMT members with innovation-related experiences would have a positive moderation effects on these relationships. The hypotheses are tested using a dataset containing biographical information of the TMT members, financial, and patent data of 89 firms in U.S. high-tech industries from 2006 to 2009. Firm's explorative R&D activities are analyzed using data on patent citations, patent classes, and non-patent references. The empirical analysis shows that the top managers' educational background in science or engineering as well as their previous functional experiences with R&D have a positive effect on the firm's explorative innovation activities. This research also finds that the size of these effects increases with a longer tenure of these TMT members. Findings of this research provide implications related to the effects of organizational characteristics on the establishment of a R&D strategy and highlight the role of TMT members with innovative experiences in directing a firm's R&D activities and outcomes.

Chapter 5 investigates the effects of various knowledge factors in upstream alliances between industrial firms and scientific institutions on post-alliance innovation performance. Approaching from the knowledge-based view, this study analyzes how scientific partner's knowledge factors such as research performance, knowledge diversity, knowledge stock and knowledge similarity with the industrial firms influence the industrial firms' post-alliance innovation. Moreover, Chapter 5 investigates the moderation effects of the industrial firm's scientific capacity on these relationships. The empirical analysis was performed using data on 143 upstream alliances, as well as patents, journal publications and financial indexes of firms in high-tech industries. The results show that research performance, knowledge diversity and knowledge similarity of the scientific partner positively influence innovation performance. This study also confirms the moderating role of the industrial firm's scientific capacity on these relationships. Results of this research highlight factors to be considered by industrial firms when searching for potential scientific partners to source external scientific knowledge.

Lastly, Chapter 6 provides a summary of the key results of the three empirical studies and highlights their implications, as well as provides suggestions for future research.

Chapter 2. Literature Review

2.1 Organization's R&D strategy and science

2.1.1 Two directions of R&D strategy

Innovation can be divided into explorative innovation and exploitative innovation depending on how much new knowledge has been used in the invention processes (March 1991; Benner and Tushman 2003). Exploitative innovation influences firms' short-term performance by refining and implementing existing knowledge (March 1991; Benner and Tushman 2003). R&D processes related to exploitative innovation are characterized by a relatively low level of technological uncertainty as they are based on either accumulated knowledge or familiar technologies with the goal of incrementally improving existing products (March 1991). By utilizing established facilities and employees and pursuing projects based on familiar knowledge and skills, firms can conduct exploitative R&D activities with small budgets and at relatively low risk. In contrast to exploitative R&D, explorative R&D requires the firm to deal with unfamiliar and new knowledge (Stuart and Podolny 1996) and often involves testing experimental alternatives that might create outcomes only in the long-term (March 1991; Ahuja and Lampert 2001; Benner and Tushman 2003). In addition, accessing and searching for novel, emerging, pioneering technologies (Ahuja and Lampert 2001), and basic sciences (Gibbons and Johnston 1974; Rosenberg 1990) requires considerable resources to both increase the understanding of the new knowledge and to apply the new concepts towards innovative outcomes. Even deploying substantial resources into explorative R&D projects, high technological uncertainties during the invention process may result in outcomes that are far different from the initial expectations and might not be commercially viable (March 1991). In this respect, previous literature discussed ambidexterity strategies allowing firms to balance risk and performance by simultaneously conducting both exploitative and explorative R&D (He and Wong 2004; Li et al. 2008). Especially given the increasing volatility and speed of change of the technological environment, in which firms face high risks and uncertainties, ambidexterity is an effective R&D strategy (Uotila et al. 2009). However, even if organizations pursue such an ambidexterity strategy, they tend to favor one strategy over the other (Greve 2007). Recent research showed a tendency towards investing more resources into exploitative R&D projects due to their relatively lower risk compared to explorative R&D (Greve 2007; Mudambi and Swift 2014). However, overly focusing on exploitative innovation can result in organizations falling victim to structural inertia (Hannan and Freeman 1984) which reduces the ability to adapt to the fast-changing technological environment and prevents them from capturing future opportunities (He and Wong 2004; Uotila et al. 2009). Organizations which mainly depend on their established routines and learning through exploitative activities can fall into a so-called competency trap (Levitt and March 1988; Katila 2002). In high-tech industries where being the first to adopt new technologies often translates into a competitive advantage, explorative R&D projects can provide a larger potential for future growth than exploitative activities (Rosenberg 1990; Greve 2007). Consequently, for firms in these industries, even though they are trying to balance their R&D activities under ambidexterity strategies, long-term survival requires them to focus on increasing the proportion of their explorative R&D (Rosenberg 1990; D'Aveni 1994; Garcia et al. 2003; Gupta et al. 2006; Belderbos et al. 2010).

2.1.2 Role of science in R&D process

In general, scientific knowledge is produced in scientific institutions and contains generating and testing theories for understanding principles of natural phenomena or fundamental problems (Fleming and Sorenson 2004). These research outcomes are usually described and published in journal articles, conference proceedings, textbooks and other documents, as well as being embedded in individual researchers. Traditionally, scientific research institutes conducted research activities focused on solving the problems related to basic science. Nowadays, however, scientific institutes are increasingly contributing to technological innovation by conducting research close to applied science which aims at overcoming technological barriers identified by industries (Nelson 1982; Fabrizio 2007). In other words, science-oriented organizations, such as government-funded laboratories, universities, and other non-profit research institutes, simultaneously lead the advancement of both science and industrial technology (Narin et al. 1997; McMillan et al. 2000). Results of a survey conducted by Cohen et al. (2002) further confirms this tendency as many R&D managers in high-tech industry reported that industrial R&D is frequently stimulated by scientific research. This is due to research outputs from scientific institutions providing key ideas as well as indirect research contributions to industrial researchers (Grossman et al. 2001). These scientific contributions to technology are more significant in high-tech industries such as biopharmaceutical, chemical, telecommunication and computer which are characterized by a faster technologic pace (Nelson 1982).

Based on the above, Fleming and Sorenson (2004) argued that a comprehensive understanding of fundamental problems or phenomena based on scientific knowledge allows organizations to gain several advantages in their R&D processes. To begin with, science can introduce the newest instruments and skills for assessing possible technological alternatives with high efficiency (Fleming and Sorenson 2004; Fabrizio 2007). Scientific knowledge can contribute to the advancement of industrial tools and production processes that can reduce both cost and time required for experiments and invention processes (Grossman et al. 2001). Experiments with upgraded facilities can produce more accurate results and allow researchers to test up to the extreme limit conditions which is impossible with older equipment. Also, scientific knowledge could reduce trial-and-error in industrial R&D due to an increasing reliance on theoretical estimations (Fleming and Sorenson 2004; Gilsing et al. 2008). Science can guide the

R&D towards the most feasible way to accomplish set development goals as well as advise on the most appropriate search methods to produce the expected results in accordance with scientific theories (Fleming and Sorenson 2004). Even if scientific theories do not cover all possible alternatives, it can help to improve efficiency by reducing the number of alternatives that need to be reviewed and tested. Moreover, science can support the initiation of high-potential R&D projects as assessing R&D projects based on scientific knowledge allows industrial firms to estimate expected results as well as required resources more accurately (Cohen et al. 2002). Last, scientific disciplines can act as a "guiding map" for technological search processes which aim at explorative innovation (Fleming and Sorenson 2004; Sorenson and Fleming 2004). With a thorough understanding of the causes and effects of operation mechanisms based on science, industrial researchers can apply fundamental concepts as well as cutting-edge scientific ideas to their R&D processes. In summary, scientific knowledge increases invention rates and reduces unnecessary activities in R&D processes. The resulting increased efficiencies allow firms to conduct more explorative and distance research for accomplishing impactful innovation.

2.2 Effects of convergence on innovation

2.2.1 Convergence of science and technology

Recently, the boundaries of industries, markets, and knowledge such as science and technology are gradually blurred, a phenomenon that previous research has termed convergence (Hacklin 2008; Curran et al. 2010). The notion of the convergence is combining different knowledge from interdisciplinary fields or different types of sources to develop new innovation, rather than solely depend on particular fields or knowledge sources (Hacklin 2008; Curran et al. 2010; Curran and Leker 2011; Jeong et al. 2015). Hacklin (2008) sees convergence as a sequential action of science, technology, markets, and industries, with the convergence between knowledge levels such as science and technology acting as a trigger for further convergence stages. Incorporating scientific knowledge into the research process occurs during the early stages of convergence (Karvonen and Kässi 2013), and is the precedence of technological and industrial convergence (Curran et al. 2010). Fundamentally, convergence at the knowledge level is an important prerequisite for conceptualizing new innovation (Curran and Leker 2011; Kim et al. 2014).

Meanwhile, both knowledge sources have distinguished characteristics and play distinctive roles in the invention process (Brooks 1994). The main purpose of science is creating new knowledge and solving fundamental problems while developing scientific laws and theories that describe and explain the causes and effects of nature's phenomena (Fleming and Sorenson 2004; Sorenson and Fleming 2004). Therefore, output from scientific research is rarely directly applicable when releasing new product in the market (Rosenberg 1990). Even in scientific research-intensive industries like the chemical or pharmaceutical industries, the scientific knowledge from basic research institutes is difficult to apply right away (Van Vianen et al. 1990). On the other hand, technological knowledge is better suited to satisfying technological trends (No and Park 2010) and market needs than scientific knowledge. Technology is needed not only when establishing and reviewing alternatives to reach a certain R&D goal, but also when forecasting possible problems and solving them during the innovation process. In sum, science acts as exploratory action in R&D (Gibbons and Johnston 1974; Tijssen et al. 2000) while technology aims at an effective recombination of existing knowledge and its practical improvement.

By converging these two distinguished knowledge sources, new paradigms can spread. Especially, during the invention process, inventors can be inspired and stimulated by the convergence between cross-sources of knowledge (Brooks 1994). Since science provides fundamental ideas and helps in finding effective methods for problem solving with a technological aim (Brooks 1994; Tijssen et al. 2000), its use allows for a more efficient innovation process when organizations develop new products or are adapting new technologies (Brooks 1994). Also, technological knowledge can provide inputs for understanding technological trends and market needs while basic science contributes to the development of solutions that address these needs and requirements (Shibata et al. 2010). In this regard, engineers and scientists' collaboration in R&D is complementary, maximizing convergence synergy (Anselin et al. 1997; Gittelman and Kogut 2003).

2.2.2 Factors influencing the relationship between convergence and innovation

Although the convergence of science and technology plays an important role in innovation by enhancing the efficiency of the innovation process, there are several factors when convergence occurs in invention activities that can lead to different impacts of convergence. One of the important factors of knowledge management is the organization's capacity for handling knowledge (Grant 1996; Argote et al. 2003). To exploit and recombine knowledge with novelty, organizations are required to build up their internal capacity for specific domains (Grant 1996; Caloghirou et al. 2004). With enhanced organization capacity for specialized knowledge such as science, organizations can efficiently identify, acquire, and exploit the knowledge related to scientific domains (Cohen and Levinthal 1990; Grant 1996). Another factor leading to a different impact of convergence is knowledge spillover (Liebeskind et al. 1996; Lawson and Lorenz 1999). Unlike codified and explicit knowledge, which can be obtained and accessed through the records stored in archives and databases (Nonaka 1994), tacit knowledge usually resides in human capital (Hitt et al. 2001). Due to the tacit characteristics of scientific knowledge, it is difficult to transfer scientific knowledge without mobility of researchers (Almeida and Kogut 1999; Lawson and Lorenz, 1999) as well as communication between individuals (Nonaka 1994). The mobility of researchers from basic R&D positively influences an industrial organization's innovation processes (Almeida and Kogut 1999; Herrera et al. 2009), and personal relationships as well as social networking between scientists and industrial practitioners are critical for an effective transfer of scientific knowledge (Siegel et al. 2004). Last, the maturity of scientific knowledge can influence the innovation impact of convergence (Capaldo et al. 2014). The notion of knowledge maturity is defined as "the time elapsed between the original discovery of that knowledge and its incorporation in a new innovation" (Capaldo et al. 2014, pp.5). Cutting-edge knowledge-based innovation usually suffers from limited ways of applications as well as requires additional tests to prove it (Capaldo et al. 2014). As time goes by, innovations based on matured knowledge are shown to be more reliable and applicable because sufficiently matured knowledge is investigated in-depth and has proven its usefulness (Capaldo et al. 2014). In addition, matured knowledge becomes codified and thus can be more easily transferred and understood between researchers (Zander and Kogut 1995). In this notion, the maturity of scientific knowledge determines the efficiency of knowledge searching in convergence.

One of the impactful characteristics for organizations pursuing convergence of science and technology is their differentiated ability for handling scientific knowledge. Organizations' capabilities for handling scientific knowledge, referred to as their scientific capacity, can be determined by the level of the organizations' R&D activities which help to understand fundamental and basic phenomena as well as their accumulation of scientific knowledge (Dierickx and Cool 1989; Gambardella 1992; McMillan et al.

2000). On one side, industrial organizations are usually conducting their innovation activities from a technological perspective and their lack of experience in dealing with scientific knowledge causes them difficulties in engaging in R&D activities based on the scientific domain (Gittelman and Kogut 2003). In other words, a low level of scientific capacity results in organizations having trouble with utilizing scientific knowledge and prevents them from establishing R&D activities based on converging knowledge from science and technology. One the other side, organizations which focused on basic and fundamental research in the past, naturally possess and accumulate scientific knowledge (Dierickx and Cool 1989; DeCarolis and Deeds 1999) that consequently strengthens their scientific capacity and allows them to identify which scientific knowledge is best suited for innovation purposes (Gambardella 1992; Brooks 1994). In case of dealing with both of scientific and technologic knowledge, therefore, the level of scientific capacity determines whether organizations can benefit from convergence or not.

Another factor that can influence the relationship between convergence and the resulting innovation is the possibility for spillover of scientific knowledge through indirect ways (Almeida and Kogut 1999). Both science and technology exchange, interact and converge with each other through direct and indirect ways. Examples of direct ways are obtaining and citing scientific literature from journal articles, textbooks, or handbooks (Gibbons and Johnston 1974; Verbeek et al. 2002), while knowledge spillovers occuring through informal contact and mobility of researchers, mostly on a regional level, are examples of indirect ways (Jaffe 1989; Acs et al. 1994; Anselin et al.

1997; Vedovello 1997; Almeida and Kogut 1999; Bottazzi and Peri 2003; Sorenson 2003). In comparison with technological knowledge, which is usually described in codified forms, scientific knowledge is considered as more tacit. This results in indirect ways of knowledge spillover having considerable stronger effect on the understanding of the scientific regime than direct ways. Therefore, informal communication with scientists will help innovators to better understand the scientific disciplines (Liebeskind et al. 1996; Simeth and Raffo 2013). To enable such communication, being located in proximity to scientific research institutes such as universities or government-sponsored research institutes helps as it increases the chance of formulating social networks between scientists and engineers (DeBresson and Amesse 1991; Anselin et al. 1997). These networks and informal contacts help with both a deeper understanding of science and its practical application (DeCarolis and Deeds 1999). In this regard, scientific knowledge spillover through indirect ways can be considered as an important determinant of the impact of convergence.

Last, the maturity of the employed scientific knowledge can affect the innovation outcomes. Science aids the resolution of technological problems and helps to accumulate novel knowledge. However, there is a 10- to 20-year time lag between advancements of science and their technological applications (Gibbons and Johnston 1974; Van Vianen et al. 1990; Tijssen et al. 2000). The main reason for this lag is the problem of accessibility and codifiability of the scientific knowledge (Cardinal et al. 2001). The newest scientific knowledge, still in its tacit form, is only accessible to the researchers who directly perform the research, and is not yet available in the form of systematically codified knowledge. Accordingly, other researchers cannot easily access it, and even if information was available, it would take a tremendous amount of time and cost for researchers to fully internalize it.

2.3 Organizational factors and explorative R&D

2.3.1 Organization internal factor: top management team

Upper echelon theory assumes that there are substantial differences between each TMT member's cognitive base and their way of perceiving the business environment (Hambrick and Mason 1984; Hambrick 2007). Strategic choices are established through bounded rationality or selective perception based on each individual's past experiences or accumulated knowledge (Cyert and March 1963; Hambrick and Mason 1984). In other words, decisions and evaluations related to the external environment and business opportunities are the reflection of the managers' cognitive base (Tushman and Romanelli 1985; Wiersema and Bantel 1992; Hambrick 2007). The cognitive base is influenced by individual experiences and traits, which previous literature has investigated using observable characteristics of the TMT members such as age, tenure in the organization, functional experience, or educational background (Hambrick and Mason 1984; Wiersema and Bantel 1992; Daellenbach et al. 1999; Tabak and Barr 1999). Therefore, it is necessary to consider the characteristics of the TMT to understand decision making as well as organizational behavior and performance (Hambrick and Mason 1984; Wiersema and Bantel 1992).

Some previous studies addressed the relationships between the characteristics of the TMT and the firm's behavior related to either R&D or innovation (Green 1995; Daellenbach et al. 1999; Alexiev et al. 2010; Chen et al. 2010; Talke et al. 2010). Bantel and Jackson (1989) investigated the innovation adoptions of firms and the composition of their TMT. They revealed that an increase in the TMT's average educational level is positively associated with the firm's technical innovation (Bantel and Jackson 1989). They also confirmed that the heterogeneity of the TMT members' functional background positively influences the firm's innovation. Another work of Ding (2011) focused on the relationship between the educational level of the firm's founders and the firm's adoption of science in the biotechnology sector. Ding (2011) showed that firms are more likely to apply open-science knowledge as the proportion of Ph.D. holders among the firm's founders increases. Chen et al. (2010) addressed how the firm's R&D investment-financial leverage relationship is moderated by several TMT-related factors such as tenure, age, educational level, and stock ownership. According to Daellenbach et al. (1999), a firm's commitment to innovation is positively related with its TMT members' average years of work experience in the current firm as well as in the industry that the firm belongs to. Focusing on the composition of the TMT, rather than on individual members, Talke et al. (2010) addressed how TMT diversity influences innovation-related strategic choices. With regard to explorative innovation, Alexiev et al. (2010) showed the influences of both internal and external advice seeking activities of the TMT and TMT heterogeneity on the firm's explorative innovation. Results of Heavey and Simsek (2013)'s research suggest that perceived technological uncertainties within the TMT affect the firm's entrepreneurship activities related to R&D. In summary, previous research focused on the TMT's characteristics such as age, tenure, education level and heterogeneities. However, there is still a lack of understanding of how the cognitive base is formed by the TMT's past innovation-related experiences and how it subsequently influences the firm's R&D activities.

Functions within an organization can be classified into "output functions", "throughput functions" and "peripheral-functions" (Hambrick and Mason 1984). Both "throughput functions" and "peripheral-functions", including areas such as financing, accounting, marketing, law, and sales, usually use mostly managerial skills to reach their business goals (Daellenbach et al. 1999). Additionally, these functions emphasize the reduction of operation cost, uncertainties and risks to accomplish a stabilized and sustainable management (Hambrick and Mason 1984). Working in one of these jobs for a longer period of time causes individuals to develop risk-averse tendencies in managing activities (March and Shapira 1987; March 1988). As explorative R&D is inherently more risky than exploitative R&D, TMT members who have functional experience in either throughput or peripheral functions will avoid explorative activities and instead prefer exploitative activities. On the contrary, "output functions", such as R&D, usually reach the objective of organizational growth by archiving innovation or capturing technological opportunities through exploring new technologies (Hambrick and Mason 1984). By working on R&D tasks, individuals can directly experience that innovation affects the growth of an organization. Consequently, though the costs and risks of R&D are high, TMT members with functional experiences in R&D will have positive perceptions of innovation.

Not just the functional experience but also the educational background such as formal education in engineering, natural sciences, social sciences, humanities, law, or business administration shape the individual's way of thinking, the response to problems, perception of opportunities and preferences for risk-taking (Hambrick and Mason 1984; Wiersema and Bantel 1992; Daellenbach et al. 1999). Wiersema and Bantel (1992) suggested that majors such as business administration and law tend to emphasize avoiding risks or uncertainties which might pose a danger to the organization. Therefore, members of the TMT who majored in these fields will have more conservative views in regard to risk-taking, which results in managerial decision favoring R&D projects with a low level of risk (Barker and Mueller 2002). On the other hand, majoring in science and engineering leads individuals to recognize the value of innovation clearly and allows them to understand the inherent risks of problem solving processes. Similar to R&D functional experience, studying science and engineering contributes to building a positive cognitive base for innovation by emphasizing that the development of technology is achieved through innovation activities. In short, both functional experience and educational background have an influence on the cognitive base (Hambrick and Mason 1984; Daellenbach et al. 1999) and risk-taking propensity (Tabak and Barr 1999) of each TMT member.

2.3.2 Organization external factor: upstream alliance

Alliances provide efficient ways for organizations to access required resources as well as complementary assets (Teece 1986; Grant and Baden-Fuller 2004). Alliance is often classified as either horizontal or vertical in accordance with where the alliance partners are located in the focal organization's value chain and what resources they are able to provide (Rothaermel and Deeds 2006). In a horizontal alliance, where focal organization and partners belong to the same industry, alliance members are used to compete with each other due to similar objectives and goals (Rothaermel and Deeds 2006). This leads to them also considering each other as potential competitors even though they engage in a joint alliance. For this reason, there are frequently conflicts of interest between members that result in reluctance to share resources or the desire to only provide limited access to their core knowledge. As a result, organization cooperating with horizontal partners may be prevented from obtaining the full advantages of the alliance due to opportunistic behaviors. On the other hand, a vertical alliance is able to avoid such opportunistic behaviors because the partners in this type of alliance are located either upstream or downstream within the focal organization's value chain (Rothaermel and Deeds 2006; Stuart et al. 2007). Industrial organizations often engage in downstream alliances to make practical use of their alliance partners' tangible assets such as manufacturing facilities. Recently, however, upstream alliances have been receiving increasing attention as a primary method for sourcing external knowledge in terms of open innovation (Chesbrough 2003), because knowledge is being nowadays considered as the most strategically important factor among the firm's resources (Grant 1996). Obtaining external knowledge through alliances enables firms to span their boundaries and to combine existing and new knowledge to accomplish innovation (Kogut and Zander 1992). In other words, the increased importance of knowledge in the recent industrial environment has induced firms to put their strategic focus on alliances for learning knowledge rather than alliances for simply utilizing other firms' tangible resources (Powell et al. 1996; Lane and Lubatkin 1998).

Meanwhile, despite firms deploying a large amount of resources to overcome technological barriers, industrial R&D is characterized by high levels of uncertainties and risks during the invention process. These could be overcome by recombining knowledge from different scientific disciplines rather than applying knowledge from narrow fields (Fleming and Sorenson 2004; Gruber et al. 2013). Even scientific disciplines can help to overcome technological barriers, conducting basic scientific research requires enormous resources and entail high risks. Consequently, many firms decide to collaborate with scientific organizations to reduce these costs and risks. For this reason, alliances with scientific institutions have been receiving increasing attention by industrial firms as a primary method for sourcing scientific knowledge (Teece 1986; Grant and Baden-Fuller 2004). Obtaining scientific knowledge through scientific partners enables firms to span their technological boundaries and to combine existing and new knowledge to accomplish innovation (Kogut and Zander 1992). In other words, the increased importance of scientific knowledge in the recent industrial environment has induced firms to put their strategic focus on alliances with scientific partners for learning scientific knowledge rather than alliances for simply utilizing other organizations' tangible resources (Powell et al. 1996; Lane and Lubatkin 1998).

In this sense, industrial firms are actively looking for scientific partners such as universities and scientific research institutes to access the scientific knowledge including principals of operation mechanisms or guiding information for new inventions that could be applied in the early stages of industrial R&D (Rothaermel and Deeds 2006; Stuart et al. 2007). In addition, upstream alliances could provide cutting-edge and emerging scientific information as well as fundamental ideas to industrial firms that help increase the creativity of the industrial researchers (Henard and McFadyen 2005; Stuart et al. 2007; Jong and Slavova 2014) and innovation outputs (Stuart et al. 2007). Also, firms engaging in upstream alliances may increase the efficiency of their R&D processes as the ability to access scientific knowledge, which require a large amount of resources to investigate, from upstream partners allows the firms to focus on practical R&D which requires the investment of a relatively smaller amount of resources than basic research (Katz and Martin 1997; Baum et al. 2000; George et al. 2002; Jong and Slavova 2014).

Chapter 3. Convergence between Science and Technology[1]

3.1 Introduction

With the ever increasing complexity of innovation, resolving technological problems as well as contriving new concepts by depending solely on technology results in less impactful innovation outcomes (Van Vianen et al. 1990). To surmount the technological problems, which can arise in the invention process, and to realize creative ideas, it is important to effectively recombine and apply knowledge from more than one source such as knowledge from scientific fields (Caraça et al. 2009; Simeth and Raffo 2013). Actually, industrial engineers seek the advice of scientists to solve their technological problems (Gibbons and Johnston 1974) and this scientific searching activity can increase efficiency at the invention level (Fleming and Sorenson 2004). Science can foster innovation (Fleming and Sorenson 2004) and, through the explanation and understanding of natural phenomena, provides insight for solving technological problems occurring during the research and development (R&D) process (Gibbons and Johnston 1974; Dalrymple 2003). In this sense, previous literature has increasingly focused on the effects and importance of science for innovation (Van Vianen et al. 1990; Brooks 1994;

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Tijssen 2002; Verbeek et al. 2002; Gittelman and Kogut 2003; Cassiman et al. 2008; Caraça et al. 2009; Subramanian and Soh 2010). The common notion found in these studies is that science assists in solving difficulties in the invention process and, as a result, positively influences innovation.

Meanwhile, innovation is the response of industrial R&D organizations to the needs of customers and markets and is generally approached from the practical and application side (Abernathy and Clark 1985). Because the objectives and aims of science mainly focused on solving fundamental issues, an overexploitation of scientific knowledge in the R&D process lead to solutions which are far from the demands of the technological market. This would lead to innovation which has less industrial impact than innovation derived from a balanced use of scientific (basic) and technological (applied) knowledge (Gittelman and Kogut 2003). In order to archive impactful innovation, it is important to understand the combined effects of science and technology, referred to as the convergence of science and technology, as well as the individual effects of science and technology (Caraça et al. 2009). Many studies on R&D and innovation have so far focused on the contributions of science to R&D or innovation (Brooks 1994), or the relationship between basic and applied research (Rosenberg 1982), however, the converged effects of science and technology to innovation, especially empirical aspects, have not yet been sufficiently addressed. Moreover, innovation is a process that combines knowledge with new ideas in a creative way from the knowledge side (Kogut and Zander 1992; Pisano 1994; Nonaka and Takeuchi 1995). Scientific knowledge usually is very complex and may involve tacit elements, which raises the need to also investigate the factors that affect learning and obtaining the tacit elements of scientific knowledge during the invention process in order to comprehensively understand the effects of the convergence of both scientific and technological knowledge on innovation.

