J Technol Transf
DOI 10.1007/s10961-016-9480-9

The impact of convergence between science and