From the perspective of knowledge, this study defines the concept of convergence as combining knowledge from different fields or sources such as science and technology to create innovation which contains not only the integrated value but also synergies of the combined knowledge (Kogut and Zander 1992; Hacklin 2008; Curran et al. 2010; Curran and Leker 2011). Due to complementary roles and effects of science and technology in the invention process, the convergence of science and technology produces the synergies that leads to the development of more impactful innovation than processes purely depending on either science or technology (Brooks 1994). In spite of synergistic effects of convergence affecting the innovation outcomes, organizations enjoy different level of these synergy effects. Because the characteristics of scientific knowledge are different compared to those of technological knowledge, organizations are required to accumulate scientific knowledge to build up the capabilities for efficiently dealing with the integration of science (Dierickx and Cool 1989; Gambardella 1992; DeCarolis and Deeds 1999; McMillan et al. 2000). Furthermore, due to the tacit aspects of scientific knowledge, knowledge spillover by nearby researchers with regard to solving technological problems through scientific domains would contribute to convergence effects (Liebeskind et al. 1996; Anselin et al. 1997; Almeida and Kogut 1999; DeCarolis and Deeds 1999; Simeth and Raffo 2013). Also, the accessibilities and codifiability of scientific knowledge influences the benefits that organizations can derive from convergence (Cardinal et al. 2001).

In this sense, this chapter investigates the effects of convergence between science and technology on innovation impact as well as the influences of moderating factors on this relationship at the organizational level. Specifically, I analyzed how the innovation impact is influenced by increasing the proportion of scientific knowledge in convergence. Aiming to provide a more comprehensive picture of this relationship, this research also examine how an organization's science capacity, regional scientific knowledge spillover, and the maturity of the scientific knowledge moderate the relationship between convergence and innovation impact. To conduct an in-depth analysis of convergence, this research employs data on patents and scientific publications.

This chapter has several implications. First, this study identifies multiple factors which affect innovation by empirically examining convergence effects of science and technology which were largely ignored by existing literature. In addition, this chapter points out the importance of R&D collaboration and investment in basic science, specifically, the effects of convergence on innovation, which has implications for strategy decisions of R&D organizations. Lastly, this research examines the regional aspects of scientific knowledge spillover and formulate recommendations for policy to boost convergence or the interaction of science and technology.

3.2 Research hypotheses

3.2.1 Effects of the convergence of science and technology on innovation

Positive effect of convergence of science and technology on innovation is like followings. First, increasing convergence increases R&D efficiency. Technology-based R&D activities involve performing routines through the use of accumulated knowledge and experiences, and as a result of the path dependency focus on innovation through recombination (Fleming and Sorenson 2004). Therefore, purely relying on technology can lead to a trial and error based problem solving, which is not only time and cost consuming but also fails to address the underlying problems and causes. Science, on the other hand, enables the prediction of technological components' characteristics, even if they have not directly been experienced before (Fleming and Sorenson 2004). Therefore, when science and technology converge in the recombination based research and development process, it allows organizations to find appropriate solutions without the need to test all possible combinations, saving time and resources (Brooks 1994; Nightingale 1998; Cassiman et al. 2008). This allows the focus to be placed on the best alternative or the most promising research direction. Improving the research efficiency and reducing the unnecessary use of resources by defining a clear research field is important to improve innovation performance (Gambardella 1992; Cassiman et al. 2008).

Moreover, as convergence of science and technology increases, the new ways of solving problems arise. Whereas only using technology makes it difficult to uncover the fundamental causes and solutions of problems, science allows to take a deeper look into the fundamental causes of problems, enabling to reach solution by profound understanding rather than trial and error (Ahuja and Katila 2004; Fleming and Sorenson 2004). Therefore, engineers often consult scientific sources by looking into scientific literature handbooks and textbooks when they are solving technological problems (Gibbons and Johnston 1974; Fleming and Sorenson 2004). According to a survey of engineers who engage in industry R&D performed by Gibbons and Johnston (1974), scientific knowledge did not only directly provide solutions for technological problems, but also even if it did not, science could provide the insights which contributed to reaching a solution. This implies that science not only helps to reinterpret technological problems, but can also serve as an information source providing direct solutions. Therefore, the alternatives resulting from convergence of science and technology could contribute to an enhanced innovation impact by enabling new ways of problem solving.

On the other hand, as the proportion of science in research and development increases, an increasing amount of resources is required for internalizing the scientific knowledge while at the same time, the uncertainty of research increases (Ahuja and Lampert 2001; Ahuja and Katila 2004). To better understand scientific knowledge, it is necessary to understand the underlying laws, theories and concepts of natural phenomena, which results in the organization having to perform basic research in order to be able to incorporate scientific knowledge. Unlike technology, scientific knowledge is usually tacit, and requires a huge amount of time and resources to understand (Cardinal et al. 2001). Consequentially, as the proportion of science in innovation increases, the efficiency of R&D declines as the organization's resources are invested more on the internalization of scientific knowledge than on other R&D activities. By extension, depending too much on scientific knowledge could result in losing the focus of the research. If the innovation process relies more on scientific knowledge, which is related to the results of basic research, rather than technological knowledge, the organization is at risk of losing touch with changes of technology and market needs. Therefore, over-reliance on scientific knowledge rather than balancing it with technological knowledge will diminish the positive effects of the convergence on the innovation impact.

Hypothesis 3-1*: The proportion of science in the convergence of science and technology has a curvilinear (inverted U-shape) relationship with innovation impact.*

3.2.2 Organizations scientific capacity

Scientific capacity is the ability of an organization to identify the most appropriate scientific knowledge as well as effectively apply it in convergence. If organizations mainly conducted their R&D activities focusing on finding technological alternatives and solving technological problems, researchers will be unfamiliar with handling scientific knowledge and equipment, increasing the chance of inappropriate use of science as a result (DeCarolis and Deeds 1999). Because the characteristics of scientific knowledge are different from those of technological knowledge, it is hard for researchers who are accustomed to technology-based invention processes to employ and apply knowledge from the scientific discipline into their innovation processes within a short period of time (Gambardella 1992). Even if technology-oriented researchers are given sufficient time to review scientific literature, their lack of direct experiences with scientific knowledge causes difficulties in understanding it completely. Therefore, it can be argued that a low level of scientific capacity results in organizations having difficulties utilizing scientific knowledge and conducting R&D activities based on convergence. These difficulties amplify with an increase in the proportion of scientific knowledge in the convergence process. However, if organizations possess experience with scientific activities as well as technological activities that accumulated considerable scientific knowledge, they can more efficiently identify the most appropriate scientific knowledge in convergence (Dierickx and Cool 1989; Gambardella 1992; DeCarolis and Deeds 1999). Additionally, their strengthened scientific capacity enables them to put scientific knowledge to practical use in more effective ways. In summary, researchers that are familiar with scientific knowledge will act in important roles when identifying scientific knowledge and applying it to solve technological problems (Brooks 1994; Verbeek et al. 2002; Gittelman and Kogut 2003). Consequently, at each proportion of science in the convergence, firms with a higher level of scientific capacity will be able to produce more impactful outcomes of the innovation process.

Hypothesis 3-2*: An organization's scientific capacity positively moderates the relationship between the proportion of science in the convergence of science and technology and innovation impact.*

3.2.3 Regional scientific knowledge spillover

Generally, researchers in organizations which mainly focus their R&D activities on solving technological problems have difficulties in applying and handling scientific knowledge in convergence. To overcome this challenge, it is important for engineers to be placed in regions where they can easily seek advice from experts in scientific domains. Engineers in industrial R&D were found to source considerable scientific knowledge and idea for solving technological problems through social relationships with scientists (Gibbons and Johnston 1974; DeBresson and Amesse 1991; Vedovello 1997; DeCarolis and Deeds 1999; Simeth and Raffo 2013). To take benefit of knowledge spillover through informal communications, industrial organizations are actively building relationships with scientific institutes, e.g., industry-academic joint research or other collaborations such as the sharing of equipment to foster conditions for their engineers to work together with experts in science (Anselin et al. 1997; Vedovello 1997; Zucker et al. 2002; Cassiman et al. 2008). Personal contacts with scientists can provide information about theories and principles to help solve technological problems by transforming scientific literature into readily understandable language for engineers (Gittelman and Kogut 2003). Additionally, scientific institutes such as universities and basic research institutes can provide qualified manpower, i.e., employees who are well trained for handling scientific phenomena, to adjacent industrial organizations (DeCarolis and Deeds 1999; Simeth and Raffo 2013). This mobility of researchers is another way of knowledge spillover (Almeida and Kogut 1999) and Angel (1989) insisted that these researchers will seek jobs in the same regional area rather than moving to other areas. These researchers can also increase the possibility of identifying optimal solutions by evaluating the practicality of existing alternatives. These effects of knowledge spillover enable engineers to borrow the ideas and opinions from scientific experts and resolve the difficulties arising from a high proportion of science in convergence (Liebeskind et al. 1996). In summary, the scientific knowledge spillover at the regional level can help organizations to overcome the obstacles in convergence of science and technology. Thus, I expect the regional scientific knowledge spillover to positively moderate the relationship between innovation impact and the convergence of science and technology, which leads to the following hypothesis:

Hypothesis 3-3*: The regional scientific knowledge spillover positively moderate the relationship between the proportion of science in the convergence of science and technology and innovation impact.*

3.2.4 Scientific knowledge maturity

Before applying knowledge in the invention process, organizations need to understand the principles of the particular knowledge and procedures for dealing with it. To achieve successful innovation outcomes from convergence, it is important for industrial researchers who are unfamiliar with scientific disciplines to easily access scientific knowledge. In comparison with cutting-edge technological knowledge, which is usually quickly re-tested by other engineers and recorded systematically in codified forms, investigating and verifying recently discovered scientific phenomena require substantial amounts of time and resources (Cardinal et al. 2001; Capaldo et al. 2014). In order to directly apply the newest scientific knowledge created by universities and research institutes, additional experiments to verify the results are required. Conducting such experiments requires a large amount of resources to examine recently published works and discern the useful knowledge contained within them. Even when only a small proportion of new scientific knowledge is used in convergence, these additional investigations reduce the efficiency of the innovation process. As the proportion of new scientific knowledge in the convergence increases, spending substantial resources on knowledge searching makes it more difficult to focus on possible alternatives, ultimately decreasing the possibility of finding the optimal solution, and reducing the impact of the resulting innovation.

As time goes by, however, matured scientific knowledge can reduce the input of unnecessary resources through rigid verification performed by other researchers (Pisano 1994; Cardinal et al. 2001; Capaldo et al. 2014). In other words, accessing mature scientific knowledge, which is verified, codified and proven to be effective, places less demand on an organization's resources (Brooks 1994; Zander and Kogut 1995; Cardinal et al. 2001). Moreover, matured scientific knowledge would have been investigated from various perspectives which helps researchers to postulate diversified alternatives and increases the chance of producing impactful innovation (Capaldo et al. 2014). As organizations pursuit and use pre-verified matured scientific knowledge in convergence, rather than the newest scientific knowledge, they gain more benefits from the convergence of scientific and technology. Ultimately, at each proportion of scientific knowledge, a more mature knowledge allows the organization to produce more impactful innovation.

Hypothesis 3-4*: The maturity of the scientific knowledge positively moderates the relationship between the proportion of science in the convergence of science and technology and innovation impact.*

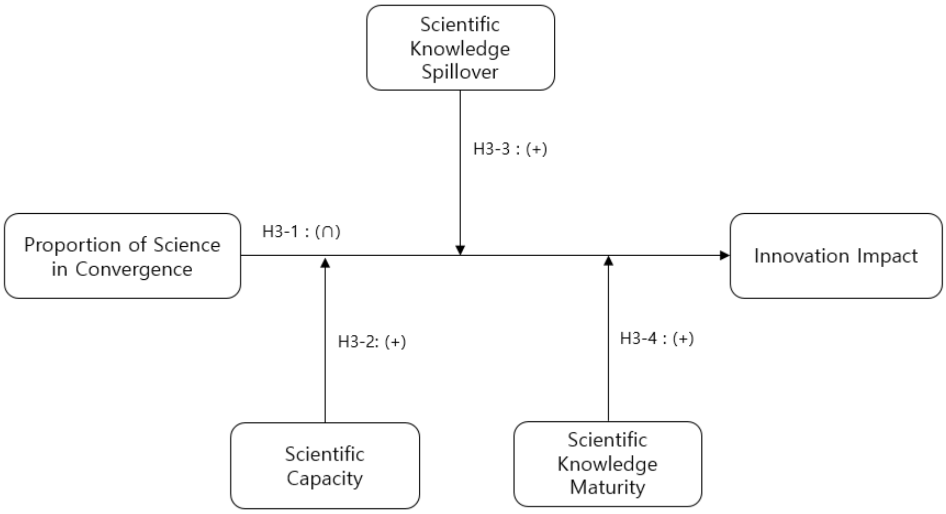

Figure 3-1. Conceptual Model for Chapter 3

The conceptual diagram in Figure 3-1 shows the relationships between the suggested hypotheses.

3.3 Methods

3.3.1 Data

The patent, which is the basic form of intellectual property in industrial R&D, is a useful tool to get information about technological knowledge and to recognize an invention's technological novelty. Patent documents provide technological information which containing an abstract, as well as detailed claims and a description of the invention.

Moreover, citation information and general information on inventor, assignee and lawyer on the front page enable analysis on innovation contained in the patent from various points of view. In a patent submitted to the United States Patent and Trademark Office (USPTO), the assignee and the examiner should list references to the sources of knowledge which were used in the invention process. In general, patent references can be divided into backward citation references -references cited by the focal innovation- and forward citations -other sources citing the focal innovation-. Analyzing the backward citation references enables identification of prior knowledge which inspires the invention process, while analyzing the forward citation references allows for tracing descendant knowledge such as inventions which were influenced by the patent (Trajtenberg et al. 1997; No and Park 2010). Backward citation references are further divided into patent references and non-patent references (NPRs) which consist of references to journal articles, conference proceedings, books, databases, textbooks, corporate reports and other documents (McMillan et al. 2000; Callaert et al. 2006). Previous literature has used science related references from non-patent references as a tool to represent the direct relationship between an innovation and scientific knowledge (Narin and Noma 1985; Van Vianen et al. 1990; Tijssen et al. 2000; Verbeek et al. 2002; Cassiman et al. 2008). To consider the influence of science related references, this research limited the scientific knowledge to journal articles which were published in Science Citation Index (SCI) listed journals only (McMillan et al. 2000; Gittelman and Kogut 2003). The information of SCI listed scientific publications was retrieved from

Web of Science provided by Thomson Reuters.

Even though all technology fields require a certain extent of scientific knowledge, its contribution varies in different industries. In particular, technology fields related to pharmaceuticals are highly concerned with the scientific knowledge to the extent that it is often referred to as a science-based industry (Narin and Noma 1985; Van Vianen et al. 1990; Schmoch 1997; Tijssen et al. 2000). According to Callaert et al. (2006) and Van Vianen et al. (1990), the research and development process of patents assigned to organizations in the pharmaceutical field depended more on science than technology. Moreover, comparing the pharmaceutical industry to other industries, it exhibits a high tendency of protecting intellectual property by patenting (Rosenberg 1990). Accordingly, using patent data is a suitable approach to analyze innovation in the pharmaceutical industry. I selected patents containing pharmaceutical technology by following the United States Patent Classification (USPC) used by the USPTO. Specifically, I selected only U.S. patents, which are classified in USPC 424 or 514 and were granted in 2008 to organizations located in the U.S. (Narin and Noma 1985; Van Vianen et al. 1990; Penner-Hahn and Shaver 2005). As this research focuses on the organizational level, I excluded patents assigned to individual inventors. The final dataset included 2,074 patents granted to 702 organizations. The total number of backward patent citations was 43,208 while 68,540 references were SCI listed journal articles. Over the timeframe of five years, the focal patents received a total of 4,989 forward citations.

3.3.2 **Variables**

3.3.2.1 Dependent variable

Number of forward citations received: To proxy innovation impact, the number of forward citations received by each focal patent had been counted (Gittelman and Kogut 2003). Forward citations are an indicator for the technological and economical value of a patent (Trajtenberg et al. 1997; Harhoff et al. 1999; Sorenson and Fleming 2004; Cassiman et al. 2008). The higher the number of forward citation received, the more follow-up innovation has been influenced by the concepts and ideas of the focal patent. Since patented technology loses most of its value within the first few years after publication, I only considered forward citations received until five years after the patent was granted to measure innovation impact (Sorenson and Fleming 2004; Mehta et al. 2010).

3.3.2.2 Independent variables

Convergence ratio: To calculate convergence of science and technology, this research adopts a measurement which was suggested by Trajtenberg et al. (1997). The variable of this research represents the ratio of the scientific knowledge relative to the entire knowledge, both scientific and technological, that was used in innovation as described in the patent. While Trajtenberg et al. (1997) considered the entire non-patent references as scientific knowledge, this research takes a more fine grained approach and only considers scientific publications listed on the SCI as scientific knowledge sources (Gittelman and Kogut 2003; Callaert et al. 2006). The variable is calculated by the number of scientific publications over the total references of the focal patent.

$$Convergence\ ratio = \frac{Number\ of\ Scientific\ Publications}{Number\ of\ Total\ References}$$

Scientific capacity: I identified each organization's capability for handling scientific knowledge in the innovation process. If the organization's innovation process is biased towards focusing on more fundamental phenomena than technological issues, its outcomes will be released in the form of scientific publications rather than patents. In this notion, I identified the number of scientific publications listed on the SCI by each organizations' employees in the periods of 2003 to 2007 to proxy organizations' scientific capacity.

Regional scientific knowledge spillover: To proxy the scientific knowledge spillover on the regional level, I adopted the method used in Almeida et al. (2011). They captured the magnitude of regional knowledge spillover through the total knowledge created in each region, in the case of the US the individual states. In this respect, they assumed that the number of total patent granted to entities in each state represents the probabilities for knowledge spillover occurring in that region. Compared to Almeida et al. (2011), I identified the total scientific publications instead of patents due to this research focusing on scientific knowledge spillover rather than technologic knowledge spillover. Specifically, I obtained the total number of scientific publications listed on SCI for each state in the US during the 2003–2007 period. Thereafter, I calculated the regional scientific knowledge spillover of each state through the average number of total publications created in each state and transforming it to the log scale.

Maturity of the scientific knowledge: I identified the year of publication for each journal paper from the non-patent reference information of the patents. I then calculated the average time lag between the knowledge sources' year of publication and the patent granted year (2008) for each patent (Van Vianen et al. 1990). This variable represents a measure of how much an innovation depends on mature scientific concepts or ideas. For example, for an innovation which is based on scientific knowledge, which was published on average 10 years ago (1998), the value of this variable was calculated as 10.

3.3.2.3 Control variables

Research capacity: To capture the research and development capacity of the R&D organization, I identified the total number of patents granted to the organization in the past five years. For R&D organizations, successful research experience in the past hints at an efficient internal organization of research and development. Because the efficiency to conduct research and development can directly influence innovation output, the research capacity of each R&D organization should be controlled (DeCarolis and Deeds 1999). Due to the large variation of the number of patents granted to the different organizations, I reverted to using the log scale.

Pharma-specific experiences: Besides the general patenting and R&D experience of an organization, it's experience with a specific field of technology can have an impact on its innovation outputs. To control for this, I measured the organizations' experience in the pharmaceutical industry by identifying the year in which it was granted its first pharma-related (USPC 424, 514) patent. Based on this date, I calculated the time lag between the year of the first pharma-related patent granted and the focal year (2008) for each organization.

Originality: The impact of patented innovation can be influenced by its cited knowledge. Specifically, the notion of originality, which is proposed by Trajtenberg et al. (1997), refers to how much the focal innovation is affected by prior innovation from various technological fields. Increasing originality (employing concepts or ideas from diverse backgrounds) shows that the focal innovation consists of divergent ideas and is considered to be rather basic. The Herfindahl index was used to calculate the originality of each focal innovation.

$$Originality = 1 - \sum_{k}^{N} \left(\frac{Number\ of\ cited\ patents\ in\ class\ k}{Number\ of\ cited\ patents} \right)^2$$

Technological diversity: An organization's R&D experiences in diverse fields can influence the efficiency of R&D such as reducing search times and costs. I obtained the list of the entire patents which were granted to each organization and adopted the

Herfindahl index as following

$$Technological\ diversity = 1 - \sum_{i \in F} {p_i}^2$$

where p_i represents the proportion of organization's patent classified in technological class i and F is the set of technological patent classes.

Technological knowledge maturity: Similar to scientific knowledge maturity, I also considered the maturity of the technological knowledge which is used in convergence and can influence the impact of innovation (Skilton and Dooley 2002). Similar to the method used to calculate scientific knowledge maturity, I identified the granted year of the cited patents of the focal innovations. After that, I calculated the average time lag between the granted year of the cited patents and the focal year (2008) for each innovation.

Assignee type: I introduce two dummy variables to take into account possible effects of the type of organization. Following the assignee type provided by the USPTO, I classified organizations as firms, universities, and other research institutes such as hospitals or governmental research laboratories.

Pharma-related technology type: In this research, I analyzed the pharmaceutical related technologies through patent data which are classified into USPC 424 and 514 (Van Vianen et al. 1990). Even though both classes are defined by USPTO using the same title, "Drug, bio-affecting and body treating compositions", these two classes represent slightly different technologies. To account for this effect, I included a dummy variable distinguishing both patent classes in the empirical models.

3.3.3 Model

The dependent variable of this research, the number of forward citations received, is a nonnegative count variable. Generally, non-negative count variables are supposed to follow a Poisson or negative binomial distribution. Before adopting the Poisson model, I must have to confirm that the variance equals the average value. However, in the case of the dependent variable of this study, the variance exceeds the average and the performed likelihood-ratio test confirmed an over-dispersion problem. Consequently, for this case, a negative binomial model is more appropriate than using the Poisson model. The negative binomial model can be used even when an over-dispersion problem occurs because, unlike the Poisson model, it accounts for a bias due to omitted variables and estimates for unobserved heterogeneity. While it is known that most forward citations are received within the first five years after a patent is granted (Mehta et al. 2010), some patents may have influenced others even after that time span due to a slower pace of technological development or a change of technological trends. Therefore, the forward citation received might have been calculated as zero value excessively, as I do not consider citations received after five years. I performed a Vuong statistic to address the goodness of fit of a zero-inflated negative binomial model. The results of the Vuong statistic test indicate that a zero-inflated negative binomial model shows a higher goodness of fit than a negative binomial model. Previous research had analyzed the citation variable of patent data using a zero-inflated negative binomial model (Lee et al. 2007) and in this research, I also decided on using a zero-inflated negative binomial model to test suggested hypotheses.

3.4 Results

Table 3-1 shows the descriptive statistics and correlations between the variables. On average, there were 2.25 forward citations received to each pharmaceutical technology related patent within the five years after it had been granted. Actually 1,214 patents within the sample did not received any forward citation from follow-up inventions while 149 patents received more than ten forward citations. This shows that only a small number of inventions has the potential to influence subsequent innovations in the same industry field. Moreover, on average, 54 % of all citations in the patents were made to scientific sources, indicating that the high level of convergence between science and technology in the pharmaceutical field and that research and development in the industry was mainly influenced by science rather than technology (Van Vianen et al. 1990). The average maturity of scientific knowledge, was 13.6 years. This finding indicates the existence of a time lag between the knowledge creation and application of about 15–16 years when considering the 2-3 years lag between patent application and grant.

Table 3-1. Descriptive statistics and correlations matrix of the variables

	Mean	S.D.	1	2	3	4	5	6	7	8	9	10
1. Forward Citations	2.2523	4.0014	1									
2. Convergence Ratio	.5461	.3204	-.0769	1								
3. Scientific capacity[1]	4.2114	2.8925	-.0870	.2517	1							
4. Knowledge spillover[1]	8.7646	.9061	.0938	-.0130	-.0712	1						
5. Knowledge maturity (Sci)	13.6050	6.2580	.0338	-.0910	-.0221	.0066	1					
6. Innovation experience[1]	3.3106	2.1966	-.0361	-.0275	.4039	-.0695	.0152	1				
7. Pharma specific experience	15.0374	11.6525	-.1196	.1720	.5312	-.0807	-.0202	.3901	1			
8. Originality	.4243	.2728	.1289	-.2113	-.1579	.0591	.0786	-.1323	-.1579	1		
9. Technological diversity	.3462	.2592	.0632	-.1583	-.4887	.0386	.0301	-.4354	-.6095	-.0195	1	
10. Knowledge maturity (Tech)	10.7156	4.3782	-.0297	-.1204	-.0550	.0104	.2532	.0001	-.0248	.2407	.0126	1

Note: N=2,074. [1] Transposed to log scale. Dummy variables were excluded.

Table 3-2. Regression results for innovation impact

Dependent Variable (Number of forward citations)	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Control Variables						
Innovation experience	.0160 (.0156)	.0180 (.0157)	.0143 (.0164)	.0190 (.0156)	.0185 (.0164)	.0127 (.0171)
Pharma specific experience	-.0079** (.0031)	-.0080*** (.0031)	-.0093*** (.0032)	-.0067** (.0031)	-.0110*** (.0032)	-.0101*** (.0033)
Originality	.456*** (.105)	.470*** (.108)	.476*** (.108)	.449*** (.108)	.487*** (.114)	.459*** (.115)
Technological diversity	-0.0451 (.147)	-.0324 (.147)	-.0168 (.148)	.0073 (.147)	-.0393 (.155)	.0065 (.156)
Knowledge maturity (Tech)	-.0185*** (.0062)	-.0180*** (.0062)	-.0173*** (.0062)	-.0172*** (.0062)	-.0173** (.00679)	-.0155** (.0068)
Assignee type (Dummy)			*Included*			
Technological field (Dummy)			*Included*			
_Cons	1.515*** (0.142)	1.390*** (0.153)	1.280*** (0.171)	1.342* (0.705)	1.833*** (0.246)	1.808* (1.057)
Independent Variables						
Convergence Ratio		.354** (.327)	.820** (.540)	6.895*** (3.335)	3.136*** (.983)	10.03** (4.563)
Convergence Ratio^2		-.188** (.347)	-.635** (.584)	-8.413** (3.379)	-3.792*** (1.016)	-11.76*** (4.296)
Scientific capacity			.0425 (.0259)			-.0407 (.0423)
Convergence Ratio x Scientific capacity			.143* (.117)			.210* (.169)
Convergence Ratio^2 x Scientific capacity			-.130** (.120)			-.169* (.155)
Knowledge spillover				.0021 (.0793)		.0094 (.116)
Convergence Ratio x Knowledge spillover				.815** (.378)		.730 (.499)
Convergence Ratio^2 x Knowledge spillover				-.970** (.383)		-.864* (.469)
Knowledge maturity (Sci)					-.0194* (.0114)	-.0167 (.0114)
Convergence Ratio x Knowledge maturity (Sci)					.206*** (.0625)	.189*** (.0627)
Convergence Ratio^2 x Knowledge maturity (Sci)					-.252*** (.0677)	-.237*** (.0678)
Observations	2074	2074	2074	2074	2074	2074
Log-Likelihood	-3160.79	-3158.54	-3156.98	-3151.58	-2866.21	-2858.84
Chi-Square	47.59***	52.08***	55.22***	66.01***	63.32***	78.05***

Note: ***p<0.001; **p<0.01; *p<0.05; two-tailed tests.

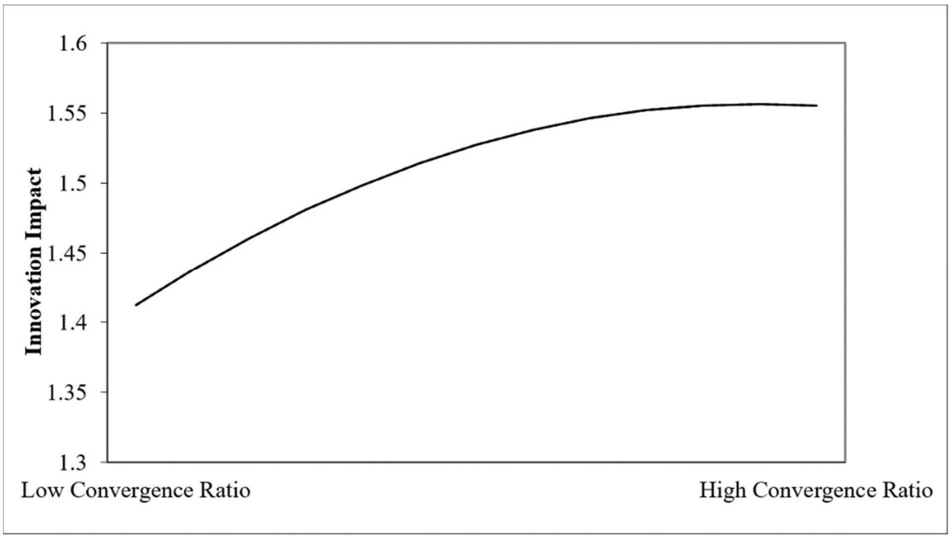

Figure 3-2. The relationship between the convergence of science and technology and innovation impact

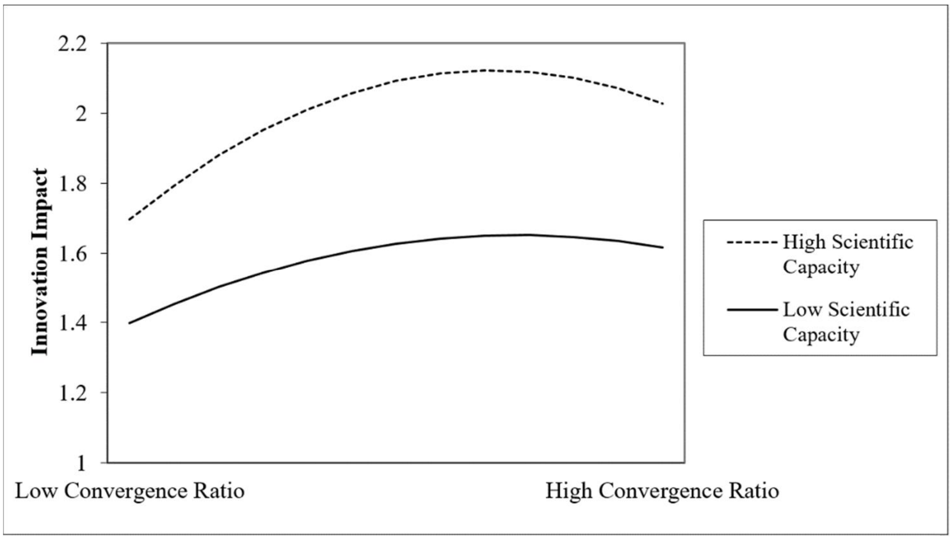

Figure 3-3. The moderation effect of scientific capacity on the relation between the convergence of science and technology and innovation impact

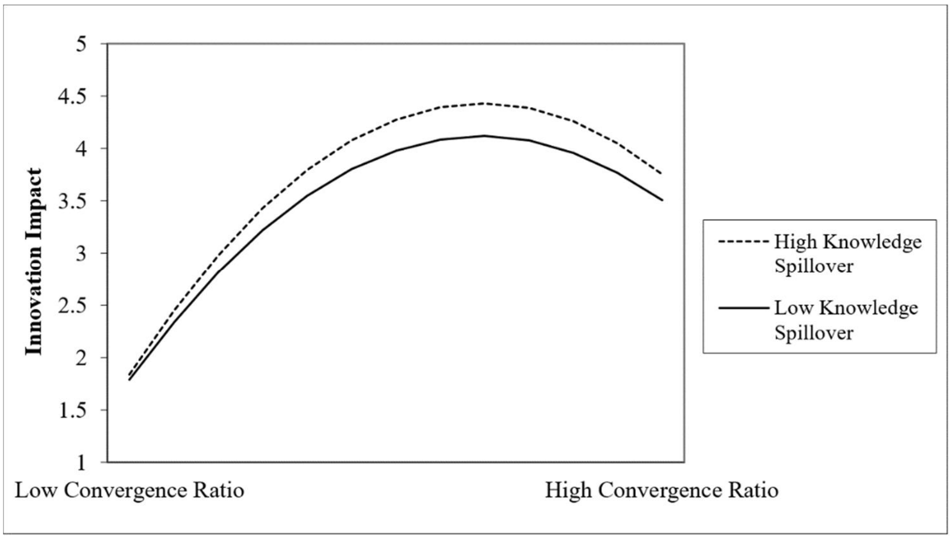

Figure 3-4. The moderation effect of knowledge spillover on the relation between the convergence of science and technology and innovation impact

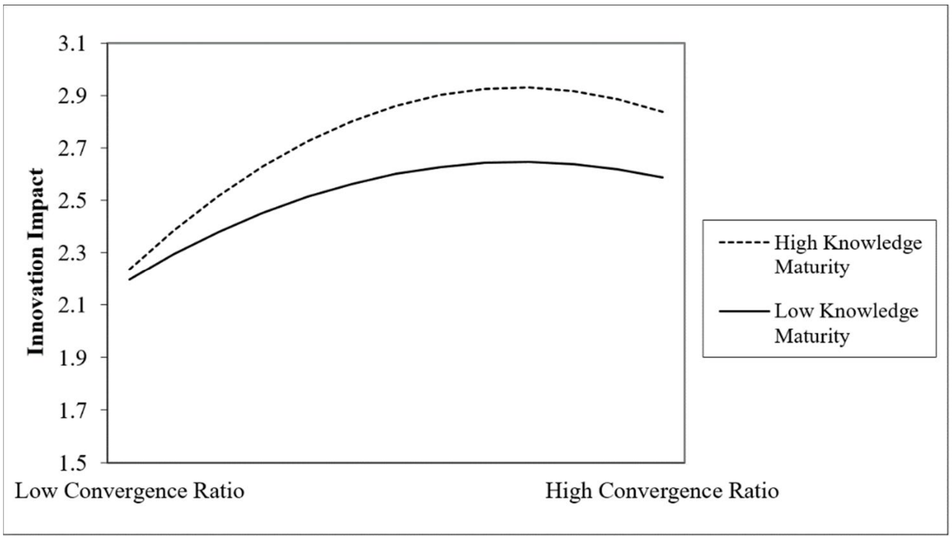

Figure 3-5. The moderation effect of knowledge maturity on the relation between the convergence of science and technology and innovation impact

Table 3-2 shows the results of the zero-inflated negative binomial regression. Model 1 is the basic model containing only the control variables. The independent variables were analyzed hierarchically in Model 2 to Model 5. Model 6 is the full model, containing all the variables used in the analysis. The square term of the convergence ratio has been included to test Hypothesis 3-1 which proposed a non-linear relationship with the dependent variable. Meanwhile, Dawson (2014) and Aiken and West (1991) indicated that both coefficient's equal sign and statistically significance of the interaction term of the moderation variable and the square term of the main effect are required to verify both the quadratic main effect and its linear moderation effect. In this respect, I constructed both interaction variables of the moderation variables and the linear and square terms of the convergence ratio to test Hypotheses 3-2 to 3-4.

First of all, the linear variable of convergence ratio was found to be positively significant in both Model 2 (β: 0.354, p-value<0.01) and Model 6 (β: 10.03, p-value<0.01). Similarly, the square term of the convergence ratio was negatively significant in both Model 2 (β: -0.188, p-value<0.01) and Model 6 (β: -11.76, p-value<0.001). It implies that innovation impact increases with an increase in the proportion of scientific knowledge in the convergence of science and technology. However, positive influence of the increasing scientific knowledge in convergence on innovation impact diminished and confirms the Hypothesis 3-1. To be specific, the relationship between the convergence ratio and innovation impact, as seen in Figure 3-2, shows a curvilinear. That is, high dependency on scientific knowledge, rather than balancing technology and scientific knowledge, during the innovation process diminishes the increase of the innovation impact.

Next, for testing the moderation effect of scientific capacity, I found the interaction term of scientific capacity and the square term of convergence ratio were significant and had equal signs (both negative) in both Model 3 (β: -0.130, p-value<0.01) and Model 6 (β: -0.169, p-value<0.05). As the organizations' scientific capacity increases, it positively moderates the relationship between innovation impact and convergence as can be seen in Figure 3-3. This result indicates that enhanced capabilities of organizations to handling scientific knowledge in more appropriate ways increase the probability of an impactful innovation from convergence. These results support the Hypothesis 3-2.

Following Hypothesis 3-3, I expected that the scientific knowledge spillover at the regional level positively moderates the relationship between innovation impact and convergence of science and technology. As the results of Model 4 and Model 6 show, the interaction term of knowledge spillover and square term of convergence ratio was significant in both models (β: -0.970, p-value<0.01 and β: -0.864, p-value<0.05, respectively) and had an equal sign as the square term of convergence ratio. These results indicate that the moderation effect of the regional scientific knowledge spillover on the relationship between convergence and innovation impact was, as predicted, positive. This relationship is shown in Figure 3-4. These results support the Hypotheses 3-3 and show that regional scientific knowledge spillover effects are important for innovation based on the convergence of scientific and technological knowledge, especially when the proportion of scientific knowledge is high. In other words, the most impactful innovations are developed in an environment with heavy scientific knowledge spillover.

Finally, I tested the effects of the maturity of the scientific knowledge used during the convergence on innovation impact. The results of Model 5 and Model 6 show that the interaction term of maturity of the scientific knowledge and the square term of convergence ratio were both negatively significant (β: -0.252, p-value<0.001 and β: -0.237, p-value<0.001, respectively). As scientific knowledge becomes more mature, it becomes more accessible and its usefulness is already validated, which makes it easier to produce novel alternatives based on it. Figure 3-5 shows that in the case of a high dependency on matured rather than non-matured scientific knowledge, the innovation impact by highly-matured scientific knowledge was higher than that of lower-matured scientific knowledge with an increase in the convergence ratio. It seems that improved and easier access and proven usefulness of scientific knowledge helps an organization to focus on the most promising alternatives.

Additionally, I found that the pharma-specific experience negatively affects innovation impact. This finding indicates that the probability of research output of an emergent R&D organization being an impactful solution is higher than those of older, established R&D organizations. Furthermore, this result can be understood as a catch-up strategy of latecomer firms. Latecomer firms either follow the technological ladder established by the incumbent firms to introduce incremental improvements or choose new technological paths, which were not yet discovered by the forerunners, to accomplish radical innovations (Ju et al. 2016). When latecomer firms refuse to be imitators, they conduct basic research to increase their understanding of principals (Ju et al. 2016). From the case of Huawei (latecomer) and Ericsson (incumbent) introduced by Ju et al. (2016), patents granted to Huawei cited a larger number of non-patent references, which represent the engagement with basic research, than those of Ericsson. Thus, the results of Chapter 3 complement the existing literature on catch-up strategies of firms. Another finding from the control variables is that originality positively affects innovation impact. By combining knowledge from particular technology fields, rather than a broad range of fields, increases the probability of the research output stimulating future development. Last, I found that technological knowledge maturity negatively affects innovation impact.

3.4.1 Additional analysis

One of the aims of Chapter 3 is to increase the understanding of the roles and effects of science in convergence on innovation impact, which was measured by forward patent citations. Meanwhile, U.S. patents provide various information such as patent class, and thus also other aspects of innovation could be addressed using this information. Since every U.S. patent is classified under the U.S. Patent Classification System, and could be assigned to multiple classes depending on how the much particular innovation is related to various technologic fields, it could be argued that the number of patent classes listed on a single patent represents the level of convergence among different technological fields. In this notion, I additionally tested whether the increasing use of scientific knowledge in the innovation process would affect the classification of the resulting innovation into various technological fields. Because the dataset of this research only covers biopharmaceutical-related technologies which are classified in USPC mainclasses 424 and 514, it is difficult to distinguish convergence effects of focal patents when analyzing patents at the mainclass level. In order to capture the convergence effects more precisely, I retrieved the patent subclass information of the patents which were classified into at least two mainclasses. The final sample consists of 1,452 patents and the results of the negative binomial regression model are shown in Table 3-3.

Similar to the innovation impact, the negative coefficients of the square term of the convergence ratio and the positive coefficients of the convergence ratio in Model 2, Model 4, and Model 6 indicate that there is a curvilinear relationship (inverted-U) between increasing proportions of science in convergence and the number of subclasses listed on the patent. Compared to technological knowledge, which usually provides specific solutions to overcome R&D barriers, scientific knowledge contains fundamental ideas and the law of nature. Thus, it could be argued that increasing the application of scientific notions in industrial R&D results in the innovation being related to more diverse concepts from various fields. However, the scientific capacity of the R&D organization and scientific knowledge maturity are insignificant in Model 3, Model 5 and Model 6. Even though scientific capacity and knowledge maturity positively moderate the relationship between the convergence of science and technology and innovation impact, I was unable to find statistical evidence of these two factors moderating the relationship between the use

Table 3-3. Additional analysis for convergence effects on patent subclass

Dependent Variable (Number of patent subclass)	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
Control Variables						
Innovation experience	.0108 (.0112)	.0109 (.0112)	.0062 (.0119)	.0105 (.0113)	.0099 (.0113)	.0044 (.0120)
Pharma specific experience	.0008 (.0022)	.0006 (.0022)	.0002 (.0023)	.0005 (.0022)	.0008 (.0022)	.0001 (.0023)
Originality	.0735 (.0764)	.0698 (.0786)	.0772 (.0788)	.0689 (.0785)	.0636 (.0788)	.0720 (.0788)
Technological diversity	-.138 (.107)	-.144 (.107)	-.140 (.107)	-.160 (.108)	-.148 (.107)	-.160 (.108)
Knowledge maturity (Tech)	.0075* (.0044)	.0079* (.0043)	.0082* (.0044)	.0085* (.0043)	.0062 (.0045)	.0073 (.0045)
Assignee type (Dummy)				*Included*		
Technological field (Dummy)				*Included*		
_Cons	1.560*** (.101)	1.467*** (.126)	1.486*** (.149)	-.681 (.779)	1.465*** (.180)	-.735* (.799)
Independent Variables						
Convergence Ratio		.432** (.319)	-.0363 (.526)	7.913** (3.182)	.323 (.737)	7.431** (3.290)
Convergence Ratio^2		-.372** (.297)	.230 (.518)	-6.283** (2.896)	-.349 (.741)	-5.611* (3.014)
Scientific capacity			.0084 (.0297)			.0163 (.0299)
Convergence Ratio x Scientific capacity			.0760 (.116)			.0510 (.117)
Convergence Ratio^2 x Scientific capacity			-.109 (.105)			-.0906 (.105)
Knowledge spillover				.242*** (.0870)		.250*** (.0874)
Convergence Ratio x Knowledge spillover				.844** (.358)		.855** (.359)
Convergence Ratio^2 x Knowledge spillover				-.667** (.327)		-.665** (.328)
Knowledge maturity (Sci)					.0019 (.0092)	.0007 (.0091)
Convergence Ratio x Knowledge maturity (Sci)					.0072 (.0479)	.0126 (.0478)
Convergence Ratio^2 x Knowledge maturity (Sci)					-.0007 (.0500)	-.0066 (.0498)
Observations	1452	1452	1452	1452	1452	1452
Log-Likelihood	-3719.27	-3718.32	-3716.32	-3714.33	-3717.13	-3711.01

Chi-Square	18.65**	20.54**	24.55**	28.52**	22.91**	35.18**

Note: ***p<0.001; **p<0.01; *p<0.05; two-tailed tests.

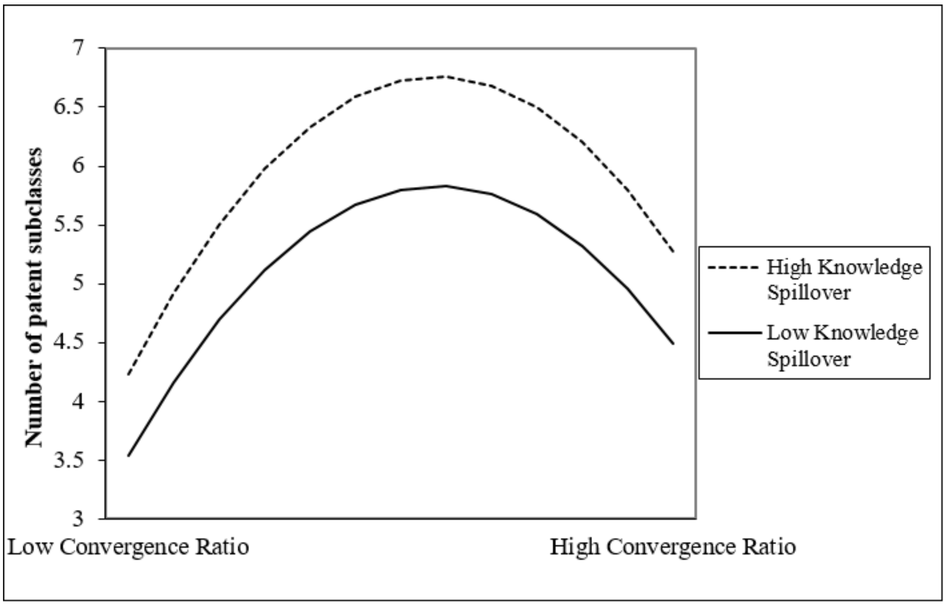

Figure 3-6. The moderation effect of knowledge spillover on the relation between the convergence of science and technology and patent subclass

of science in the R&D process and the association of the resulting innovation with various technologic fields. Comparing to these two factors, Model 4 and Model 6 indicate that the regional spillover effect of scientific knowledge positively moderates the relationship between the convergence ratio and the level of the involvement of different technologies in the focal innovation. This result is also shown in Figure 3-6. Increasing opportunities of receiving tacit knowledge through social communication between researchers leads to the R&D process encompassing various ideas and concepts from different technological fields. In summary, the increasing proportion of science in convergence affects not only the innovation impact but also the level to which the resulting innovation is related to various technological fields. Also, regional scientific knowledge spillover effects positively moderate this relationship.

3.5 Discussions

This research empirically analyzes the impact of convergence of science and technology on innovation impact. This study analyzes the relationship between convergence and innovation impact by using patent data from the U.S. pharmaceutical industry, moreover I test suggested hypotheses considering possible moderation effects of organization's capabilities, knowledge spillover, and characteristic of knowledge. To begin with, this chapter addresses how the organization's scientific capacity influences the impact of innovation from convergence. Moreover, I consider the scientific knowledge maturity used in innovation, while following the knowledge spillover, I investigate and considered a research environment in which personal contacts among researchers easily occur. I use focal patents' backward references as well as SCI listed scientific publications in non-patent references to represent and measure convergence of science and technology and I operationalize innovation impact by the number of forward citations received. Applying the zero-inflated negative binomial regression model, this study obtains a number of key results.

First, this study categorized an innovation's background knowledge into scientific and technological knowledge and analyzed the impact of converging scientific and technological knowledge on the resulting innovation. The results show that convergence of science and technology has a significant impact on innovation, and the effect varies with the ratio of scientific to technological knowledge. While the addition of scientific knowledge increases innovation impact when innovation is mostly based on technological knowledge, increasing the ratio of scientific knowledge beyond a certain point diminishes the influences of innovation impact, yielding a curvilinear relationship. Second, increasing the organization's scientific capacity positively moderates the relationship between convergence of science and technology and innovation impact. As R&D organization can handle scientific knowledge in more effective ways and accept more scientific knowledge in convergence, the potential to evaluate and find more possible solutions to technological problems increases the success rate of innovation (Fleming and Sorenson 2004; lo Storto 2006). This research further finds that the environment in which convergence of science and technology takes place, has an effect on the relationship between convergence and innovation impact. The higher probability of informal communication between researchers and scientists enhances innovation impact when science plays a large role in the research and development process (Liebeskind et al. 1996). This shows that the advice from scientist for identifying technological problems or understanding scientific knowledge is important for organizations to raise their innovation quality (Simeth and Raffo 2013). Therefore, I argue that innovation based on science and technology convergence is most successful when being conducted in an environment where researchers can interact with each other and spillovers occur (Jaffe 1989; Acs et al. 1994). A similar effect was found for the maturity of the scientific knowledge. Using mature, and thus tested and proven, scientific concepts or theories has a more positive moderation effect on the relationship between convergence and innovation impact than using the latest scientific knowledge. In other words, in situations where innovation relies more on scientific rather than technological knowledge, matured scientific knowledge increases innovation impact. These results indicate that an organization’s strengthened scientific capacity, regional knowledge spillover, and mature scientific knowledge in the innovation process, allow organizations to gain more advantages from convergence and obtain impactful innovation outcomes.

The results are consistent with the effects in previous studies which show that scientific searching activity has a positive effect on innovation (Jaffe 1989; Grupp 1996); however, from a convergence perspective, this study provides evidence that an overreliance on scientific knowledge diminishes positive effects of convergence on innovation. In this respect, scientific knowledge helps to solve technological problems (Brooks 1994) or offers novel alternatives to stimulate industrial R&D (Shibata et al. 2010) as well as technological knowledge and technology trends relate to market needs and indicate which direction of innovation also required in convergence for most impactful innovation. Therefore, it is important to maintain a balance between science and technology rather than overly reliance on one side.

Chapter 4. Top Management Team (TMT) and Firm's R&D Propensity[2]

4.1 Introduction

Exploitative innovation and explorative innovation are both essential for firms in terms of ambidexterity (March 1991; Gupta et al. 2006), but their individual characteristics and potential returns are different and firms might not be able to pursue both to the same extent at the same time (March 1991; He and Wong 2004). Industries which are characterized by long product life-cycles and established technologies are often focusing on the pursuit of exploitative innovation which improves their performance by using accumulated technological knowledge to enhance process management (Benner and Tushman 2003). On the other hand, for high-tech industries, known for short life-cycles and cutting-edge technology, pursuing mainly exploitative innovation poses the danger of diminishing competitiveness as the repeated application of existing technologies and knowledge prevents the firms from seizing new technological opportunities and entering new markets (D'Aveni 1994). Rather than relying on existing knowledge, firms in today's technology intensive industries, i.e., industries which focus on research and development (R&D) rather than manufacturing, have to pursue new and emerging

[2]An earlier version of this chapter has been published in *Scientometrics* (2017), Vol. 111(2), pp.639-663.

technologies to increase their competitiveness (Schumpeter 1942; Garcia et al. 2003; Gupta et al. 2006). Consequently, for firms in these industries, the importance of explorative innovation, which aims to explore new technologies through research and experimental activities, has increased (Rosenberg 1990; Uotila et al. 2009).

An important element of firms' R&D strategies in high-tech industries is to determine the proportion of explorative R&D activities among the total R&D (Mudambi and Swift 2014). Still, even though the need to pursue ambidexterity strategies in order to capture advantages and complement of both exploitative and explorative innovation is clear (Rothaermel and Alexandre 2009), a large number of firms emphasize exploitative innovation to lower the uncertainties of the R&D process (Greve 2007). Though firms in high-tech industries generally have a high propensity to engage in explorative R&D and face similar external influences such as the intensity of the competition, individual firms place different emphasis on explorative activities (Greve 2007; Uotila et al. 2009; Mudambi and Swift 2014). Firm strategies, including the R&D strategy, are conscious decisions of the firm. Thus, even firms in the same industry, which face a similar technological environment, exhibit different approaches to solving technological problems and planning for the future. One of the reasons for this difference is the decisions makers of each firm have different perceptions about future opportunities and the role of R&D in achieving set business objectives (Heavey and Simsek 2013). As R&D activities are considered to be one of the most important and resource-consuming activities for firms in high-tech industries, the firms' top level decision makers are actively involved in planning and conducting R&D projects (Qian et al. 2013). Consequently, previous research highlighted the influence of the firm's decision makers, such as the top management team (TMT), on organizational behavior such as R&D investments (Kor 2006; Chen et al. 2010). (Revision) Because the organization's TMT, which consists of CEO, CFO, COO, CIO, CTO and vice presidents of each business unit, has the responsibility of managing the organization by making decisions including R&D (Wiersema and Bantel 1992).

Hambrick and Mason (1984) proposed the upper echelon theory which explains the behavior and performance of organizations as the result of managerial decisions which are mainly influenced by the cognitive base of the TMT. They argued that the characteristics of TMT members such as their background, age, or tenure influence the formation of the individuals' cognitive base, which is reflected in the TMT's decision making (Hambrick and Mason 1984; Bantel and Jackson 1989; Wiersema and Bantel 1992; Daellenbach et al. 1999). From the perspective of the upper echelon theory, an organization's R&D strategy is mainly influenced by the TMT's propensity to favor explorative activities, its perception of technological opportunities, and its risk perception (Hambrick and Mason 1984; Tabak and Barr 1999). For example, a risk-avoiding conservative TMT is more likely to pursue exploitative R&D projects whose risk can be better estimated rather than explorative R&D projects which are inherently more prone to risks. On the other hand, a preference for solving problems through investigating new technologies and innovation increases the likelihood of the TMT giving more support to explorative R&D (Alexiev et al. 2010).

Previous studies on the influence of TMT characteristics have often focused on individual characteristics and did not study the interaction of different characteristics on the decision making (Tabak and Barr 1999; Barker and Mueller 2002). Studies which investigated the relationship between the TMT and the firm's R&D activities have often adopted a financial perspective and focused on total R&D investments (Barker and Mueller 2002; Kor 2006; Chen et al. 2010). Even though the importance of R&D for firms is ever increasing, not much literature focused on which factors related to the firm's decision makers affect the firm's organizational behaviors in terms of R&D activities. While recent research paid attention to the relationship between TMT characteristics and the firm's R&D (Alexiev et al. 2010; Talke et al. 2010; Ding 2011; Qian et al. 2013; Li et al. 2014), those studies did not provide an in-depth analysis of the two different kinds of R&D activities, i.e., explorative and exploitative R&D, a firm can pursue. From a methodological perspective, previous literatures focused on the technological side of the firm's R&D activities (Ahuja and Lampert 2001; Geiger and Makri 2006). However, recent industrial R&D is increasingly linked to the scientific domain (Fleming and Sorenson 2004; Lee et al. 2016).

Aiming to provide a more detailed picture of how the characteristics of the TMT influence a firm's R&D activities as well as to include both scientific and technological aspects of the firm's R&D activity, this research analyzes how the R&D strategy of the firm is influenced by its TMT's preference for explorative R&D activities. Specifically, it investigates how R&D-related functional experiences as well as science or engineering oriented educational backgrounds of the TMT members influence their cognitive base and risk preferences which are related to explorative R&D. This chapter also investigates how the duration of the TMT members' tenure affects the decision making on explorative R&D projects. To allow for an in-depth analysis of the firms' R&D activities, this research goes beyond the use of financial data and adopts patent data, especially data on patent citations, patent classes, and non-patent references to include both technological and scientific aspects of innovation. This research elucidates how the firm's internal characteristics, specifically those related to its management team, affect the organization's behaviors toward R&D activities through an empirical analysis conducted using a dataset of firms in high-tech industries and their patent data.

4.2 Research hypotheses

4.2.1 Top management team background and the firm's R&D direction

According to Dearborn and Simon (1958), an individual will apply the skills and problem solving methods learned from past functional experience to solve future problems. Individuals who possess experiences of working in R&D-related functions will have experienced that an organization's technological competitiveness is enhanced by its effort to explore novel and emerging technologies, even if such a pursuit involves dealing with considerable uncertainties and risks (Daellenbach et al. 1999). Such experiences in R&D functions make individuals less sensitive towards facing the risks and uncertainties caused by explorative innovation activities (March and Shapira 1987; March 1988) which leads to them preferring explorative R&D projects (Daellenbach et al. 1999). Similar to the work experience, the educational background has been identified as one of the key factors which determine the way TMT members approach managerial decisions (Hambrick and Mason 1984; Hitt and Tyler 1991; Wiersema and Bantel 1992). Both engineering and science emphasize the importance of innovation (Gibbons and Johnston 1974) and the inevitable risky nature of problem-solving processes (Wiersema and Bantel 1992). Consequently, TMT members whose cognitive base was formed by majoring in engineering or sciences, would prefer to enhance the organization's competitiveness through technological innovation (Tyler and Steensma 1998; Barker and Mueller 2002) rather than through low-risk strategies. Therefore, they are more likely to actively support explorative R&D projects which aim at a technological paradigm shift. Together, functional experiences and the educational backgrounds of TMT members directly affect the formation of their cognitive base which shapes their attitude towards explorative R&D as well their propensity to take or avoid risks. The influence of the TMT members' background on the direction of the firm's R&D leads to the following hypotheses:

Hypothesis 4-1*: The higher the proportion of TMT members with functional experiences in R&D-related positions, the more the firm will focus on explorative R&D activities.*

Hypothesis 4-2*: The higher the proportion of TMT members with an academic background in engineering or science, the more the firm will focus on explorative R&D activities.*

4.2.2 **Moderating effect of TMT members' average tenure**

It is known that TMT members' tenure in the organization can affect their decision making (Hambrick and Mason 1984; Bantel and Jackson 1989; Chen et al. 2010). Finkelstein (1992) and Hambrick (2007) state that the TMT decision making process can be biased in accordance with the differing power of individual TMT members. In the context of TMTs, power can be divided into structural, ownership, expert, and prestige power (Finkelstein 1992). From the perspective of structural power, it is generally accepted that senior TMT members have more power than junior members and can control large amounts of resources and exert considerable influence to strategic decision more easily (Finkelstein 1992). For example, Finkelstein (1992) found that firm behavior was more focused on acquisition strategy in firms with high proportion of powerful TMT members with a financial background. Adopting this research results to the R&D perspective, it could be hypothesized that a firm's R&D-related decisions are not only influenced by the TMT members' background and experience but also their power within the TMT as represented by their tenure in the organization. When the TMT consists of only a few members which have innovative experiences and have a relatively short tenure, their limited power will make it difficult to support large resource consuming R&D projects such as explorative R&D (Hambrick 2007). In addition, individuals with a short tenure as members of a firm's TMT can feel the pressure to show their values and abilities and prove themselves within a short period of time (Kor 2006; Chen et al. 2010). Even high performance can be archived by pursuing explorative R&D, the high uncertainties and risks inherent in explorative activities make short-tenured members reluctant to support it (March and Shapira 1987). This can result in junior members of the TMT preferring to be associated with innovation projects that are able to obtain short-term performances, a characteristic of exploitative R&D projects. On the other hand, as a member with a long tenure in the TMT, the abilities are already verified and members feel less pressure to choose projects geared towards short-term performance (Kor 2006; Chen et al. 2010). Senior members also have more power within the TMT which makes it easier for them to support large and riskier R&D projects such as explorative activities. If senior members with innovative experiences hold a large majority in the TMT, the firm is expected to engage in more explorative activities. Therefore, this study proposes that the average tenure of the TMT members who possess innovation-related backgrounds or experiences will influence the relationship between the proportion of such TMT members and the firm's level of engaging in explorative R&D

activities.

***Hypothesis 4-3a**: The relationship between the proportion of TMT members with functional experience in R&D-related positions and the firm's focus on explorative R&D activities is positively moderated by the average tenure of these TMT members.*

***Hypothesis 4-3b**: The relationship between the proportion of TMT members with an academic background in engineering or science and the firm's focus on explorative R&D activities is positively moderated by the average tenure of these TMT members.*

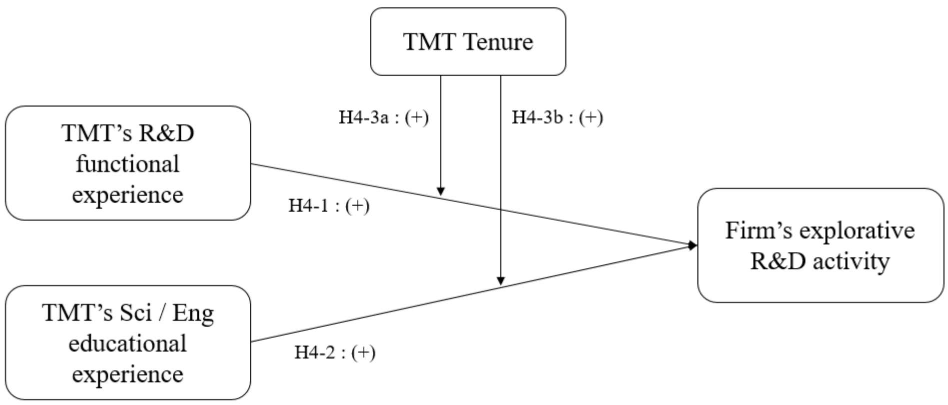

Figure 4-1. Conceptual Model for Chapter 4

The conceptual diagram in Figure 4-1 shows the relationships between the suggested hypotheses.

4.3 Methods

4.3.1 Data

Table 4-1. Composition of the data set

Industry	Number of sample firms	Percentage
Automobiles	4	4.5%
Chemicals	11	12.3%
Electronics	6	6.7%
Industrial engineering	3	3.4%
Technology hardware and equipment	26	29.2%
Pharmaceutical and biotechnology	14	15.7%
Semiconductors	4	4.5%
Software and computer services	21	23.6%

To test the suggested hypotheses, this research collected biographical information of the TMT members, firm-level financial information, and patent data of 89 US firms in high-tech industries. Specifically, I chose the sample firms from eight high-tech industries including chemicals, electronics, pharmaceutical and biotechnology and semiconductors due to the high importance of explorative innovation in these industries (Gittelman and

Kogut 2003; West and Iansiti 2003). Table 4-1 shows the detailed composition of the data set. Firms from the technology hardware and equipment as well as software and computer services industries account for around half of the sample. The sample also includes firms from industries such as chemicals or pharmaceutical and biotechnology, in which R&D is mainly based on scientific knowledge (Narin and Olivastro 1992; Makri et al. 2010; Subramanian and Soh 2010).

In the context of this study, the TMT includes the firm's CEO, CFO, COO, CIO, CTO and vice presidents of entire business units (Finkelstein and Hambrick 1996; Tabak and Barr 1999; Kor 2003). Biographical information for 1550 individual members of the TMTs who worked at the sample firms during the period from 2006 to 2009 was collected from Corporate Affiliations provided by LexisNexis and the Who's Who provided by Marquis. Financial indicators for each firm were obtained from the Compustat database provided by Standard and Poors and the Datastream database of Thomson Reuters. For analyzing R&D activities, this research relies on US patent data, especially data on patent citations, patent classes, and non-patent references (NPRs). To assign patents to different technological fields, this research uses the US Patent Classification System (USPC), which classifies each US patent into one of around 450 classes, which are further subdivided into a total of around 150,000 subclasses, based on the technological characteristics of the invention. The USPC, representing particular technologies, allows us to identify the technological fields that influenced the focal patents' invention processes. The citation information of US patents is divided into patent citations and non-patent references. Non-patent references refer to journal papers, conference proceedings, textbooks, databases, company reports and other documents that influenced the patented invention (Callaert et al. 2006). Detailed information on 13,363 patents granted to the sample firms with application dates from 2003 to 2010 were collected from the patent database provided by the United States Patent and Trademark Office (USPTO). The final dataset contains 356 firm year observations of 89 firms over a 4-year timespan (2006–2009). To test suggested hypotheses, this research adopted panel analysis which allows for a longitudinal analysis in order to capture the dynamic relations between the dependent variable and explanatory variables by observing samples from the same individuals, in this case firms, over time. Specifically, this study employed generalized estimating equations (GEEs) models with a logit link function in order to address the proportional values of the dependent variables.

4.3.2 Variables

4.3.2.1 Dependent variable

Explorative R&D activities (patent citations, classes, non-patent references): For calculating a firm's degree of focus on explorative R&D, this research adopts a concept based on the analysis of patent citations previously used in the studies of Katila and Ahuja (2002) and Phelps (2010). It is based on the understanding that using new-to-the-firm knowledge in the R&D process is exploration whereas the repeated use of the same knowledge is considered as exploitation. To investigate how explorative the firm's

R&D is, the proportion of new to previously used knowledge is calculated using backward citation data. When the firm cites a patent for the first time, it is using new knowledge, whereas further references to the same patent at a later time can be seen as using already known knowledge in the invention process. Specifically, the backward citations of patents which were applied by firm *i* in the three years preceding the observation year (t - 3 ~ t - 1) were compared with those of the patents applied for in the year after the observation year (t + 1). The delay is due to the time it takes for the TMT's decisions to have an effect on the direction of the firm's R&D activities and its outcomes.

$$Explorative\ R\&D\ activities\ (patent\ citations)_{it} = \frac{NEW\ CITATIONS_{it}}{TOTAL\ CITATIONS_{it}}$$

In addition to the methodology described above, I also calculated the firm's explorative R&D activities using patent class and non-patent reference data. Patent class data is used in a similar way to patent citations, i.e., to distinguish new knowledge and technologies used in the innovation process from knowledge and technologies that the firm used before. In this case, if an applied patent is classified in a subclass that the firm has not been applying in for the three years before the focal year, it is considered as exploring a new technological field. On the other hand, future applications for patents in the same subclass are seen as exploitative activities using previously known technology.

$$Explorative\ R\&D\ activities\ (patent\ classess)_{it} = \frac{NEW\ SUBCLASSES_{it}}{TOTAL\ SUBCLASSES_{it}}$$

Finally, I proxy the firm's explorative R&D using non-patent references. As these non-patent sources, e.g., scientific articles, are often related to basic science, patents which cite a large number of these sources are considered more fundamental and explorative (Trajtenberg et al. 1997; Callaert et al. 2014). On the other hand, patents whose citations are mostly directed at other patents are seen as containing more applied innovation or improvements to existing innovations. Meanwhile, Callaert et al. (2006) proposed that among the various non-patent references, only journal papers, conference proceedings, and books reflect scientific sources. Therefore, I only consider these scientific references as non-patent references in the context of this study. Specifically, similar to the approach of Verbeek et al. (2002) and Shirabe (2014), I used a text parsing algorithm to classify the elements of the non-patent reference including fields such as {author name}, {publication title}, {journal title}, {conference name}, {volume and issue number}, {publication year}, {publisher}, {publisher location}, and {pages}. I then standardized the texts and used the available information to classify them as journal papers, conference proceedings, books, or others. For example, citations of journal papers generally contain the following fields: {author name}, {publication title}, {journal title}, {volume and issue}, {publication year}, and {pages}. Manual checks were conducted to ensure the correct classification of each non-patent reference. To measure the explorative R&D activities of the firms using non-patent references, this study employs the science index, proposed by Trajtenberg et al. (1997), as described in the following formula:

$$Explorative\ R\&D\ activities\ (NPRs)_{it} = \frac{NPCITES_{it}}{NPCITES_{it} + NCITED_{it}}$$

where $NPCITES_{it}$ is the average number of scientific references and $NCITED_{it}$ is the average number of patent references of the patents applied by firm *i* in year *t*, respectively (Callaert et al. 2012).

4.3.2.2 Independent variables

TMT R&D experience: To measure TMT innovative experience, i.e., working experience in R&D functions, I used biographical information of the TMT members. I coded each member of the TMT of a firm with 1 if they had experiences of working in R&D-related functions, and 0 if the individual had no such experience (Barker and Mueller 2002). The variable TMT R&D experience is the proportion of TMT members coded 1 for each firm and observation year.

TMT Eng/Sci education: Similar to the R&D-related experience of the TMT members, also the information on their educational background is derived from biographical data. I coded each member of the TMT of a firm with 1 if they obtained a Bachelor, Master, or Ph.D. degree in an engineering or science related field, and 0 if the individual had no such degree (Barker and Mueller 2002). The variable TMT Eng/Sci education is the proportion of TMT members coded 1 for each firm and observation year.

TMT average tenure: Biographical information was also used to determine the individual TMT members' tenure. To address the influence of the tenure of TMT members with R&D related experiences and backgrounds, I only considered individuals who had been coded by 1 for experience or education as described above. TMT's average tenure is then calculated as the average time in years that the individuals had served as members of the firm's TMT for each firm and observation year.

4.3.2.3 Control variables

R&D intensity: A larger R&D budget helps to maintain and expand the number of researchers, facilities and materials for testing alternatives that can lead to innovation outputs. The amount of resources the firm is investing into R&D is expressed through the R&D intensity, i.e., the proportion of the firm's R&D expenses relative to its sales, of each firm in year *t*.

Firm size: The size of the firm influences the type of R&D as well as the level of R&D activities. The resources of large firms might allow them to conduct more costly and risky R&D. Therefore, I included the log transformed volume of sales to control for differentiated innovation activities and performances between organizations of different sizes.

Firm innovation experience: An organization with a lot of experience of successful R&D projects in the past indicates not only the existence of efficient routines for R&D processes but also serves as a measure for the technological capacity of each firm. This study uses the number of granted patents applied for in the past three years before the focal year to proxy for innovation experience. The variable is log transformed.

Technological diversity: It can be argued that firms with a highly-diversified technology portfolio may be better at exploring knowledge from various fields while a low level of diversity indicates that the firm tends to focus on only a few fields. I adopted the Herfindahl index to calculate the firms' technological diversity. I measured technological diversity by analyzing the diversity of patent classes in which each firm applied for ultimately granted patents during the past three years. The formula used is

$$Technological\ diversity = 1 - \sum_{i \in F} {p_i}^2$$

where *F* is the set of technological categories (patent classes) and p_i is the proportion of the firm's patents classified in technological category i. A value of the index close 1 indicates that the firm's R&D activities are conducted in various technology fields (high technological diversity) whereas low values close to 0 show that the firm's R&D is focused on a small range of technologies (low technological diversity).

TMT average age: Previous research has suggested that the age of the TMT members has an influence on their managerial decisions (Hambrick and Mason 1984; Bantel and Jackson 1989; Kor 2003). Younger individuals prefer more challenging projects with high-risk and uncertainties, while older individuals often have a tendency to avoid risks (Carlsson and Karlsson 1970; Vroom and Pahl 1971). I calculated the average age of all the members in each firm's TMT in year *t* and standardized it.

Heterogeneity of the TMT (educational and functional background): Low heterogeneity of the TMT members, i.e., members share the same functional and educational background makes the communication easier because the knowledge base and ways of thinking of TMT members with shared backgrounds are very similar (Hambrick et al. 1996; Kor 2003). Increasing heterogeneity, however, causes conflicts of opinions (Hambrick and Mason 1984; Priem 1990) due to the different perspectives of TMT members with various experiences and knowledges (Bantel and Jackson 1989; Hambrick et al. 1996; Daellenbach et al. 1999). This research classified the educational background into engineering, science, economic, accounting/finance, business, legal and others. The functional background consists of R&D, accounting/finance, legal, production operations, administration, general counsel, marketing/sales and others (Daellenbach et al. 1999; Barker and Mueller 2002). The Herfindahl index was adopted to calculating the heterogeneity of the TMTs background for both education and functional experience respectively (Wiersema and Bantel 1992; Hambrick et al. 1996; Kor 2006).

4.4 Results

Prior to testing the proposed hypotheses, the descriptive statistics and the correlations between the variables were analyzed. Table 4-2 indicates that on average 24% of TMT members have R&D related functional experiences and 33% of TMT members possess degrees in science or engineering related fields, although differences exist between different industries. For example, for firms in the pharmaceuticals and biotechnology industry, individuals with a higher education in science or engineering account for about 45% of the TMT. A similarly high level, 41%, can be found in firms operating in the technology hardware and equipment industry. On the other hand, firms in industrial engineering exhibit a low propensity to constitute their TMT members with individuals possessing either R&D-related work experience (15%) or a science or technology education for (23%). The average of technological diversity was calculated as 0.82 and shows that the firms in the sample conducted their R&D activities in various technology fields rather than focusing on a few particular technologies. This indicates that firms are actively searching for diverse technologies to capture future opportunities in advance. The correlation results show a high level of correlation between Explorative R&D (Citation) and Explorative R&D (Class), indicating that firms who are patenting technologies in new technological fields are also actively exploring new knowledge.

Table 4-2. Descriptive statistics and correlations matrix of the variables

	M	SD	Min	Max	1	2	3	4	5	6	7	8	9	10	11	12	13
1. Explorative R&D (Citation)	0.52	0.23	0.03	0.99	1												
2. Explorative R&D (Class)	0.22	0.18	0	0.99	.78**	1											
3. Explorative R&D (NPR)	0.27	0.17	0	0.93	-.30*	-.16*	1										
4. TMT R&D experience	0.24	0.16	0	0.83	-.28*	.24*	.28*	1									
5. TMT Eng & Sci education	0.33	0.19	0	0.8	-.18*	-.22*	.27*	.56*	1								
6. TMT average tenure	5.91	2.24	1.5	13.9	-.13*	-.05	.01	.02	.02	1							
7. R&D intensity	0.14	0.20	0.01	2.16	-.14*	-.14*	.44*	.35*	.39*	.14*	1						
8. Firm size[1]	8.73	1.53	4.15	12.11	.02	-.10	-.18*	-.17*	-.11	.02	-.42*	1					
9. Firm innovation experience[1]	5.59	1.65	1.61	9.80	-.21*	-.51*	-.19*	.07	.11	.15*	-.15*	.61**	1				
10. Technological diversity	0.82	0.14	0.23	1	.17*	.15*	-.34*	-.12	-.05	.06	-.27*	.41*	.37*	1			
11. TMT average age[2]	0	0.74	-2.25	1.87	.02	.02	.03	-.08	-.01	.18*	.04	.31*	.15*	.15*	1		
12. Educational heterogeneity	0.66	0.10	0	0.82	.13*	.16**	.04	-.08	-.01	.07	-.16*	.30*	.07	.24**	.09	1	
13. Functional heterogeneity	0.76	0.04	0.5	0.84	-.05	-.09	.16*	.30**	.12	-.02	.17*	-.16*	.05	-.18*	-.17*	.21*	1

Note: N=356. **p<0.01; *p<0.05; two-tailed tests. [1]Transposed to log scale. [2] Standardized.

Table 4-3. Regression results for explorative R&D based on patent citations

Dependent variable Explorative R&D (citations)	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Control variables						
R&D intensity	-0.186	-0.0734	-0.149	-0.0831	-0.139	-0.108
	(0.282)	(0.283)	(0.279)	(0.289)	(0.295)	(0.292)
Firm size[1]	0.0449	0.0391	0.0421	0.0299	0.0416	0.0316
	(0.0624)	(0.0599)	(0.0625)	(0.0598)	(0.0640)	(0.0630)
Firm innovation experience[1]	-0.269***	-0.254***	-0.263***	-0.232***	-0.248***	-0.236***
	(0.0554)	(0.0569)	(0.0572)	(0.0559)	(0.0551)	(0.0580)
Technological diversity	2.409***	2.319***	2.389***	2.299***	2.376***	2.304***
	(0.734)	(0.710)	(0.726)	(0.694)	(0.690)	(0.703)
TMT average age[2]	0.140*	0.129*	0.138*	0.169**	0.163**	0.171**
	(0.0789)	(0.0786)	(0.0786)	(0.0785)	(0.0774)	(0.0795)
Educational heterogeneity	-0.0313	-0.144	-0.0597	0.00350	-0.0162	0.0131
	(0.899)	(0.968)	(0.925)	(1.030)	(0.959)	(1.045)
Functional heterogeneity	1.014	1.744	1.044	1.630	1.157	1.678
	(1.370)	(1.369)	(1.354)	(1.283)	(1.342)	(1.371)
_Cons	-1.499	-1.699	-1.423	-1.008	-1.067	-1.110
	(1.321)	(1.279)	(1.334)	(1.254)	(1.294)	(1.345)
Independent variables						
TMT R&D experience		1.030**		2.479**		2.668**
(R&D Exp)		(0.478)		(1.117)		(1.305)
TMT Sci / Eng education			0.229*		0.808*	0.334*
(S&E Edu)			(0.384)		(0.858)	(0.937)
TMT average tenure				0.124**	0.0928	0.121
(Tenure)				(0.0509)	(0.0574)	(0.0591)
R&D Exp × Tenure				0.246*		0.254*
				(0.150)		(0.183)
S&E Edu × Tenure					0.101*	0.0158*
					(0.130)	(0.153)
Observations	356	356	356	356	356	356
Wald Chi-square	30.75***	35.56***	32.85***	46.23***	41.01***	46.01***

Note: ***p<0.001; **p<0.01; *p<0.05; two-tailed tests. Robust standard errors are in parentheses. [1] Transposed to log scale. [2] Standardized.

Table 4-4. Regression results for explorative R&D based on patent classes

Dependent variable Explorative R&D (classes)	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Control variables						
R&D intensity	-0.351	-0.203	-0.271	-0.234	-0.248	-0.214
	(0.393)	(0.402)	(0.391)	(0.388)	(0.404)	(0.408)
Firm size[1]	0.0979*	0.0953*	0.0939*	0.0954*	0.0938	0.0891
	(0.0577)	(0.0561)	(0.0570)	(0.0551)	(0.0572)	(0.0566)
Firm innovation experience[1]	-0.517***	-0.507***	-0.509***	-0.511***	-0.513***	-0.508***
	(0.0413)	(0.0426)	(0.0424)	(0.0439)	(0.0436)	(0.0455)
Technological diversity	2.826***	2.721***	2.785***	2.752***	2.765***	2.709***
	(0.562)	(0.539)	(0.555)	(0.545)	(0.564)	(0.551)
TMT average age[2]	0.139*	0.147**	0.138*	0.144**	0.127*	0.150**
	(0.0725)	(0.0718)	(0.0735)	(0.0728)	(0.0743)	(0.0729)
Educational heterogeneity	0.349	0.248	0.303	0.286	0.231	0.266
	(0.754)	(0.759)	(0.767)	(0.771)	(0.767)	(0.767)
Functional heterogeneity	0.856	1.650	0.865	1.615	0.805	1.350
	(1.108)	(1.138)	(1.115)	(1.137)	(1.133)	(1.165)
_Cons	-2.541**	-2.810***	-2.389**	-2.796***	-2.564**	-2.714**
	(1.067)	(1.032)	(1.054)	(1.032)	(1.101)	(1.099)
Independent variables						
TMT R&D experience		1.002**		1.459*		2.144*
(R&D Exp)		(0.391)		(1.112)		(1.272)
TMT Sci / Eng education			0.349*		0.248*	1.100*
(S&E Edu)			(0.318)		(0.879)	(0.888)
TMT average tenure				0.0455	0.0533	0.0294
(Tenure)				(0.0495)	(0.0573)	(0.0589)
R&D Exp × Tenure				0.0868*		0.207*
				(0.163)		(0.192)
S&E Edu × Tenure					0.106*	0.190*
					(0.135)	(0.150)
Observations	356	356	356	356	356	356
Wald Chi-square	207.06***	189.33***	214.26***	209.90***	218.69***	199.31***

Note: ***p<0.001; **p<0.01; *p<0.05; two-tailed tests. Robust standard errors are in parentheses. [1] Transposed to log scale. [2] Standardized.

Table 4-5. Regression results for explorative R&D based on non-patent references

Dependent variable Explorative R&D (NPRs)	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Control variables						
R&D intensity	-0.0264*	-0.00981*	-0.00293*	-0.00080*	-0.0664*	-0.00534*
	(0.160)	(0.160)	(0.165)	(0.156)	(0.162)	(0.159)
Firm size[1]	-0.103**	-0.105**	-0.0919**	-0.114**	-0.102**	-0.106**
	(0.0807)	(0.0805)	(0.0745)	(0.0806)	(0.0728)	(0.0744)
Firm innovation experience[1]	-0.0548	-0.0566	-0.0688	-0.0657	-0.0730*	-0.0735*
	(0.0469)	(0.0468)	(0.0442)	(0.0442)	(0.0426)	(0.0427)
Technological diversity	-0.411	-0.385	-0.399	-0.299	-0.350	-0.321
	(0.441)	(0.442)	(0.435)	(0.459)	(0.448)	(0.451)
TMT average age[2]	-0.00343	-0.00319	-0.00150	-0.0195	-0.0130	-0.0166
	(0.0622)	(0.0627)	(0.0613)	(0.0630)	(0.0619)	(0.0624)
Educational heterogeneity	0.554	0.642	0.737	0.638	0.765	0.769
	(0.281)	(0.275)	(0.319)	(0.283)	(0.326)	(0.322)
Functional heterogeneity	1.356	1.132	1.275	1.144	1.135	1.070
	(0.994)	(1.032)	(0.961)	(1.005)	(0.950)	(1.034)
_Cons	-0.852	-0.834	-1.118	-1.100	-1.319	-1.335
	(0.981)	(0.979)	(0.958)	(0.953)	(0.952)	(0.988)
Independent variables						
TMT R&D experience		0.425		1.001		0.497
(R&D Exp)		(0.229)		(0.445)		(0.434)
TMT Sci / Eng education			0.526**		1.152**	0.966**
(S&E Edu)			(0.213)		(0.450)	(0.472)
TMT average tenure				0.0538**	0.0655**	0.0732**
(Tenure)				(0.0265)	(0.0318)	(0.0321)
R&D Exp × Tenure				0.0979**		0.0430*
				(0.0599)		(0.0753)
S&E Edu × Tenure					0.116*	0.0991*
					(0.0642)	(0.0810)
Observations	356	356	356	356	356	356
Wald Chi-square	16.50**	20.06**	22.66***	24.93***	26.39***	29.24***

Note: ***p<0.001; **p<0.01; *p<0.05; two-tailed tests. Robust standard errors are in parentheses. [1] Transposed to log scale. [2] Standardized.

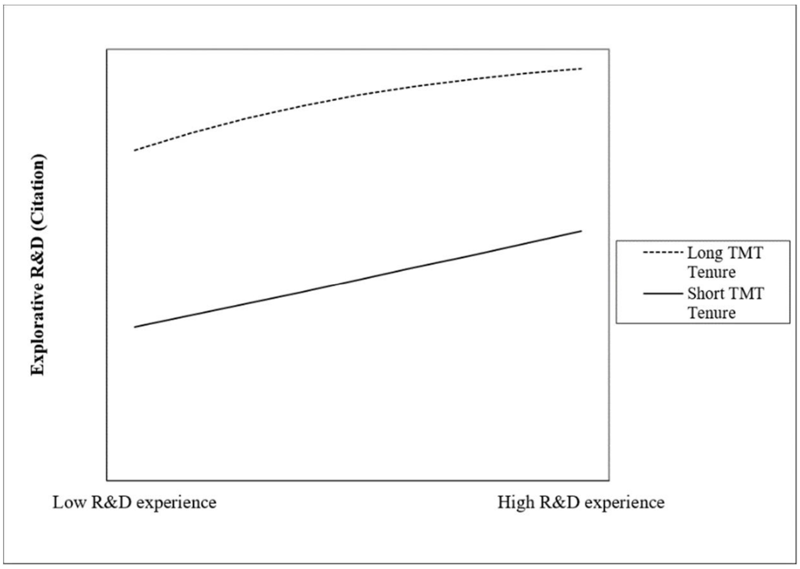

Figure 4-2. The moderation effect of average tenure on the relationship between firm's explorative R&D (patent citation) and TMT's R&D experience

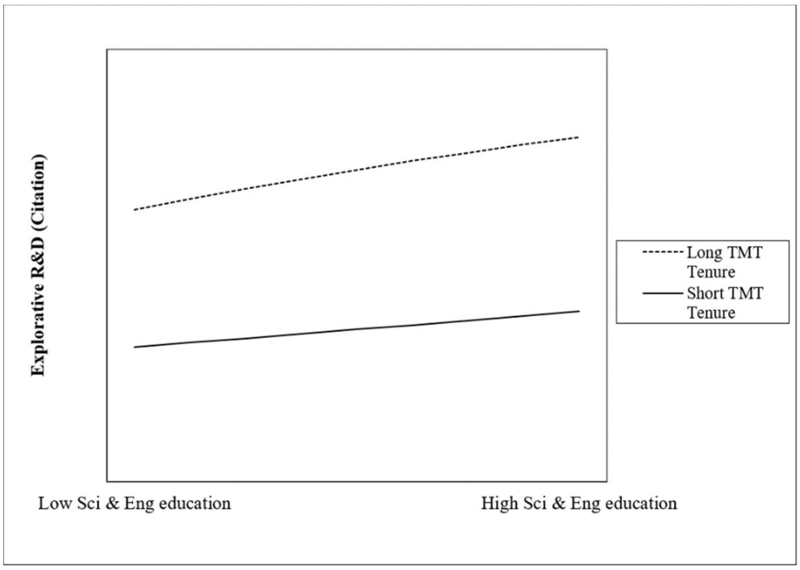

Figure 4-3. The moderation effect of average tenure on the relationship between firm's explorative R&D (patent citation) and TMT's Sci / Eng education

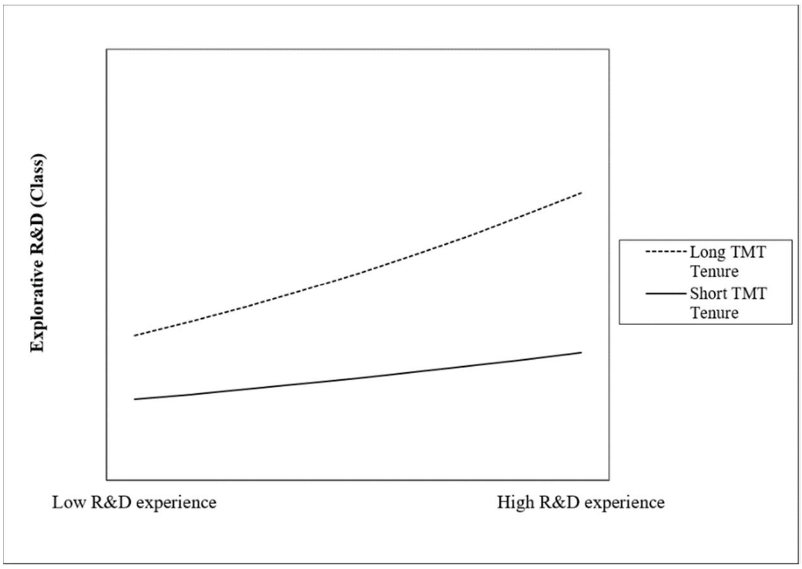

Figure 4-4. The moderation effect of average tenure on the relationship between firm's explorative R&D (patent class) and TMT's R&D experience

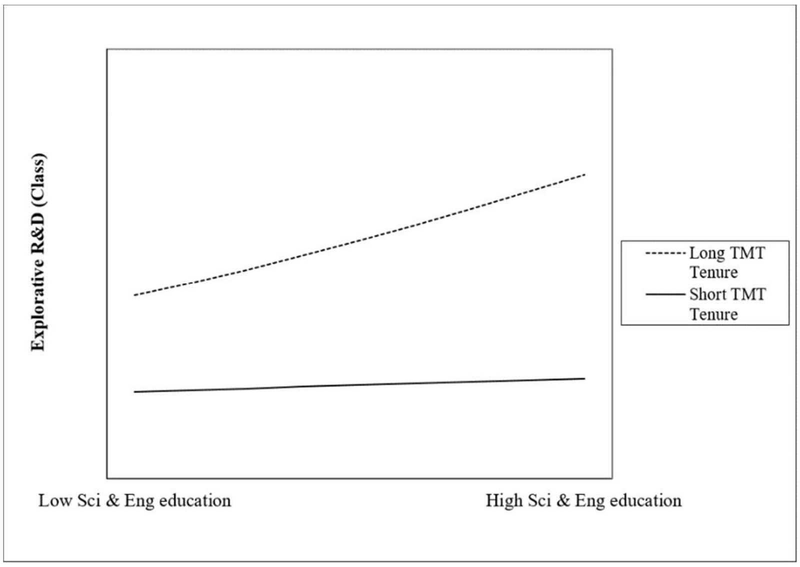

Figure 4-5. The moderation effect of average tenure on the relationship between firm's explorative R&D (patent class) and TMT's Sci / Eng education

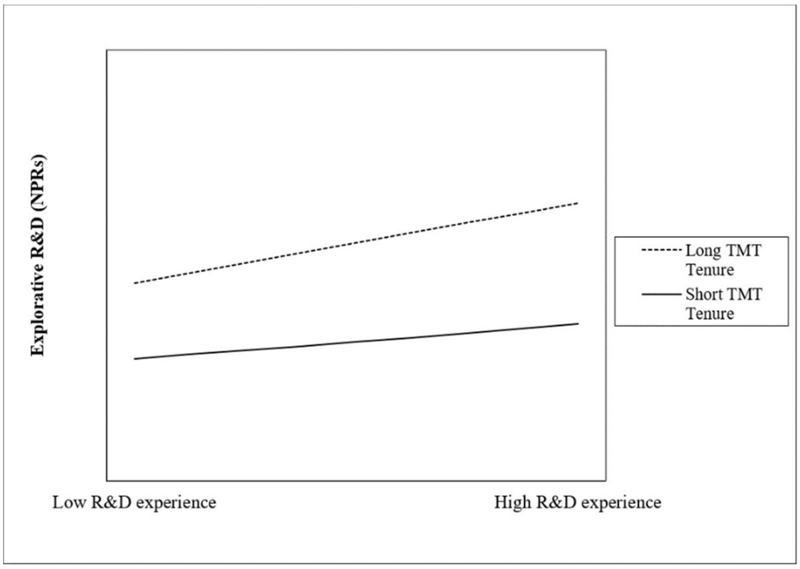

Figure 4-6. The moderation effect of average tenure on the relationship between firm's explorative R&D (non-patent references) and TMT's R&D experience

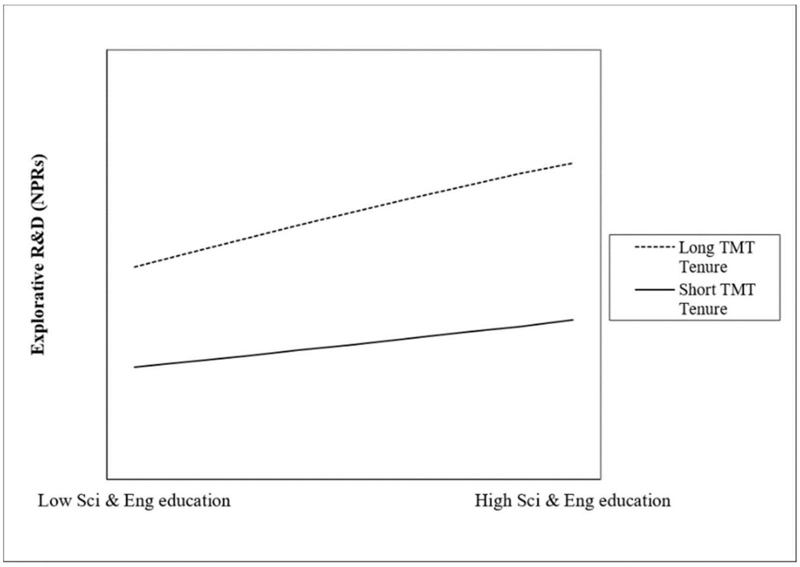

Figure 4-7. The moderation effect of average tenure on the relationship between firm's explorative R&D (non-patent references) and TMT's Sci / Eng education

Table 4-3, Table 4-4, and Table 4-5 show the results of the empirical tests based on measuring explorative R&D activities through patent citations, patent classes, and non-patent references, respectively. In all three tables, Model 1 contains all of the control variables and Model 6 contains all control and independent variables as well as further explanatory variables including interaction effects. The results in Table 4-3 show that the firm's innovation experience negatively influences its explorative R&D activities. On the contrary, firms are more turning towards explorative R&D as the average age of the TMT members and the technological diversity of the firms increase. The results of Model 2 show a positive and significant (β: 1.030, p-value<0.01) relationship between TMT members' R&D-related functional experience and the firm's explorative R&D. Model 4 also show a similar positive and significant relationship (β: 2.479, p-value<0.01). These results support the Hypothesis 4-1, which stated that an increasing proportion of TMT members with R&D-related functional experience leads firms to engage more in explorative R&D activities. Model 3 tests the proposed relationship between the TMT members' science or engineering oriented academic background and the firm's explorative activity and finds a positive and significant relationship (β: 0.229, p-value<0.05). These results are further supported by Model 5 (β: 0.808, p-value<0.05), lending further support for the Hypothesis 4-2. To test the moderation effect of the average tenure of TMT members with R&D-related functional experience or education, interaction terms of both R&D functional experiences and science or engineering academic experiences with the tenure variable were included in Model 4 and Model 5.

Both models show positive significant interaction effects (β: 0.246 and 0.101, both with p-value<0.05). Model 6, the full model, shows consistent results as well. Figure 4-2 and Figure 4-3 show how both the effects of R&D experiences and science or engineering academic experience on explorative R&D were positively moderated by the TMT tenure. These results support both Hypothesis 4-3a and Hypothesis 4-3b.

Next, Table 4-4 contains the results of the empirical test using a definition of explorative R&D activities based on patent class data. Similar to the results presented in Table 4-3, it can be seen that the firm's innovation experience negatively influences its explorative R&D activities while the technological diversity of the firms and TMT's age increase the proportion of explorative R&D. The coefficient of TMT's R&D experience in Model 2 and Model 4 were 1.002 (p-value<0.01) and 1.459 (p-value<0.05), respectively, supporting the Hypothesis 4-1. The coefficients for the TMT members' science or engineering related academic experience were positive and significant in both Model 3 (β: 0.349, p-value<0.05) and Model 5 (β: 0.248, p-value<0.05). These results support Hypothesis 4-2. Moreover, the positive and significant interaction terms in Model 4 (β: 0.0868, p-value<0.05) and Model 5 (β: 0.106, p-value<0.05) confirm the proposed moderation effects of the average tenure of TMT members with R&D-related functional or education experience on the relationship between TMT characteristics and the firm's pioneering activities in new technological fields. Those results were supported by the results of the full model, Model 6. The moderation effect is also clearly visible in Figure 4-4 and Figure 4-5.

Last, Table 4-5 contains the results of the empirical tests using a definition of explorative R&D activities based on non-patent references (NPRs). Model 1 indicates negative influences of R&D intensity and firm size on the firm's explorative R&D activities. Another difference the between previous analysis based on patent citation and class data and the models based on NPRs is that the effect of R&D-related functional experience of TMT members on the firm's explorative activities was statistically insignificant, not supporting Hypothesis 4-1. However, in support of Hypothesis 4-2, the influence of educational background in science or engineering was positive and significant in Model 3 (β: 0.526, p-value<0.01) and Model 5 (β: 1.152, p-value<0.01). These results imply that TMT members which are educated in science or technology lead to firm's R&D being more focused on basic science. The moderation effects of average tenure were positive and significant in both Model 4 (β: 0.0979, p-value<0.01) and Model 5 (β: 0.116, p-value<0.05). Above results were also statistically supported in the full model, Model 6. Figure 4-6 and Figure 4-7 show this positive interaction effect of average tenure on both relationships and support the Hypothesis 4-3a and Hypothesis 4-3b.

4.4.1 Additional analysis

Even though this study confirms how organizational behaviors, especially towards the firm's R&D direction are influenced by the top managers, it could be argued that the micro level of an organization's R&D projects is mainly affected by the manager overseeing the R&D. In many organizations, the CTO or vice president of the R&D division are responsible for managing and evaluating each R&D project, while other top managers are only signposts for the organization's macroscopic direction. Since this research measured the firm's R&D activities based on the patented R&D outputs which well reflect the details of R&D projects, I additionally conducted an empirical analysis to address the role of managers of R&D divisions and the CTO. Compared to the original research model, the additional tests only considered the biographical information of the CTO and vice president (VP) of the firm's R&D divisions. Due to the average tenure of the CTO and VP of R&D divisions being included in the regression models as an explanatory variable, I controlled for the average tenure of TMT members. I only included the empirical results for two of the dependent variables (patent citation and patent class) because there is no statistical supports for an effect on the other dependent variable (non-patent references). The results are shown in Table 4-6 and Table 4-7, respectively.

Unlike the results of the original research model, which shows positive effects of R&D functional experiences and science or engineering education experiences, there are negative effects of the CTO and VP of R&D's characteristics on the firm's explorative R&D activities. Specifically, Model 2, Model 4, and Model 6 in Table 4-6 and Table 4-7 indicate that past experiences in R&D function lead the CTO and VP of R&D divisions to steer the firm's R&D projects away from conducting explorative activities, especially for sourcing new technological knowledge and searching new technological fields. Moreover, Model 3 in Table 4-6 and Table 4-7 also indicates that science or engineering

Table 4-6. Additional analysis for explorative R&D based on patent citations

Dependent variable Explorative R&D (citations)	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Control variables						
R&D intensity	0.0083	0.0391	0.0367	0.0243	0.0288	0.0276
	(0.0757)	(0.0758)	(0.0764)	(0.0773)	(0.0780)	(0.0784)
Firm size[1]	0.0183	0.0284	0.0242	0.0324	0.0267	0.0312
	(0.0231)	(0.0225)	(0.0225)	(0.0226)	(0.0232)	(0.0230)
Firm innovation experience[1]	-0.0458**	-0.0421**	-0.0407**	-0.0441**	-0.0406**	-0.0453**
	(0.0201)	(0.0192)	(0.0194)	(0.0194)	(0.0200)	(0.0200)
Technological diversity	0.563***	0.516***	0.520***	0.492***	0.518***	0.493***
	(0.1646)	(0.158)	(0.160)	(0.157)	(0.161)	(0.159)
TMT average age[2]	-0.0030	-0.0031	0.0012	-0.0022	0.0011	-0.0010
	(0.0274)	(0.0267)	(0.0270)	(0.0267)	(0.0273)	(0.0271)
Educational heterogeneity	0.3561	0.416	0.359	0.389	0.362	0.372
	(0.4412)	(0.431)	(0.433)	(0.431)	(0.437)	(0.435)
Functional heterogeneity	-0.2969	-0.345*	-0.309	-0.362*	-0.310	-0.365*
	(0.2117)	(0.209)	(0.210)	(0.211)	(0.213)	(0.214)
TMT average tenure[3]	-0.0201**	-0.0247**	-0.0255**	-0.0279**	-0.0267**	-0.0280**
	(0.0099)	(0.0099)	(0.0102)	(0.0123)	(0.0124)	(0.0124)
_Cons	0.1647	0.157	0.198	0.250	0.209	0.273
	(0.396)	(0.384)	(0.388)	(0.389)	(0.391)	(0.395)
Independent variables						
CTO and VP_R&D		-0.0210**		-0.0425**		-0.0481*
R&D exp (R&D Exp)		(0.0088)		(0.0183)		(0.0287)
CTO and VP_R&D			-0.0174*		-0.0292	0.0098
Sci / Eng edu (S&E Edu)			(0.0089)		(0.0197)	(0.0304)
CTO and VP_R&D				-0.0078	-0.0046	-0.0059
Average tenure (Tenure)				(0.0097)	(0.0104)	(0.0104)
R&D Exp × Tenure				0.0035		0.0045
				(0.0027)		(0.0037)
S&E Edu × Tenure					0.0021	-0.0020
					(0.0031)	(0.0043)
Observations	200	200	200	200	200	200

Wald Chi-square	19.35*	24.86*	22.87**	26.56**	23.15*	26.52*

Note: ***p<0.001; **p<0.01; *p<0.05; two-tailed tests. Robust standard errors are in parentheses. [1] Transposed to log scale. [2] Standardized. [3] Excluding CTO and R&D (VP)

Table 4-7. Additional analysis for explorative R&D based on patent classes

Dependent variable Explorative R&D (classes)	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Control variables						
R&D intensity	0.0128	0.0292	0.0296	0.0170	0.0214	0.0199
	(0.0446)	(0.0448)	(0.0451)	(0.0457)	(0.0460)	(0.0464)
Firm size[1]	0.0363***	0.0414***	0.0395***	0.0456***	0.0426***	0.0446***
	(0.0131)	(0.0130)	(0.0129)	(0.0132)	(0.0134)	(0.0134)
Firm innovation	-0.0800***	-0.0789***	-0.0778***	-0.0826***	-0.0803***	-0.0830***
experience[1]	(0.0113)	(0.0110)	(0.0111)	(0.0113)	(0.0115)	(0.0117)
Technological diversity	0.4767***	0.457***	0.456***	0.452***	0.463***	0.454***
	(0.0938)	(0.0919)	(0.0923)	(0.0914)	(0.0930)	(0.0928)
TMT average age[2]	0.0054	0.0062	0.0087	0.0089	0.0102	0.0097
	(0.0158)	(0.0156)	(0.0157)	(0.0156)	(0.0159)	(0.0159)
Educational	0.226	0.251	0.219	0.209	0.196	0.200
heterogeneity	(0.2561)	(0.252)	(0.253)	(0.253)	(0.255)	(0.256)
Functional	-0.171	-0.196	-0.177	-0.225*	-0.197	-0.225*
heterogeneity	(0.1242)	(0.123)	(0.123)	(0.124)	(0.125)	(0.126)
TMT average tenure[3]	-0.0062	-0.0085	-0.0093	-0.0144**	-0.0138*	-0.0146**
	(0.0057)	(0.0058)	(0.0060)	(0.0072)	(0.0073)	(0.0073)
_Cons	-0.0960	-0.0947	-0.0693	-0.0326	-0.0541	-0.0208
	(0.228)	(0.224)	(0.225)	(0.228)	(0.227)	(0.231)
Independent variables						
CTO and VP_R&D		-0.0109**		-0.0205*		-0.0228
R&D exp (R&D Exp)		(0.0051)		(0.0108)		(0.0169)
CTO and VP_R&D Sci / Eng edu (S&E Edu)			-0.0100*		-0.0138	0.0048
			(0.0052)		(0.0116)	(0.0180)
CTO and VP_R&D				0.0013	0.0030	0.0025
Average tenure (Tenure)				(0.0057)	(0.0061)	(0.0061)
R&D Exp × Tenure				0.0017		0.0022
				(0.0016)		(0.0022)
S&E Edu × Tenure					0.0008	-0.0011
					(0.0018)	(0.0025)

Observations	200	200	200	200	200	200
Wald Chi-square	66.06***	72.78***	71.62***	75.79***	72.24***	74.65***

Note: ***p<0.001; **p<0.01; *p<0.05; two-tailed tests. Robust standard errors are in parentheses. [1] Transposed to log scale. [2] Standardized. [3] Excluding CTO and R&D (VP)

educated CTOs or VPs of R&D divisions also have a negative cognitive base towards their firm's explorative R&D projects.

Last, there is no statistical evidences for moderation effects of the average tenure of the CTO and VP of R&D divisions. In summary, top managers who possess innovation-related experiences tend to favor explorative R&D activities, while CTO and VP of R&D divisions are reluctant to conduct explorative R&D projects. In comparison with other top managers, the CTOs and VPs of R&D divisions are held responsible for the firm's R&D performance, which leads them to have a more conservative attitude towards risky R&D activities, even though they possess innovation-related experiences.

4.5 Discussions

This research analyzed the effects of TMT's innovative experiences and backgrounds as well as their average tenure on the firm's explorative R&D activities. This study hypothesized that either functional experiences in R&D or academic backgrounds in engineering or science among the observable characteristics of the TMT affect the extent to which firms engage in explorative R&D projects. Also, I proposed that the relationship between the proportion of TMT members with R&D-related experience or educational background and the firm's explorative R&D is moderated by the average tenure of these TMT members. The hypotheses were tested on a sample of TMTs biographic information, financial, and patent data of 89 firms in US high-tech industries from 2006 to 2009. All suggested hypotheses were supported and allow me to draw the following conclusions.

The innovation-related experiences of TMT members affect the firm's R&D activities. In other words, R&D activities were more focused on exploration in firms in which a larger proportion of TMT members have innovative experiences such as R&D-related employment experience or majoring in engineering or sciences. Specifically, this research analyzed three different aspects of explorative R&D in terms of applying new technological knowledge (patent citations) as well as scientific knowledge (non-patent references), and exploring new technological fields (patent classes), to address the effects of TMT member's decision on the firm's R&D activity. The empirical results show that there are positive influences of TMT members with R&D functional experiences on firms' explorative R&D when explorative R&D is defined focusing on technological, rather than science aspects. If an organization's decision makers have more work experiences related to R&D, the organization's R&D tends to apply new technological knowledge as well as knowledge from new technological fields. Nonetheless, I was unable to find evidence for a relationship between the R&D functional experience of the TMT members and the firm's explorative R&D in terms of adopting scientific knowledge (non-patent references). For TMT members with an academic background in science or engineering, on the other hand, I find positive effects on the firm's explorative R&D activity in terms of both technological and science aspects. Specifically, increasing the proportion of science and engineering educated TMT members in an organization leads to the organization actively applying new technological knowledge, knowledge from new technological fields, and scientific knowledge in their R&D. It seems that these different results are due to the different way of achieving objectives and methods when developing the individual's cognitive bases through experiences in R&D functions or through science or engineering education. Individuals with functional experiences in R&D usually tend to accomplish their R&D objectives in technological ways due to their unfamiliarity with scientific knowledge. Moreover, scientific knowledge also requires considerable time to understand and is difficult to directly apply in the development process. Meanwhile, individuals with science or engineering education usually emphasize problem solving based on technological knowledge as well as scientific knowledge. During their higher education, students are encouraged to solve fundamental problems which require an approach from the scientific perspective.

Based on the upper echelon theory suggested by Hambrick and Mason (1984), the results of this chapter confirm that past experiences of individuals affect organizational behavior such as the direction of the innovation activities. R&D departments and science or engineering subjects put strong emphasis on innovation, and TMT members with such experiences have R&D-favoring cognitive bases and strive to enhance the organization's competitiveness through R&D and innovation. Therefore, increasing proportions of members with innovative experiences in TMTs lead to firms investing more resources into explorative R&D projects.

Next, this chapter demonstrated how the average tenure of these TMT members affects the decision-making process of and moderates the relationship between innovative experiences and explorative R&D activities. Even if TMT members with innovative experiences are willing to conduct explorative projects, in case of being junior members with a short tenure, their weak power in the TMT can make it more difficult for them to lend support to high-risk explorative R&D. TMTs with a large proportion of members experienced in innovation, who also hold more power due to a long tenure in the TMT can allow them to better manage and deploy large amounts of resources to support explorative R&D. The empirical results of this study demonstrate the positive moderating effect of the average tenure of TMT members with innovation-related experiences on the relationship between innovation-related TMT characteristics and the explorative activities of the firm.

Chapter 5. Scientific Knowledge Transfer in Upstream Alliance[3]

5.1 Introduction

Highly complex and fast-changing environments cause industrial firms to increasingly rely not only on technological knowledge but also the science, e.g. the research being performed in universities and research institutes such as government-funded laboratories, to solve the fundamental problems encountered during their research and development (R&D) activities (Bettis and Hitt 1995; Cohen et al. 2002; Fabrizio 2007). Even though they require the investment considerable resources and time, scientific outputs from basic research enable firms to access distinguished technological opportunities with high potential (Hicks 1995). Therefore, it is necessary to put scientific knowledge as well as technologic knowledge to practical use in the R&D process to archive successful innovation. However, basic research requires the deployment of a large amount of resource while at the same time its outputs are often not directly applicable to commercial products leads to most industrial firms shying away from engaging in scientific knowledge creation activities such as scientific experiments. Due to this lack of internal scientific research, industrial firms usually source the required scientific knowledge

[3]Chapter 5 is now under revision in *Journal of Technology Transfer*

through contracting with scientific institutes for joint research, forming R&D alliances (Lane and Lubatkin 1998; Stuart et al. 2007; Almeida et al. 2011; Mindruta 2013). Because of the high levels of tacitness and complexity of scientific knowledge, it is known that informal interactions through personal communication facilitate the learning process of scientific knowledge (Cohen et al. 2002; Rothaermel and Deeds 2006). Therefore, alliances are effective means to foster collaboration between individuals from different organizations and accessing and applying scientific knowledge into firm-level patented innovation (Almeida et al. 2011; Mindruta et al. 2016).

In this respect, a growing number of literature has discussed the increasing role of industry-science collaboration, i.e., upstream alliances. Meyer-Krahmer and Schmoch (1998) showed how interactions of industry and universities affect the development of science-based technologies. The studies of Andries and Thorwarth (2014) and Añón Higón (2016) investigated the benefits gained by industrial firms outsourcing their basic research. Moreover, D'Este and Patel (2007), Perkmann and Walsh (2008), and Wright et al. (2008) analyzed several types of academic cooperation and their effectiveness on the industry-science relationship. Siegel et al. (2003, 2004) focused on how scientific knowledge is transferred from universities to firms through university technology transfer offices (TTOs).

Even though these studies investigated several aspects of the industry-science link, only a few studies addressed the factors that affect the innovation performance of upstream alliances. Furthermore, there is a lack of studies related to partner choices in industry-science relationships, especially from the perspective of the industry. Consequently, there is a large knowledge gap related to which characteristics and factors affect the learning processes of scientific knowledge for industrial firms in upstream alliances. In the case of alliances for scientific knowledge sourcing, considerable search efforts and costs are required to identify and learn scientific knowledge with a high potential to overcome technological problems (Gulati and Singh 1998; Almeida et al. 2011). Since firms have limited resources, it is important for industrial firms to identify adequate scientific partners to effectively perform the desired alliance activities and accomplish successful innovations (Bodas Freitas et al. 2013; Jong and Slavova 2014). Especially for industrial firms which are mainly accomplishing innovation through technology, their lack of experience in dealing with scientific knowledge prevents them from properly evaluating their potential scientific partners. Because the characteristics of scientific knowledge are different from those of technological knowledge (Brooks 1994), the mechanisms of sourcing and accessing technological knowledge via alliances might not be applicable to the investigation of alliances primarily focusing on scientific knowledge.

For this reason, this chapter investigates industry-science link with a focus on the post-alliance innovation performance. From the knowledge-based view, this research aims at investigating which knowledge characteristics of both industrial firms and their scientific partners will enhance the productivity of alliances for scientific knowledge sourcing. Specifically, it attempts to show how knowledge characteristics such as size of the knowledge stock, knowledge diversity, knowledge similarity, and research performance of scientific partners (scientific knowledge providers) and the scientific capacity of industrial firms (scientific knowledge receivers) influence post-alliance innovation performance. The hypotheses of this study are empirically tested on a dataset assembled using upstream alliance information, patenting, and scientific publication data. For practitioners, this research provides important implications by identifying the knowledge factors which should be considered when industrial firms evaluate potential scientific partners. This chapter also shows the importance of conducting pioneer research before entering into R&D alliances with scientific partners to increase the benefits gained from the access to external scientific knowledge sources. Particularly, this research shows empirical evidence of science positively affecting industrial innovation. This highlights the benefits of industry-science alliances for firms at a practical level. Compared to previous literature which generally discussed and emphasized the importance of interactions between industry and science, but lacked empirical proof, empirical results of this chapter complement the existing literature in this field.

5.2 Research hypotheses

5.2.1 Research performance of scientific partner

Although every scientific institute performs its research activities with the aim to discover and understand natural phenomena in a broad sense, the influence of their research output on follow-up research as well as their contributions to advancing technology are differentiated because of each institution's distinctive research abilities. In literature on the knowledge-based view, the research abilities of an R&D organization are related to the level of their research output that can stimulate future research, also referred to as core knowledge or impactful knowledge. The core knowledge is defined as "knowledge – often scientific or technological – that is at the heart of, and forms the foundation for, a product or service" (Helfat and Raubitschek 2000, p. 963). Because the core knowledge forms the basis for almost all relevant-knowledge or products, an organization possessing a large amount of core knowledge would have a strong influence on follow-up innovation. Also, organizations possessing such core knowledge are able to introduce new replacement products which displace existing products (Helfat and Raubitschek 2000). Similarly, possessing impactful knowledge or architectural competence in relevant areas enables researchers to explore and integrate new knowledge components in a more efficient way (Kim et al. 2016). Previous studies suggested that several factors related to the R&D environment are generally identified in organizations which have experience of creating core and impactful knowledge (Vanhaverbeke et al. 2012). One of these factors is the presence of effective routines for R&D processes. Organizations with effective routines will have knowledge processing systems which are better suited for creating influential research. Effective routines enable organizations to conduct new research with less investments, leading to an increased R&D efficiency. Also, outstanding researchers such as star scientists are known to contribute to research performance. Zucker et al. (2002) analyzed that partnering with star scientists positively affects the level of influence on innovation performance. The creative ideas and remarkable intuition of such skilled researchers lead the directions and objectives of research projects towards significant discoveries. In summary, industrial firms can take advantage of their scientific partners' research ability stemming from their effective routines and outstanding researchers. Also, the experience of upstream partners in creating influential research will positively contribute to the outcomes of R&D collaborations.

Hypothesis 5-1: *In upstream alliances, the level of research quality of scientific partners will positively influence the industrial firm's post-alliance innovation performance.*

5.2.2 Knowledge diversity of scientific partner

By performing collaborative research with organizations with a diversified knowledge base, focal organizations can derive benefits from an economy of scope (Teece 1980; Miller 2006). Shared knowledge and know-how obtained from various areas will generate considerable synergy effects in the invention processes. In other words, scientific knowledge obtained by conducting diversified research generates complementarities that contribute to increasing the probability of successful innovation. Referring to Kim et al. (2016), decreasing marginal returns to R&D will be minimized when R&D resources are deployed into various areas. Organizations with strengthened capabilities in various fields can solve more complicated problems as well as explore more opportunities (Kim et al. 2016). Taken together, the diversity of research fields is related to the R&D productivity level and R&D cooperation with highly-diversified partners enables the focal organization to benefit from their partners' high level of R&D productivity (Kim et al. 2016).

Meanwhile, Fleming and Sorenson (2004) and Mindruta (2013) suggested that advantages of research collaboration with organizations which have broader scientific knowledge base are both providing different points of view on problems, as well as reducing R&D uncertainties. On one side, organizations with a broader scientific knowledge base can look at research problems from various angles and allow their industrial partner to access related knowledge immediately (Mindruta 2013). Alliance partners with a broader scientific knowledge base can offer knowledge which allow to understand fundamental and operating mechanism from various research fields and support the industrial R&D using a multi-disciplinary approach. On the other hand, industrial firms can avoid inefficient experimentation and reduce uncertainties arising from the variety of alternatives (Mindruta 2013). In summary, knowledge diversity of scientific partner allows for a higher efficiency in R&D collaboration due to economies of scope as well as by reducing unnecessary procedures and providing various perspectives on problems. Thus, it could be expected the increased knowledge diversity of upstream partner to positively affect the joint R&D processes, which leads to the following hypothesis:

Hypothesis 5-2: *In upstream alliances, the level of knowledge diversity of scientific partners will positively influence the industrial firm's post-alliance innovation performance.*

5.2.3 Knowledge stock of scientific partner

Prior literature has argued that the level of knowledge stock, i.e., accumulated knowledge assets, positively influences an organization's performance (Dierickx and Cool 1989; DeCarolis and Deeds 1999). Organizations with considerable accumulated scientific knowledge will naturally have more intuitions and insights for directing research projects to have the most positive results (Nelson 1982; Fabrizio 2007). Accumulated experience of creating scientific knowledge also results in an increased ability of applying science to successfully achieve innovation outcomes. (Al-Laham et al. 2011). In other words, testing scientific theories by conducting repeated experiments allows organizations to establish optimized routines and be accustomed to using scientific data more effectively. Meanwhile, the accumulated general knowledge stock has a positive impact on creating new knowledge (Zucker et al. 2007). From the view of the cumulated advantage model, the level of accumulated knowledge determines the rate of new knowledge creation. As more knowledge has been accumulated, new knowledge is created in a short period of time. Therefore, in an alliance with scientific organizations with abundant stocks of knowledge, industrial firms can receive more and better assistance and guidance for their invention processes.

Additionally, a high-level of knowledge stock enables to enjoy the advantages of the scale of search (Gambardella 1992). From the viewpoint of path-dependency, technological search processes in industrial R&D usually depend on existing knowledge as the previous knowledge acts as a starting point or building blocks for future research (Teece et al. 1997; Wu and Shanley 2009). Therefore, if an organization has a large amount of accumulated knowledge, the number of alternatives created through the recombination of existing knowledge is also increased, allowing to find more optimal solutions. Accumulated knowledge allows to overcome the barriers occurring in R&D processes more quickly and at lower costs. Consequently, an extended scale of search increases the efficiency of R&D as well as the probability of successful innovation (Fleming and Sorenson 2004; Sorenson and Fleming 2004; Fabrizio 2007). Together, industrial firms partnering with scientific organizations with an abundant knowledge stock can access the existing knowledge and experiences and get better and faster assistance for their R&D projects. These positive influences of experienced scientific partners on industrial firms lead to the following hypothesis:

Hypothesis 5-3: *In upstream alliances, the level of knowledge stock of scientific partners will positively influence the industrial firm's post-alliance innovation performance.*

5.2.4 Knowledge base similarity with scientific partners

In the knowledge-based view, it is important to minimize the level of knowledge transfer or cross-learning between researchers of both focal and partner organizations to increase the efficiency of knowledge integration (Grant 1996). Transferring knowledge from unfamiliar areas requires considerable efforts of both the teaching and student organizations (Lane and Lubatkin 1998), which unintentionally consumes R&D resources and might result in delayed R&D plans. Scientific knowledge, which consists of both codified and tacit knowledge, is especially difficult to share and transfer even though communication occurs at the individual level (Almeida et al. 2011). Additionally, the profoundness of scientific discipline often impedes industrial organizations from understanding scientific theories.

From the perspective of relative absorptive capacity, an individual's learning of new knowledge is maximized if the knowledge is close to the structures of existing knowledge (Lane and Lubatkin 1998). Shared traditions, techniques, disciplines, and mechanisms of fundamental phenomena in particular research areas allow to transfer scientific knowledge more smoothly even if the scientific knowledge contains complex elements. Also, having common experiences of solving similar problem sets for both student and teacher organization allows the student organization to facilitate new knowledge application in more appropriate ways (Cohen and Levinthal 1990; Lane and Lubatkin 1998). Consequently, a similar knowledge base between industrial firms and scientific institutions allows for interactions with less communication efforts which increases the efficiency of the collaborative research. This leads to the following hypothesis:

Hypothesis 5-4*: In upstream alliances, the similarity of the knowledge bases of the scientific partners and the focal organization will positively influence the industrial firm's post-alliance innovation performance.*

5.2.5 Internal scientific capability of focal firm

The impact of innovation depends upon the focal organization's capability of integrating specialized knowledge such as scientific knowledge from other organizations (Grant 1996). In-house scientific activity of the industrial organization is related to the number of performed R&D projects which are similar to those of conducted by scientific institutions such as universities or government laboratories (Gambardella 1992). By conducting scientific R&D projects, industrial organizations can increase their scientific knowledge capacity which leads to an improved application of knowledge into their internal R&D processes (Cohen and Levinthal 1990). When industrial firms have a thorough understand of their scientific partner's knowledge, they can more rapidly identify suitable knowledge among the partner's accumulated scientific knowledge stock (Fabrizio 2007). Organizations also tend to adopt a more open approach in their innovation processes as the contribution of scientific disciplines to their industrial R&D increases (Jong and Slavova 2014). The more industrial firms conducting scientific projects, the more their knowledge processing systems will resemble those of scientific organizations (Lane and Lubatkin 1998), which in turn eases interaction and reduces sources of conflict during in research collaboration. Additionally, firms involved in basic science benefit from science-driven R&D processes as well as an improved productivity (Henderson and Cockburn 1994; Stuart et al. 2007). For instance, Almeida et al. (2011) stated that both the firm's level of engaging in scientific activities as well as the adequate of its scientific workforce improve innovative output. Furthermore, Gambardella (1992) empirically discovered that firms in the US pharmaceutical industry with enhanced in-house scientific research benefitted from increased opportunities to take advantage of external scientific knowledge. According to Mindruta (2013), an organization's scientific knowledge creation capability in industry-scientific alliance enhances post-alliance value creation. The results of this research indicate that industrial researchers in firms with a high level of scientific capability are better able to understand external scientific knowledge which leads them to more efficiently performing science-based R&D activities (Gittelman and Kogut 2003; Jong and Slavova 2014). Together, I expect that scientific knowledge absorption processes are be enhanced by increasing levels of the industrial firm's scientific capacity.

Hypothesis 5-5*: In upstream alliances, the scientific capability of the focal organization will positively moderate the relationships between the scientific partner's (research performance / knowledge diversity / knowledge stock / knowledge similarity with industrial firm) and the industrial firm's post-alliance innovation performance.*

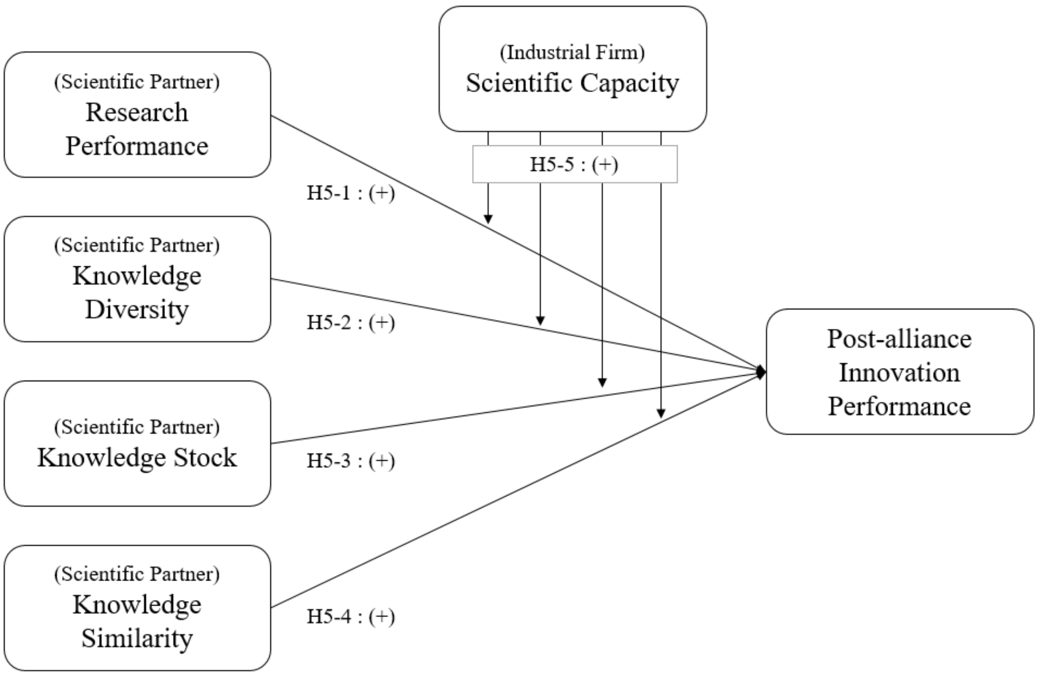

Figure 5-1. Conceptual Model for Chapter 5

The conceptual diagram in Figure 5-1 shows the relationships between the suggested hypotheses.

5.3 Methods

5.3.1 Data

To empirically test the suggested hypotheses, this research collected samples and data from various sources. First of all, I compiled a sample of alliance-active firms in high-tech industries including biopharmaceutical, chemical, telecommunication, electronic and computer, equipment and manufacturing, and other high-tech related industries. The focus on high-tech industries stems from the high importance of scientific knowledge in those industries (Lane and Lubatkin 1998; Rothaermel and Deeds 2006; Sampson 2007; Stuart et al. 2007; Almeida et al. 2011). For firms operating in these industries, scientific institutes are favorable alliance partners because firms can expect more impactful innovation performances while at the same time they can save R&D expenses (George et al. 2002), outputs from such scientific organizations complement those of the firms, and they do not directly compete with industrial firms (Almeida et al. 2011). Next, this research collected alliance deal information on the sample firms for the 1990 to 2008 period from the Securities Data Company (SDC) Platinum database provided by Thomson Reuters. In previous studies related to upstream alliances, Stuart et al. (2007)

considered upstream alliances as alliances between industries and universities while Rothaermel and Deeds (2006) set the subject of research as alliances with non-profit organizations including universities and other research institutions. Referring to these studies, this study defined upstream alliances as alliances between industrial organizations and scientific research institutes including universities, government-sponsored research laboratories, and other institutes. Furthermore, I manually reviewed the alliance deal descriptions provided by the SDC Platinum database and have only considered alliances whose purpose was explicitly stated to be joint research or the sourcing of knowledge from scientific research institutes.

For measuring scientific knowledge, this research focused on scientific publications. Although there are many documents classified as scientific publications such as journal articles, conference proceedings, textbooks, and other scientific related papers, for the purpose of an objective comparison, I only considered scientific publications to be articles published in journals listed in the Science Citation Index (SCI) (Audretsch et al. 2004; Han 2007). Publishing a research paper in an SCI-listed journal widely regarded as a sign for exceptional scientific research and a high potential for influencing follow-up research. This study collected information on published journal papers through the Web of Science (WOS) provided by Thomson Reuters. Meanwhile, patents are considered as a useful proxy for industrial innovation (Fabrizio 2007), because issued patents reflect that a particular invention is considered highly novel as well as an advancement of existing technologies. Also, most industrial organizations tend to protect their R&D outputs by applying for patents because the assignee of patent has an exclusive right for commercially exploiting the invention and legal protection to these claims. While different countries operate their own intellectual property systems for patents, globally competing industrial organizations usually protect their technological ideas through United States (US) patents. Each issued US patent provides detailed information including the assignee, technological fields classified by the US Patent Classification (USPC), backward citations, and forward citations. This research retrieved patent data from the United States Patent and Trademark Office (USPTO). In addition to alliance deals and knowledge data, the dataset of this research includes firm-level financial data retrieved from Compustat provided by Standard and Poor's and Worldscope provided by Thomson Reuters. The final dataset consists of 143 upstream alliances formed between 134 firms and 108 scientific organizations. The chosen method for the empirical analysis is ordinary least square (OLS) regression. Before conducting the empirical analysis, I performed a Variance Inflation Factor (VIF) analysis to identify potential multicollinearity problems between the variables. The average VIF index did not exceed 5, suggesting that there is no evidence for multicollinearity issues in analysis of this study.

5.3.2 Variables

5.3.2.1 Dependent variable

Post-alliance innovation performance: Previous studies focused on knowledge transfer had addressed the post-alliance innovation performance based on counting the articles or patents to measure the volume of the created knowledge (Moed et al. 2005; Zucker et al. 2007). However, these indicators unable to capture the distinguished level of influences toward on follow-up innovations or real worlds. To avoid this problem, this research captures the number of forward citation received of each innovation outputs. Specifically, I calculated the average number of forward citations received within 7 years of entire patents which were assigned to industrial firms and granted during in 5 years after the alliance announced.

5.3.2.2 Independent variables

Scientific research performance: Research performance of scientific institutions is related to the quality of their research outputs. Prior literature has suggested that citations of journal articles are a suitable proxy for the value of the research (Almeida et al. 2011). For this reason, this study identified the average number of journal article citations for each scientific institution. I collected the citation information of all journal articles published in the 10 years preceding the alliance. As older articles have more opportunities to be cited, I only calculated the citations received within 10 years after the publication year of each journal article, respectively. For example, journal articles published in 1991 to 2000 were chosen to represent the research performance of a scientific institution entering into an alliance in 2001. In the next step, I counted all citations received in 1992 to 2001 for the institution’s articles published in 1991, and repeated this process for all article years up to the year 2000.

Scientific knowledge diversity: Studies on knowledge diversity have frequently used an entropy index of diversification to calculate an organization's knowledge diversity (Mindruta 2013). Previous studies calculated the diversity based on patent classes, whereas I calculate the entropy based on scientific research areas, classified by the 156 distinct research areas listed in Thomson Reuters' Web of Science. Excluding non-scientific areas such as arts reduces the number to 113 research areas. As this high number of research areas makes it difficult to provide clear distinctions and later match the technological areas with the patent classification system, the research areas were reclassified. While existing classification schemes such as the Field of Science and Technology (FOS) classification by OECD offer the advantage of previously compiled matching tables with the Web of Science classification, they were too fine-grained for this approach. Consequently, this research, under the guidance of several consulted scientists from various research backgrounds, rearranged the 113 fields into 11 distinctive research areas (agricultural, biotechnologies, chemical, computer and information, communication, drugs and medical, electrical, electronic, environmental, mechanical, and others). I then identified the number of published journal articles in each of these 11 scientific fields in the 10 years preceding the alliance announcement and calculated the diversity based on the following equation:

$$Knowledge\ diversity = \sum_{i}^{k} f_i * \ln(1/f_i)$$

where f_i represents the proportion of published articles in the ith scientific field and k indicates the total number of scientific fields.

Scientific knowledge stock: To measure the size of the knowledge stock of scientific institutions, Zucker et al. (2007) suggested a way of proxying the knowledge stock through the organization's total amount of prior accumulated knowledge in all fields. Adopting this way of measuring quantities of knowledge, I counted the number of journal articles published by each scientific partner organization in the 10 years preceding the year of the alliance announcement (Mindruta 2013).

Knowledge base similarity: Although an increasing tendency of scientific institutions to apply for patents and for industrial firms to generate journal publication can be seen, these types of knowledge only cover a small portion of the entire knowledge typically found in each type of organization. For this reason, this research only retrieved the data of journal publication records of scientific institutions and patent grants to industrial firms during the 10 years preceding the alliance announcement to measure the relevance of their respective knowledge bases. Following experts' guidance, I matched the research areas of the scientific institutions' journal publications and the patent categories of the industrial firms' patents into the 11 research areas mentioned previously. I then calculated the knowledge base similarity using the following equation:

$$Knowledge\ base\ similarity = \frac{F_i F_j'}{\sqrt{(F_i F_i')(F_j F_j')}}$$

where i and j represent the organizations in particular alliances and a multidimensional vector, $F_i = (F_i^{\ 1}, F_i^{\ 2}, \cdots, F_i^{\ 11})$ contains the number of journal publications or patents in 11 different research areas (Sampson 2007).

Firm's scientific capability: Publication activity of industrial firms is not only a mean of expanding the scientific knowledge network but also represents a suitable indicator for an organization's internal scientific capabilities (Mindruta 2013). Thus, this research counted the total number of journal articles published during the 10 years preceding the alliance announcement by individuals associated with the industrial firms to capture the focal firm's in-house scientific capability (Gambardella 1992; Almeida et al. 2011).

5.3.2.3 Control variables

R&D expense: As a resource flow, the amount of R&D spending influences the firm's R&D capabilities (Dierickx and Cool 1989). Also, R&D expense is not only related to the organization's absorptive capacity (Cohen and Levinthal 1990; Lane and Lubatkin 1998), but also determines the directions of R&D projects. Thus, this research included the firm's R&D expense in the year of the alliance announcement (Almeida et al. 2011).

Firm size: Previous research found that the influence of science on industrial R&D differs according to the organization's size (Cohen et al. 2002), because the scale and range of R&D can be expanded as the size of the firm increases (Rothaermel and Deeds 2006; Almeida et al. 2011; Mindruta 2013). As a proxy for the size of organizations, this research adopted the number of employees (in thousands).

Firm's innovation capacity: According to Mindruta (2013), the innovation capability of the industrial organization may influence the productivity of its collaborations with scientists from scientific institutions. Moreover, experiences of successful R&D activities indicate that the firm has an R&D environment suitable to conduct invention processes. As the basis of the firm's knowledge stock, patents represent the particular R&D projects that were successfully completed (DeCarolis and Deeds 1999). Therefore, this research controlled the industrial firm's innovation capacity through the total number of patents assigned to each firm in the 5 years preceding the year of the alliance announcement.

Firm's knowledge diversity: Diversified firms require less efforts to understand scientific knowledge due to their experiences and acquired knowledge in various technologic fields (Rothaermel and Deeds 2006; Mindruta 2013). For this reason, this research controlled the technology diversity of the firms based on the distribution of its granted patents in 11 distinct research categories based on patent classes (Mudambi and Swift 2014). I calculated firm's knowledge diversity in the same way as the scientific knowledge diversity described above.

Alliance experience: Prior experience with alliances influences the establishment of routines for collaborative working processes. Additionally, the number of alliances positively affects innovation performance (DeCarolis and Deeds 1999). For this reason, this research controlled the influence of alliance experience by including the total number of alliance deals the focal firm conducted in the 5-year period before the announcement of the alliance (Rothaermel and Deeds 2006; Stuart et al. 2007).

Cultural differences: National cultural differences can influence the processes of sourcing external knowledge (Morosini et al. 1998). Differences in languages, culture, and social customs often negatively impact alliance processes (Rothaermel and Deeds 2006). I included a dummy variable and coded it 1 in cases where both the industrial firm and the scientific partner were located in the same country and 0 otherwise.

Type of scientific institutions and industries: This study introduced two dummy variables to distinguish the scientific institutions (Rothaermel and Deeds 2006), and industries. I considered the universities as the base dummy variable and the others were coded to classify government-sponsored research institutes and non-profit research organizations. Also, this research included dummy variables related to the different industries in the sample to control for potential influences or characteristics of a particular industry.

5.4 Results

The descriptive statistics and correlations between the variables used in the empirical analysis are shown in Table 5-1. The average number of alliances was about 25. Especially high correlations were found between the firm's R&D expense and its scientific capacity which can be explained by the fact that the build-up of scientific capabilities requires the investment of relatively more resources. Moreover, the firm's scientific capacity is also positively related to the diversification of the firm's knowledge. Meanwhile, the level of a firm's experiences of successfully conducting R&D, measured by the number of patents granted, shows high correlations with alliance experience.

Table 5-1. Descriptive statistics and correlations matrix of the variables

	Mean	S.D.	1	2	3	4	5	6	7	8	9	10	11
1. Innovation performance	1.745	1.322	1										
2. Research performance	12.43	6.706	.064	1									
3. Knowledge diversity	1.893	0.247	.179	-.212	1								
4. Knowledge stock[1]	9.039	1.249	.139	.573	.343	1							
5. Knowledge base similarity	0.312	0.201	.045	-.205	.134	-.117	1						
6. Firm's scientific capacity[1]	3.784	2.849	-.103	.002	-.199	-.117	.028	1					
7. R&D expense	729.2	1492	.067	-.047	-.206	-.250	-.034	.545	1				
8. Firm size	39.98	85.67	.105	-.164	-.097	-.214	.206	.546	.735	1			
9. Firm's innovation capacity	592	1398	.102	-.143	-.076	-.150	.070	.496	.564	.710	1		
10. Firm's knowledge diversity	1.907	1.357	.077	-.146	-.082	-.119	.232	.605	.429	.619	.604	1	
11. Alliance experience	25.31	69.15	.107	-.114	-.133	-.223	-.039	.438	.523	.511	.810	.417	1

Note: N=143. [1]Transposed to log scale. Dummy variables were excluded.

Table 5-2. Regression results of the main effects

Dependent Variable (Innovation performance)	**Model1**	**Model2**	**Model3**	**Model4**	**Model5**	**Model6**
Control Variables						
R&D expense	-.0001 (.0001)	-.0001 (.0001)	.0001 (.0001)	-.0001 (.0001)	-.0001 (.0001)	.0001 (.0001)
Firm size	.0017** (.0025)	.0020** (.0025)	.0014** (.0024)	.0021* (.0025)	.0015** (.0026)	.0013** (.0037)
Firm's innovation capacity	-.0681 (.135)	-.0708 (.0136)	-.0519 (.134)	-.0710 (.0134)	-.0774 (.138)	-.152 (.156)
Firm's knowledge diversity	-.0001 (.0002)	-.0001 (.0002)	-.0001 (.0002)	-.0001 (.0002)	-.0001 (.0002)	-.0001 (0002)
Alliance experience	.0024* (.0028)	.0025* (.0028)	.0027* (.0028)	.0032* (.0029)	.0025* (.0029)	.0030* (.0034)
Cultural differences (Dummy)	-.432* (.248)	-.387* (.256)	-.345* (.249)	-.325* (.254)	-.439* (.249)	-.350* (.283)
Scientific institution type (Dummy)			*Included*			
Industries (Dummy)			*Included*			
_Cons	1.765*** (.241)	1.562*** (.371)	-.371 (1.025)	.219 (.940)	1.697*** (.295)	-.949 (1.394)
Independent Variables						
Research performance (RP)		.0144** (.0199)				.0233** (.0293)
Knowledge diversity (KD)			1.109** (.515)			1.147* (.661)
Knowledge stock (KS)				.165 (.0971)		.0199 (.156)
Knowledge base similarity (KBS)					.273* (.679)	.793 (.849)
Observations	143	143	143	143	143	143
Adj. R-Square	.086	.090	.119	.107	.088	.119

Note: ***p<0.001; **p<0.01; *p<0.05; two-tailed tests. Standard errors are in parentheses.

Table 5-3. Regression results of the moderation effects

Dependent Variable (Innovation performance)	**Model1**	**Model2**	**Model3**	**Model4**	**Model5**
Control Variables					
R&D expense	.0001 (.0001)	.0001 (.0001)	.0001 (.0001)	-.0001 (.0001)	.0001 (.0001)
Firm size	.0020** (.0025)	.0012** (.0024)	.0011** (.0024)	.0036** (.0026)	.0022** (.0026)
Firm's innovation capacity	.129 (.154)	.123 (.150)	.125 (.150)	.135 (.154)	.127 (.149)
Firm's knowledge diversity	-.0001 (.0002)	-.0001 (.0002)	-.0001 (.0002)	-.0001 (.0002)	-.0001 (.0002)
Alliance experience	.0035* (.0028)	.0031* (.0028)	.0030* (.0029)	.0026* (.0029)	.0012* (.0028)
Cultural differences (Dummy)	-.386* (.254)	-.329* (.244)	-.318* (.246)	-.376* (.243)	-.169* (.254)
Scientific institution type (Dummy)			*Included*		
Industries (Dummy)			*Included*		
_Cons	1.716*** (.505)	-2.818 (1.738)	-2.142 (1.621)	1.570*** (.364)	-6.320*** (2.137)
Independent Variables					
Firm's scientific capacity (SC)	.141 (.0937)	.560* (.327)	.448 (.311)	.0037 (.0843)	1.218*** (.408)
Research performance (RP)	.0267 (.0346)				.0005 (.042)
RP x SC	.0013* (.0061)				.0059* (.0089)
Knowledge diversity (KD)		2.508*** (.882)			1.931** (.934)
KD x SC		.365** (.170)			.169* (.196)
Knowledge stock (KS)			.463 (.177)		.446 (.224)
KS x SC			.0670 (.0342)		.106 (.053)
Knowledge base similarity (KBS)				1.647* (.900)	2.031** (.894)
KBS x SC				.490** (.205)	.525** (.205)
Observations	143	143	143	143	143
Adj. R-Square	.137	.182	.176	.167	.260

Note: ***p<0.001; **p<0.01; *p<0.05; two-tailed tests. Standard errors are in parentheses.

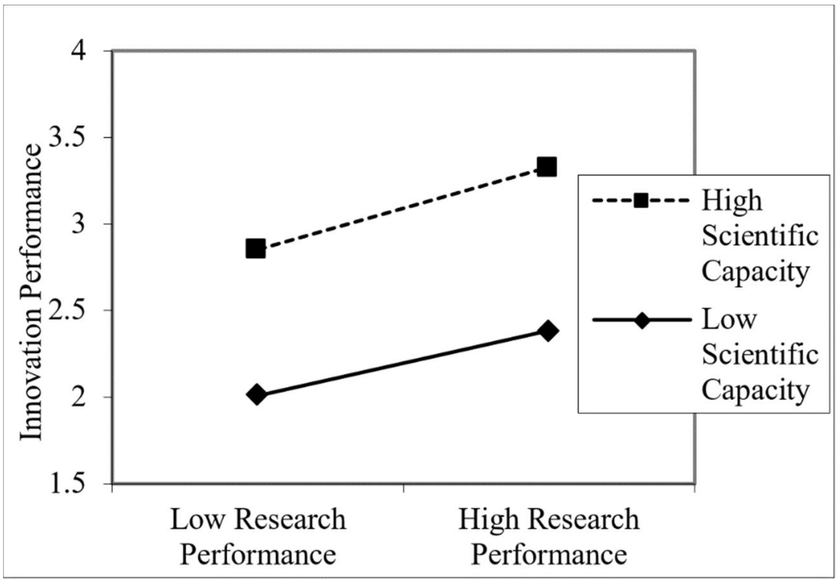

Figure 5-2. The moderation effect of firm's scientific capacity on the relationship between post-alliance innovation performance and research performance

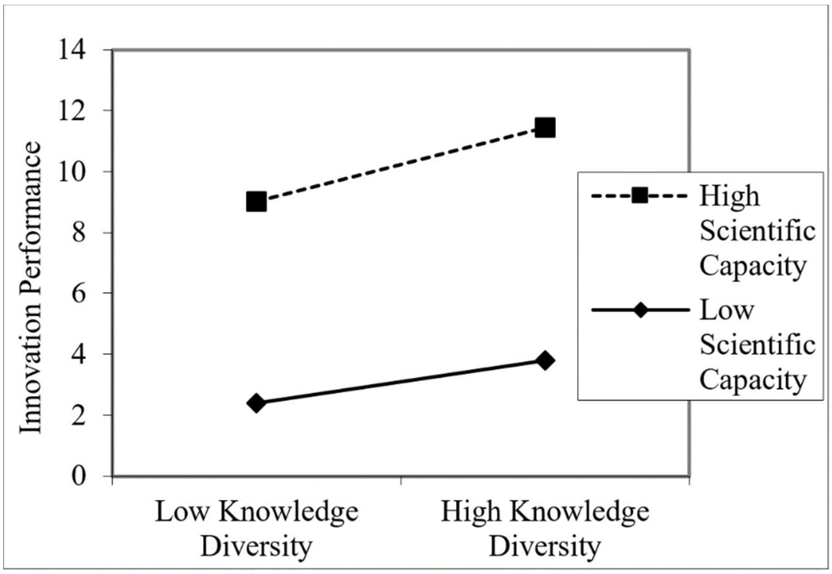

Figure 5-3. The moderation effect of firm's scientific capacity on the relationship between post-alliance innovation performance and knowledge diversity

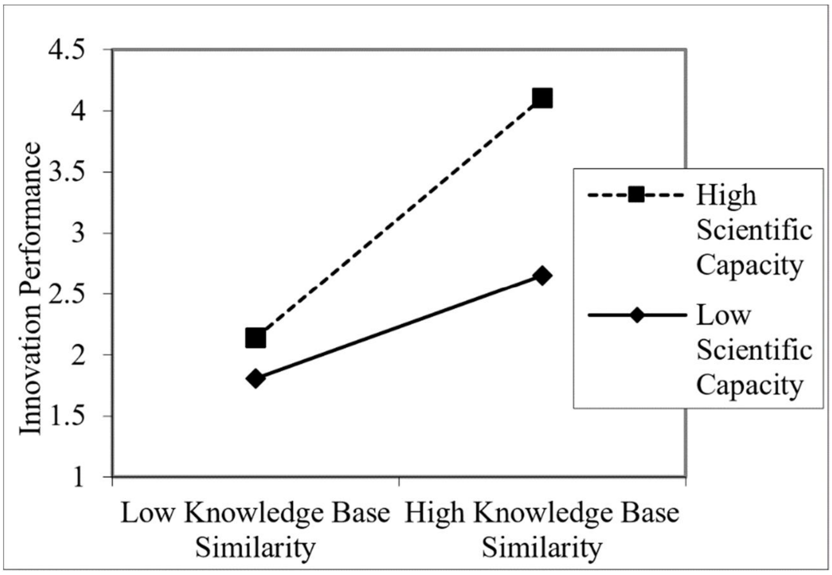

Figure 5-4. The moderation effect of firm's scientific capacity on the relationship between post-alliance innovation performance and knowledge base similarity with firm

Table 5-2 contains the results of the regression analysis for testing the main effects of knowledge factors on the post-alliance innovation performance measured by the average number of forward citation received. In Model 1, only the control variables were included and the different explanatory variables were added to Model 2 to Model 5. To begin with, the size of the industrial firm and its prior alliance experience positively influence the innovation performance of the upstream alliance. Experiences accumulated through repeated alliances contribute to establishing proven procedures for managing collaborations and effective routines for joint research. As the organizations size increases, it can invest a large amount of resources into science-based projects with a high potential for changing industry paradigms. Moreover, cultural differences between the focal industrial firm and its upstream partner negatively affect the innovation performance. This can be explained by the individual researchers from different countries suffering from communication difficulties in the invention processes, which prevent them from effectively sharing knowledge and jointly performing R&D activities. In Model 2, the research performance of the scientific partner was positively significant (β: 0.144, p-value<0.01) in its effect on post-alliance innovation performance. Also, I confirmed the positive and significant (β: 0.0233, p-value<0.01) effect of research performance in Model 6. When the scientific institutions had conducted influential research, industrial firms partnering with them also benefit from their partner's research capabilities. Thus, suggested Hypothesis 5-1 is supported. Model 3 shows that the diversity of knowledge of upstream partners has a positive and significant (β: 1.109, p-value<0.01) effect on the industrial firm's innovation performance. In Model 6, the knowledge diversity of scientific institutions has a positive effect on their alliance partner's innovation performance (β: 1.147, p-value<0.05). Scientific institutions conducting research in multiple areas are better suited to assist the industrial organization to recombine diverse knowledge and to find optimal solutions during collaborative R&D. This in turn leads to an increase in the influence of the innovation outputs. These results provide support for the Hypothesis 5-2. The amount of scientific knowledge of the upstream partner, however, was not statistically significant in both Model 4 and Model 6. Even if the scientific organization published a large number of their research outputs as journal articles, this accumulated scientific knowledge is not directly contributing to innovation performance. Nonetheless, I conducted an additional test by changing the timeframe of knowledge stock, only considering journal articles that were published during the five years preceding the alliance announced year, instead of the ten years in the original research model. This change reflects a stronger focus on the scientific partner's most recent accumulation of scientific knowledge. However, I found no statistical evidence for a positive influence of the scientific partner's knowledge stock on post-alliance innovation performance in these additional tests. The main reason for the same results of the two different timeframes was that there were no radical changes in the publication rate of each scientific institutions during the ten year timeframe. Also, I found a high correlation between the knowledge stock variable based on five and ten year timeframes, further explaining the unchanged results. Consequently, these results suggest that Hypothesis 5-3 is not supported. Meanwhile, the knowledge base similarity between the industrial firms and their scientific partners was positively significant (β: 0.273, p-value<0.05) in Model 5. In other words, the knowledge base overlap between industrial and scientific organizations will facilitate the collaborative R&D that leads to accomplishing successful innovation out of the upstream alliance. While I confirmed that the effect of knowledge similarity was statistically significant in Model 5, there was no significant relationship between knowledge similarity and innovation performance in Model 6. Therefore, the results of regression analysis indicate that Hypothesis 5-4 is weakly supported.

To test the moderation effects of the industrial firm's scientific capacity on the relationships between the knowledge characteristics of the upstream partners and post-alliance innovation performance, I added the interaction terms to the regression models. Table 5-3 contains the results of the regression analysis for testing the moderation effects. The results are graphically represented in Figure 5-2, Figure 5-3, and Figure 5-4. In Model 1, the moderation effect of the scientific capacity of the industrial firms on the relationship between research performance of scientific institutions and innovation performance was positive and significant (β: 0.0013, p-value<0.05). Figure 5-2 displays this positive moderation effect of scientific capacity. Likewise, Model 2 indicates that the firm's internal scientific capacity enhances the effects of knowledge diversity of scientific organizations on innovation performance (β: 0.365, p-value<0.01). In Figure 5-3, the positive effect of knowledge diversity is further enhanced with the firm's increasing scientific capacity. Similar to the results of the main effects, the regression results of both Model 3 and Model 5 demonstrate that the moderation effect of firm's scientific capacity on the influence of accumulated scientific knowledge on innovation performance was not statistically significant. The results of Model 4 and Model 5 confirm the presence of a positive moderation effect (β: 0.490, p-value<0.01 in Model 4 and β: 0.525 and p-value<0.01 in Model 5) of the industrial firm's scientific capacity on the relationship between knowledge base similarity and collaborative innovation performance. Figure 5-4 plots these results. In summary, the industrial firm's R&D activities related to understanding science rather than to simply solve technical barriers helps to access and utilize the upstream partner's scientific knowledge. Consequently, a high level of firm's scientific capacity leads to an increase in the efficiency of the R&D processes during collaboration which is reflected in enhanced innovation outputs. Together, these results provide partial support for Hypothesis 5-5.

5.4.1 Additional analysis

This chapter applies the same procedure as discussed in Chapter 3 and measures the dependent variable, post-alliance innovation performance, based on the forward citations of patents. Since this research mainly focuses on various knowledge characteristics of scientific partners (scientific knowledge providers), investigating different aspects of innovation would allow for a more comprehensive understanding. For instance, similar to the additional analysis of Chapter 3, industrial firms would perform their R&D activities for accomplishing innovations which are related to various technological fields rather than cover only a few areas. Furthermore, scientific knowledge provided by scientific partners could increase the understanding of fundamental aspects and principles for researchers in industrial firms which allows them to conduct explorative R&D with an enhanced capability to handle scientific notions. In this notion, I measured the level of convergence of innovation as the average number of mainclasses for all patents granted to each firm. Though the observation of the chapter 3 is patent while this chapter focused on performance of firms that it is necessarily to control for factors may affect firm's innovation. From the perspective of open innovation, mergers and acquisitions (M&A)

are recognized as a mean of sourcing external knowledge, similar to alliances. Thus, I included the number of M&A deals, specifically the number of M&A deals during the five years preceding the announcement of the alliance, as a control variable. The results of the empirical tests are shown in Table 5-4.

First of all, I found no evidence that the research performance or the knowledge stock of scientific partners is related to an increasing number of patent mainclasses. Meanwhile Model 3 and Model 6 indicate that the knowledge diversity of the scientific partner positively affects the broad classification of the industrial firm's patents. Firms are able to apply ideas and principles from diverse fields depending on their scientific partner's experience with various fields. However, there is no moderation effects of the firm's scientific capacity on the relationship between knowledge diversity of scientific partners and an increasing number of patent class. Next, there is a negative effect of knowledge base similarity between the scientific partners and industrial firms on the number of patent mainclasses. The results in Model 5 and Model 6 support that the diversity of the post-alliance innovation is decreasing when industrial firms collaborate with scientific partners which have researched common fields. Even though knowledge base similarity reduces the required efforts and increases the efficiency during the knowledge sourcing process, the exposure to limited new viewpoints results in post-alliance innovation being concentrated in a narrower range of technological fields.

Table 5-4. Additional analysis for the moderation effects on average number of mainclass

Dependent Variable (Avg number of mainclass)	**Model1**	**Model2**	**Model3**	**Model4**	**Model5**	**Model6**
Control Variables						
R&D expense	-.0001 (.0002)	-.0002 (.0002)	-.0001 (.0002)	-.0001 (.0002)	-.0001 (.0002)	-.0001 (.0002)
Firm size	.0017 (.0035)	.0018 (.0037)	.0012 (.0034)	.0009 (.0038)	.0009 (.0038)	-.0002 (.0040)
Firm's innovation capacity	.0001 (.0002)	.0001 (.0002)	.0001 (.0002)	.0001 (.0002)	-.0001 (.0002)	.0001 (.0002)
Firm's knowledge diversity	.0666 (.159)	.117 (.184)	.134 (.181)	.129 (.184)	.153 (.188)	.187 (.191)
Alliance experience	.0024 (.0040)	.0029 (.0041)	.0021 (.0040)	.0023 (.0042)	.0040 (.0041)	.0034 (.0044)
M&A experience	-.0041 (.0177)	-.0029 (.0183)	-.0018 (.0181)	-.0091 (.0190)	-.0060 (.0178)	-.0086 (.0197)
Cultural differences[1]	-.379 (.308)	-.414 (.319)	-.323 (.311)	-.405 (.318)	-.392 (.310)	-.422 (.322)
Scientific institution type[1]				*Included*		
Industries[1]				*Included*		
_Cons	6.125*** (.286)	6.644*** (.588)	1.670 (2.380)	6.922*** (1.917)	6.872*** (.499)	3.143 (3.078)
Independent Variables						
Firm's scientific capacity (SC)		-.0993 (.132)	.931* (.497)	.0330 (.405)	-.173 (.115)	.828 (.628)
Research performance (RP)		-.0334 (.0384)				-.0196 (.0552)
RP x SC		.0047 (.0082)				.0025 (.0136)
Knowledge diversity (KD)			2.367* (1.223)			2.352* (1.315)
KD x SC			-.514 (.260)			-.523 (.316)
Knowledge stock (KS)				-.0798 (.226)		-.0546 (.316)
KS x SC				-.0083 (.0477)		-.0060 (.0753)
Knowledge base similarity (KBS)					-2.228* (1.275)	-2.474* (1.291)
KBS x SC					.422 (.299)	.464 (.306)
Observations	115	115	115	115	115	115
Adj. R-Square	0.312	0.320	0.343	0.320	0.336	0.374

Note: ***p<0.001; **p<0.01; *p<0.05; two-tailed tests. Standard errors are in parentheses. [1] Dummy variable.

5.5 Discussions

This research addresses the effects of knowledge factors in upstream alliances on post-alliance performance. Approaching the issue from the perspective of the knowledge-based view, this study analyzed how upstream partners' knowledge characteristics such as size of the scientific knowledge pool, knowledge diversity, research performance, and knowledge base similarity with the industrial firm influence the processes and outcomes of collaborative R&D. Furthermore, this research hypothesized the moderation effect of scientific capacity of the industrial firms on the relationships between such knowledge factors and alliance performances. By empirically testing the hypotheses employing data on US patents, scientific articles published in SCI listed journals, firm-level financial information, and information on upstream alliance deals of firms in high-tech industries, this study was able to generate several meaningful results.

First, it identified that the research performance of upstream partner increases the impact of post-alliance innovations. The experience of research in core scientific disciplines proves that the routines, abilities of researchers and the scientific organization are superior to those of competitors. Also, creative ideas and insights from researchers along with research environments that encourage major discoveries help to guide collaborative research performed in the scope of the alliance towards successful and impactful outcomes. Possessing architectural and impactful knowledge allows researchers to investigate new knowledge components in more efficient ways (Henderson and Clark 1990). Moreover, this research demonstrates how the knowledge diversity of the scientific partner influences innovation performance. Know-how and knowledge obtained from researching various research areas can generate substantial synergy effects as well as have benefits of economies of scope (Teece 1980). Enhanced research capabilities established through conducting diversified research not only offer different points of view but also reduce R&D uncertainties. Furthermore, it confirmed that the knowledge base overlap between scientific and industrial organizations will foster the transfer of scientific knowledge (Lane and Lubatkin 1998). The existence of common knowledge between individual members, who belong to different organizations, facilitates the knowledge transfer as well as learning because of a shared common language, symbolic communication, specialized knowledge, and shared-meaning (Grant 1996). Additionally, sourcing the upstream partner's scientific knowledge will be facilitated when the industrial firm has a high level of scientific capacity. Conducting R&D projects incorporating scientific disciplines will enhance the firm's absorptive capacity for understanding scientific notions (Lee et al. 2016). Hence, already being accustomed with science enables researchers to find appropriate solutions in a shorter time. Reduced search time and cost will consequently increase the efficiency of collaborative R&D and allow researchers to focus on investigating the most suitable alternatives. As the enhanced scientific capacity of industrial firm reduces communication barriers between industrial researchers and scientists and accelerates learning processes it increases post-alliance innovation performance. However, I did not find empirical evidence for the effects of the knowledge stock of the upstream partner on post-alliance performance. Even if scientific institutions amassed a large amount of scientific information and knowledge, it seems that the aim of collaborative R&D is typically explorative rather than path-dependent. The findings of this chapter are consistent with the literature on the convergence of science and technology as well as upstream alliances (Cockburn and Henderson 1998; Bercovitz and Feldman 2007; Lee et al. 2016). In summary, because the characteristics of scientific knowledge are different from those of technological knowledge, industrial organizations should not only consider the knowledge-related factors of potential scientific partners but also develop their internal scientific capacity to foster successful collaborations.

Chapter 6. Conclusive remarks

6.1 Summary and contributions

Departing from previous literature that frequently addressed R&D strategy based on March (1991)'s framework of exploration and exploitation, or by distinguishing the types of R&D as either basic or applied, this dissertation approaches the organization's R&D through two distinguished knowledge types which are actually applied into the innovations. From the perspective of knowledge types, i.e., science and technology, this dissertation insists that R&D organizations are required to pursue an ambidexterity strategy through focusing more on science-based explorative R&D activities. The arguments of this dissertation are based on previous research streams that assert the importance of exploration. Nonetheless, the methods used in this dissertation differ from those of prior research on exploration and exploitation. Specifically, this dissertation considered the R&D organization's explorative activity as the level of applying scientific knowledge in innovation, while previous research paid attention to either the breadth and depth of technology areas or the reuse of existing knowledge and the adoption of new knowledge.

In conclusion, this dissertation contributes to a better understanding of explorative R&D, especially focused on the effects of science on industrial innovation. Since R&D

organizations try to increase their competitiveness as well as change paradigms through explorative innovation, the present dissertation provides the following significant findings and implications corresponding to different aspects of explorative R&D. First, it investigates the effects of convergence between science and technology on technological innovation impact. Additionally, the dissertation confirms the moderation effects of the R&D organization's scientific capacity, regional spillover of scientific knowledge, and maturity of scientific knowledge on the relationship between convergence and innovation. Second, this dissertation addresses the relationships between the observable characteristics of the top management team (TMT) in organizations and their R&D propensities. It confirms that TMT's innovation-related characteristics, such as R&D functional experiences or majoring in science or engineering, affect the organization to conduct more explorative R&D. It also finds that the relationships between innovation-related characteristics of the TMT and the organization's explorative R&D activities are moderated by the length of the TMT's tenure. Third, the dissertation investigates four important factors to be considered by industrial firms when considering upstream alliances with scientific institutions. Overall, this dissertation provides a comprehensive understanding of explorative R&D based on science based on empirical evidence. Each of those contributions has not only academic value but also provides implications for managers.

Besides providing valuable implications for both academia and management, the results of this dissertation can be used to suggest guidelines for the policy-makers in nations such as South Korea or Taiwan, which usually set their nation's R&D aim to catch up with the first-movers. In these countries, the national objectives for rapid economic growth lead to R&D policies that encourage conducting exploitative R&D activities to maximize national welfare. Nonetheless, there is a growing importance of explorative innovations for countries aiming to upgrading their position from fast-follower to first-mover, because today's technological environment only provides increased market opportunities for players who pursuit innovation that can change existing paradigms. R&D organizations in such countries, however, already have established routines centered on exploitative R&D, leading to limitations in conducting explorative R&D, especially focusing on scientific knowledge. Along with issues embedded in the R&D organizations, national R&D policies are still fostering exploitative innovation. In order to take a leap forward, it is necessary to enhance R&D organizations' scientific capacity through conducting internal basic research. Moreover, national policy requires efforts to reduce the distance between basic research and industrial research.

From the academic perspective of innovation research, Chapter 3 empirically analyzes the effects of convergence between science and technology on innovation. For the convergence, previous literature has generally not considered convergence from the knowledge side, but investigated the effects of science and technology individually or adopted a purely technology or industry focused approach (Curran et al. 2010; Curran and Leker 2011; Kim et al. 2014; Jeong et al. 2015). The results of Chapter 3 show how different knowledge sources influence innovation and highlights the importance of converging effects at the knowledge level for pursuing impactful innovation. Chapter 3 also elucidates the role of scientific capacity, knowledge spillover, and knowledge maturity, which so far have not been given much attention in literature and show how they affect innovation impact under convergence. Considering the increasing importance of convergence of science and technology in ongoing research and development in many industries, I expect more future research on the significant relationship of innovation and convergence.

For managers of organizations, the results of Chapter 3 present a suitable research strategy for their R&D activities. At first, results of Chapter 3 provide inputs for a successful knowledge search strategy. In order to achieve impactful innovation, rather than focusing on only technology, convergence with science at moderate levels is important and that organizations should spread their search to cover both fundamental and basic fields as well as technological domains. However, overly exploiting scientific knowledge causes R&D inefficiencies. Also, organizations need to enhance their scientific capacity by employing more scientists who are familiar with scientific language as well as encouraging R&D towards more fundamental and basic principal to archive more impactful innovation. This calls for an investment in basic research and an increase in collaborations with scientific institutions. R&D collaboration with scientific institutions such as universities generates advantages due to knowledge spillover (Cassiman et al. 2008; Subramanian and Soh 2010). This joint research should continue for retaining communication channels through informal contact between researcher and scientists. An enhanced scientific capacity also assists with the strategic decision-making related to R&D planning and future product line (Rosenberg 1990; Shibata et al. 2010).

For policy-makers, the results of Chapter 3 provide evidence for the positive effects of encouraging convergence. To increase the positive effects on innovation, investments in basic science should be increased and a focus should be placed on policies creating an environment which stimulates and encourages the exchanges between technology and science. Convergence of science and technology can be further promoted by funding joint research, and industrial-academic interaction of researchers through regional research clusters (Vedovello 1997; Van Geenhuizen and Reyes-Gonzalez 2007). These activities should include not just universities, but firms and other organizations working on science and technology. Also, it is important to increase the accessibility of scientific knowledge and gain government support for a codification of new scientific knowledge, which is usually only available in tacit forms. By investing into universities and basic research institutes, recently-discovered scientific discipline can be verified in a short time which allows R&D organizations to exploit pre-matured scientific knowledge in their R&D processes more efficiently (Cardinal et al. 2001).

Firms within high-tech industries, which mainly concern themselves with highly complicated technology, run the risk of overly focusing on exploiting existing or familiar knowledge which can have negative impacts on their competitiveness (March 1991). To achieve breakthrough innovation earlier than its competitors, a firm is forced to pioneer new technologies and test experimental alternatives (Ahuja and Lampert 2001; Mudambi and Swift 2014). In this notion, Chapter 4 shows that the extent to which a firm pursues explorative R&D is a result of the characteristics of its top management. The presented results highlight the role TMT members with innovative experiences play in shaping the direction of a firm's R&D strategy, especially towards explorative R&D. In terms of managerial implications, I suggest firms to hire TMT members with innovative experiences to examine firm's R&D projects and establish firm's R&D policies more comprehensively. Generally, having researchers and engineers with superior ability is considered a key factor of success in individual R&D projects. But, as competitiveness in high-tech industries mainly depends on technologies, the TMT setting the direction of the R&D is equally important. Traditionally, the role of TMT was limited to approving investments in innovation without examining the details of R&D projects, as TMT often consist of members with backgrounds in business, financial, accounting and law. However, considering the increasing importance of R&D for the growth of organizations, I suggest that increasing the proportion of TMT members with innovative experiences allows firms to direct their R&D strategies towards exploration which opens the opportunity to the a first-mover and capture future-opportunities in advance. Also, Chapter 4 fills a gap in the existing literature by investigating the factors which affect the organization's R&D strategy. Most existing ambidexterity literature highlights the importance of implementing an ambidexterity strategy rather than addressing the determinants that impact the relative proportions of exploitation and exploration (March

1991; He and Wong 2004; Gupta et al. 2006). By investigating the organization's internal factors in terms of TMT and their R&D behaviors, therefore, I state that firms can enhance their ambidexterity strategy by appointing innovation-experienced individuals to the TMT, which results in increasing explorative R&D.

Contributing to the literature on empirical research on innovation, Chapter 4 shows how firms' R&D activities can be analyzed in detail through patent analysis. So far, previous research only focused on patent citations or patent classes for analyzing firms' innovation activities. Though non-patent references are known to represent the basicness or scientific characteristics of patented innovation (Trajtenberg et al. 1997; Callaert et al. 2014), most prior research did not apply them to study innovation in firms. Also, the results of Chapter 4 show the consistency of measuring firm's R&D activity using various patent-based indexes.

Despite the increasing usefulness of scientific disciplines in industrial innovations which leads an increasing number of industrial firms to engage in scientific activities, most firms are still focusing their R&D capabilities on practical research for accomplishing technological innovations. In order to focus on practical applications, industrial organizations usually tend to contract with other firms or analyze market demands. Even though the effects of the convergence of science and technology on innovation outcomes are superior to solely investigating technology (Lee et al. 2016), there is still a noticeable lack of effort of industrial firms to apply scientific notions into their R&D processes. To accomplish impactful innovations such as radical innovation, Chapter 5 suggests that industrial firms need to expand their knowledge sourcing channels especially towards scientific information from the institutions such as academy or government-funded research institutes.

Furthermore, industrial organizations are required to take into account which scientific institution can be expected to be suitable partners for collaborative R&D. As the different focus on technology and science, respectively, leads to information asymmetries between industrial firms and scientific organizations, industrial firms are often choosing scientific partners among highly-ranked or large organizations without detailed evaluation and consideration of specific knowledge factors, such as the synergy effects arising out of knowledge base similarities between focal firm and potential partners. To avoid communication barriers and assess potential complementarities with upstream partners, industrial organizations need to enhance their capacity for science. For instance, hiring scientists or establishing an in-house research institute for basic research will improve their scientific absorptive capacity (Hicks 1995; Almeida et al. 2011; Gruber et al. 2013). Also, managers need to ensure that their scientists have sufficient autonomy in selecting and establishing R&D projects as well as selecting research topics to focus on basic and scientific issues (Gambardella 1992). Experiences related to finding solutions to scientific problem sets will enhance the firm's scientific capability and consequently increase the probability of archiving successful innovation based on the utilization of scientific knowledge (Lane and Lubatkin 1998).

Another suggestion of Chapter 5 is that industrial firms should establish their own knowledge base prior to forming partnerships with scientific organizations (Lee et al. 2016). Due to the complexity of scientific information, industrial researchers may find it hard to learn scientific concepts which they are unfamiliar with. Several studies argued that a larger knowledge distance will foster explorative innovation because new knowledge enables engineers to recombine an increasing number of knowledge factors that result the ability to test more alternatives (March 1991). However, this suggestion is only feasible when firms are sourcing new technological knowledge which can be recombined without the in-depth understanding required for scientific knowledge. Thus, I suggest that industrial firms conduct pioneer research before they begin to invest significant resources into science-based R&D activities.

6.2 Limitations and future research

Despite delivering a range of implications and valuable contributions to the research on innovation studies focusing on scientific aspects and helping to increase the understanding of factors and effects of explorative R&D based on science, this dissertation still has some limitations.

First, the dataset of present thesis is based on patents, meaning that innovation which was not patented cannot be analyzed. Some innovation outcomes are protected by patents whereas organizations might decide not to patent some outcomes for strategical purposes (Rosenberg, 1990). In order words, patents are used for protecting intellectual property, however, R&D organization sometimes do not apply for patents and accumulate knowledge internally because a patent application requires them to disclose the knowledge to the public. Explorative activities usually set goals for patent-unrelated outcomes (Rosenberg, 1990). Moreover, other non-patent research output such as research documents is often not open to the public. This dissertation derives significant result by measuring innovation through patent data, however, I expect future research to extend this work by including other sources of information on innovation.

Second, this thesis analyzed several industries mainly classified as high-tech industries, such as biopharmaceuticals, chemicals, computers and electronics, and semiconductors. In general, the importance as well as the role of knowledge-based innovation is emphasized in such high-tech industries. However, with the rapid development of technology and highly intensified competition among firms, the importance of knowledge-based innovation is also increasing in industries classified as mid-tech or low-tech, such as manufacturing or agriculture. Because of the increasing demand for explorative innovation in a wide range of industries, I recommend future research to address diverse industries beyond specific high-tech industries.

Last, a common characteristic of the datasets analyzed in Chapter 3 and Chapter 4 is that both datasets are comprised of U.S. organizations. Since the United States is currently leading the development of science and technology across many sectors, analyzing explorative R&D of U.S. organizations makes it possible to better observe the effects of various knowledge factors. However, analyzing a specific country's organizations may reflect unobserved national policy, which makes it difficult to generalize the results. Therefore, I suggest that future studies be conducted covering a wider range of countries to draw more generalized conclusions.

Moreover, each study has several limitations as follows. Because biopharmaceutical technologies are largely based on the scientific discipline, Chapter 3 only focused on innovations related to these technologies from U.S. patent classes 424 and 514. Meanwhile, the results of Chapter 3 may not be reflected by some low-tech industries where firms' objectives are related to reduce production costs through process innovation, which hardly uses scientific notions in the R&D process. For example, applying technological disciplines rather than scientific notions is required to lower the defect rate in the manufacturing process. Due to such different sectoral characteristics between industries, the results and implications of Chapter 3 may not be applicable to all industries.

Although Chapter 3 delivers statistical evidence for the usefulness of applying matured scientific knowledge, this strategy might not be equally suitable for all firms. As time goes by, newly-discovered scientific disciplines are proven and their accessibility is ever increasing. Using such matured knowledge allows R&D organizations to avoid unnecessary use of resources. In some industries, however, the advantages of an increasing R&D efficiency might not be higher than the advantages of adopting cutting-edge scientific knowledge. For instance, the rapid pace of technological change occurring in the software industry leads to firms introducing new services that are based on the latest algorithms. Moreover, testing and verifying new scientific concepts in this industry does not require too much resources and time. Therefore, firms are required to carefully assess the application of matured vs. cutting-edge scientific knowledge in accordance with their own necessities and the industry environment they operate in.

Especially, Chapter 3 has another limitation, mainly based on following reason. In analyzing the organizations scientific capacity, I am limited to considering only scientific publications, however, there are several indicators represent scientific capacity such as the number of employees with natural science academic degrees, experience with scientific domains, and other R&D activities related to basic research (Schmoch 1997). Due to limitations with collecting organizations' internal information and data, this research is unable to include the above indexes. Similarly, this research was unable to quantify the tacit type of scientific knowledge and, due to limits of data availability. I believe future research can deliver more detailed results by including such indexes and both tacit and codified types of scientific knowledge to proxy organizations scientific capacity.

While providing valuable insights into factors influencing the direction of organizational R&D, Chapter 4 also has several limitations, which I hope can be overcome by future research. First, this research measures individual's innovative experience based on their educational or functional backgrounds. However, some TMT members might have amassed innovative experiences without such biographical backgrounds. The cognitive base could be affected by both direct and indirect experiences and numerous latent factors that influence an individual's perceptions and recognitions. In other words, individuals may form cognitive bases for pursuing explorative R&D without any work experience in R&D-related functions because they could realize the importance of explorative innovation themselves by receiving information from indirect experiences such as exposure to mass media. Cognitive bases formed by such indirect experiences, however, cannot be identified through an individual's biographical information.

Moreover, while I collected TMT data from various sources to cross-check available information, data on the background of some individuals was partially missing. Future research can overcome the above-mentioned limitations on collecting biographical information by using other sources such as direct interviews with the TMT members to capture their innovation-related characteristics in more detail.

Furthermore, a firm's R&D activities could be reflected in various ways. For instance, product innovation also represents the direction of a firm's R&D activities. It could be argued that general top managers excluding the CTO and top managers who are in charge of R&D divisions, would make R&D-related decisions based on final products rather than the details of the R&D projects. Even though I conducted an additional analysis of the effects of the CTO and VPs in charge of the R&D divisions on the firm's R&D activities, future research could address additional aspects of the firm's R&D activities by identifying product innovations.

Last, a conceptual limitation of Chapter 4 is related to a potential reverse causality problem between TMTs and firms' strategy. I found that TMT members with high consciousness of innovation positively affect the firm's R&D strategy by focusing on explorative activities. However, there is the possibilities that these managers were specifically hired for their expertise with R&D and innovation to fit with the firm's exploration-oriented strategy (Hambrick 2007). Future research can address this issue for example by looking into the hiring process of these TMT members and the past R&D strategies of the organization.

For future research, Chapter 5 proposes to focus on several aspects that will complement the results of this study. First, due to data availability, Chapter 5 only addresses industry-science alliances operating in an institutional governance mode, however, other types of industry-science relationships such as individual contracts exist (Bodas Freitas et al. 2013). For example, some star scientists or outstanding research teams in scientific institutions would have a higher level of autonomy that allows those teams to directly enter into contracts with industrial firms. As Bodas Freitas et al. (2013) stated, however, it is difficult to identify this type of contracts between individual researchers and industrial firms. I expect future studies to find ways to collect data on both types of governance modes, institutional and individual.

Second, there are few studies investigating the factors which may influence the knowledge learning processes in industry-science alliances. Even though some studies addressed the mechanisms of knowledge transfer between universities and industry, focusing on the roles of university technology transfer offices (Siegel et al. 2003) and faculty members (Link et al. 2007), there is still a lack of understanding on the effects of factors internal to the scientific organizations. Similar to other alliance formation studies, also my approach could potentially suffer from endogeneity issues. Since I address the effects of knowledge characteristics of both industrial firms and scientific institutions on the post-alliance performance, there could be unobserved characteristics such as connectedness, i.e., scientific paper coauthoring activity between firms' researchers and scientists of public institutions (Cockburn and Henderson 1998) or industrial consulting by faculty members (Link et al. 2007). These latent factors may affect not only the firm's innovation performance but also the firm's propensity to form alliances, especially with scientific institutions. Thus, follow up studies on the industry-science link could address this potential endogeneity issues by adopting two stage models (Link et al. 2007; Stuart 2000). Latent factors such as connectedness or industrial consulting may influence the formation of an alliance, which could be considered as an instrument variable and included in the first stage to estimate the alliance formation. Then, the second stage would allow researchers to examine the effects of partner characteristics on post-alliance performance.

Last, I double-checked the data retrieving processes and confirmed that my sample firms have records of both patents and publications throughout the complete observation period of this research. This rules out that I considered firms which closed down or suddenly opened up during the observation period. I caution future researchers to put additional attention on factors such as changes in corporate ownership when they try to trace firms' historical data such as their past knowledge portfolio. I expect that future research can take advantage of more in-depth data sources and improve the accuracy of the analysis by considering the above suggestions. Finally, I hope that this dissertation is the basis for further research in technology management field.

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국 문 초 록

최근 기술의 발달이 점점 고도화되고 기술 수명주기가 점점 단축되고 있다. 새로운 기술 개발에 있어 많은 비용이 요구되고 있음에도 불구하고, 성공적인 기술 개발의 불확실성도 높아져 연구 조직에서는 투자 대비 위험성도 함께 증가하고 있다. 또한 심화되는 조직 간의 경쟁은 기술의 상업적인 성공 가능성도 낮추는 요인으로 작용한다. 이에 기업과 같은 조직에서는 연구 개발에서의 위험을 회피하고자 주로 활용(exploitation)적 혁신 활동에 집중하는 경향이 있다. 그러나 활용적 혁신은 단기적인 성과와 점진적인 개선에만 집중하기 때문에, 기술의 단절적 변화가 잦은 현 경쟁 환경에서 조직의 경쟁 우위를 유지하기 어렵게 한다. 이에 최근 연구에서는 조직의 장기적인 생존을 위해 끊임없이 새로운 지식을 탐색(exploration)하여 패러다임을 변화시킬 수 있는 탐색적 혁신을 추구하고 이를 위한 연구 개발 활동의 비중을 늘려야 한다고 강조하고 있다.

탐색적 혁신 활동의 중요성이 점점 증가함에 따라, 새로운 기술 분야 및 지식을 목적으로 한 탐색적 연구 개발이 기술 혁신에 긍정적인 영향을 준다는 상당수의 연구들이 수행되었다. 그 중에서도 기술이 복잡해지고 있는 오늘날의 환경을 감안하여, 기술에 대한 탐색을 넘어 연구 개발의 원리적 이해를 도울 수 있는 기초 과학 지식에 대한 탐색을 강조하는 연구들이 최근 주목받고 있다. 조직이 성공적인 혁신을 달성하기 위해서는 기술과 같이 응용

지식의 활용이라는 경계를 벗어나, 현상과 작동의 원리를 이해할 수 있는 근본적인 아이디어로부터 출발해야 한다는 것이다. 더 나아가 기초 과학 지식은 혁신의 결과물을 미리 예상할 수 있게 하여, 기술의 불확실성을 낮추고 연구 개발 과정에서 발생될 수 있는 시행착오를 줄일 수 있게 한다. 이에 기업과 같은 조직은 대학 및 연구소들 과의 협력을 강화하여 적극적으로 산업 혁신에 기초 과학 지식이 접목될 수 있도록 시도하고 있다.

언급한 바와 같이 학계와 실무에서 모두 기초 과학과 기술의 융합에 기반한 탐색적 연구 개발의 중요성을 강조하고 있다. 그럼에도 불구하고 과학과 기술의 융합에 초점을 맞춘 조직의 탐색적 연구 개발 활동과 관련한 연구는 아직 부족한 실정이다. 먼저 지식의 관점에서, 과학과 기술 지식의 융합이 혁신에 미치는 효과에 대해서는 아직 명확히 밝혀지지 않았다. 또한 조직 행동의 측면에서, 조직이 탐색적 연구 개발을 수행하기 위한 전략을 수립하는 것에 영향을 미치는 조직 내부적인 요인에 대한 이해가 부족하다. 마지막으로 외부 조직과의 협력을 통해 탐색적 연구 개발을 수행하고자 하는 경우에도, 협력에 의한 혁신 성과를 증진시키는 요인들에 대한 이해가 필요하다.

이에 본 논문에서는 조직의 탐색적 연구 개발 활동과 혁신 성과를 결정하는 요소들을 밝혀내고 그에 따른 영향을 분석하고자 한다. 구체적으로 ‘지식 측면’, ‘조직 내부 측면’, ‘조직 외부 측면’ 과 같은 세 가지 관점에서 분석함으로써 통합적인 시각을 제공하고자 한다. 우선 지식의 수준에서 기초 과학과 기술의 융합 효과를 검증함으로써, 탐색적 연구 개발이 실질적으로 조직의 혁신 성과를 향상시킨다는 점을 규명한다. 그 다음으로 조직

에서 탐색적 연구 개발 활동을 확대하는 전략 수립에 영향을 미치는 요인으로, 조직 내부의 최고 경영진에 의한 영향을 제시한다. 마지막으로 기업이 외부 기초 과학 지식을 도입하고자 대학 및 연구소와 같은 외부 조직과의 협력을 할 때 고려해야 하는 요소들을 분석한다.

구체적으로, 3장에서는 지식 관점에서 기초 과학과 기술의 융합의 효과가 혁신에 미치는 영향에 대해서 분석하였다. 기초 과학 지식은 현상에 대한 단편적인 시각을 벗어나게 할 뿐만 아니라 보다 근본적인 혁신의 원리를 이해하게 하여, 기술적 문제 해결에 있어 최적에 가까운 해답을 도출하는 것을 가능하게 한다. 이에 본 연구에서는 기술 혁신을 지식의 단위에서 파악하여, 기초 과학 지식의 사용 비율 및 해당 혁신의 영향력과 관계를 파악하였다. 그 결과 기초 과학 및 기술의 융합과 혁신의 영향력의 관계는 양의 관계를 보이다 점점 체감하는 역-U (inverted-U) 관계를 갖는 것으로 나타났다. 또한 조직의 과학 역량, 지역에서의 지식 확산 및 과학 지식의 성숙도가 융합과 혁신의 관계에 양의 조절 효과를 미치는 것을 규명하였다. 이 결과는 과학과 기술의 융합의 중요성을 실증적으로 규명하였을 뿐만 아니라, 융합의 성과를 증진시킬 수 있는 요인을 밝힘으로써 조직의 연구 개발 전략의 토대를 제시한다.

4장에서는 조직의 연구 개발 활동과 조직의 최고 경영진의 관계를 살펴보았다. 조직 행동은 최고 경영진의 특성 및 인식 기반에 영향을 받는다는 상층부 이론 (upper-echelon) 관점을 도입하여, 조직의 연구 개발 활동과 최고 경영진의 관계를 분석하였다. 최고 경영진 개인이 과거에 연구 개발 관련 직무 경험이 있거나, 이학 및 공학의 교육을 받은 경우 혁신을 추구하는 인식

기반이 형성되어 결국 조직 행동에도 영향을 주게 된다. 실증분석을 통해, 최고 경영진에 혁신 경험이 있는 구성원 비율이 높을수록 연구 조직에서는 탐색적 연구 개발 활동의 비중이 증가하는 것으로 나타났다. 더 나아가 혁신의 경험을 지닌 개인이 최고 경영진으로써의 재임 기간이 길수록 해당 조직에서는 탐색적 연구 개발 활동이 더 확대되는 것으로 분석되었다. 위의 결과를 통해 과학 및 기술 지식에 대한 탐색적 연구 개발 활동을 적극적으로 수행하기 위해서는 조직 내부의 의사 결정권자들의 혁신에 대한 의지와 연구 지속에 대한 뒷받침이 중요하다는 것을 유추할 수 있다. 이는 탐색적 활동에 의한 혁신 성과는 오랜 기간에 걸쳐 발생하고, 특히 기초 과학 지식을 접목한 탐색 활동은 소모되는 비용이 높아 일시적으로 조직의 재무 상황이 악화될 수 있기 때문이다. 그럼에도 불구하고 혁신을 추구하는 연구 조직에서는 재무, 회계, 법, 경영과 관련된 전통적인 최고 경영진의 구성을 벗어나 이공계 출신 및 연구 개발의 경험이 있는 경영진의 비율을 확대해야 할 필요성을 제언한다.

마지막 5장에서는 외부 조직의 기초 과학 지식을 이용하기 위한 제휴 (alliance)에 대해서 분석하였다. 기업과 같이 주로 기술에 집중된 산업 혁신을 추구하는 조직에서는 외부의 기초 과학 연구 기관과 제휴를 맺어 과학 지식을 이전 받고자 한다. 이 때 제휴 파트너 선택에 있어 기술을 위주로 하는 기업은 과학과 같이 상이한 지식을 다루는 기초 연구 기관에 대한 정보 격차로 인하여 적절한 제휴 파트너 선정에 어려움을 겪을 수 있다. 이에 본 연구에서는 지식 기반 관점에서 두 상이한 조직의 지식적인 특성을 분석하여 제휴 후 성과를 향상시키는 요소를 규명하였다. 분석 결과, 제휴 파트너인 기초 과학

기관의 연구 역량, 지식 다양성 및 제휴 기업과의 지식 유사성이 제휴 후 혁신 성과에 긍정적인 영향을 미치는 것으로 나타났다. 특히 제휴 기업이 기초과학의 역량의 수준은 위의 관계에 양의 조절 효과를 준다고 분석되었다. 본 연구 결과를 통해, 기업의 입장에서 잠재적인 기초 연구 파트너를 탐색할 때 고려해야 할 요소를 제시하였다. 더 나아가 산학연의 협력과 같이 서로 다른 지식의 확산을 목적으로 하는 제휴에서, 기업과 연구 기관과의 상호 지식적 특성이 제휴 후 성과에 영향을 준다는 점을 시사한다.

본 논문의 연구 결과는 다음과 같은 의의를 제시한다. 첫째, 기존 연구에서 과학 및 기술을 각각 분석한 것을 확장하여, 융합의 관점에서 과학과 기술을 동시에 분석하였다. 기술 혁신의 영향력을 높이기 위해 연구 개발 단계에서 적정 수준의 기초 과학 지식을 적용해야 한다는 연구 전략 수립의 근거를 제시한다. 한정된 자원으로 연구 개발을 수행하는 조직에서는 과학과 기술의 융합을 통해 연구 개발의 효율성을 개선하여 궁극적으로는 혁신의 질을 높일 수 있게 된다. 둘째, 다양한 수준에서 탐색적 혁신 활동을 분석하였다. 지식 측면, 조직 내부 측면 및 조직 외부 측면의 3가지 측면에서 분석을 실시함으로써, 탐색적 혁신 활동에 대한 통합적인 이해를 높였다. 마지막으로, 탐색적 혁신 성과에 영향을 미치는 다양한 요소들을 검증하였다. 기초 과학 지식 이전에 영향을 미치는 요소를 지식과 조직의 특성으로 구분하여 다각도로 제시함으로써 탐색적 혁신 전략 수립에 있어 필요한 판단 기준을 제공한다. 종합하자면 혁신을 이루기 위한 다양한 지식의 적용이 중요한 상황에서, 본 연구는 과학과 기술의 융합을 기초로 하는 혁신의 중요성을 강조하고 있다.

동시에 기초 과학에 기반한 탐색적 혁신 활동의 특성을 이해하는 데 필요한 요소를 규명 및 제시하고 있다.

주요어 : 과학 지식, 기술 지식, 탐색적 연구 개발, 융합, 최고 경영진, 산학연 협력
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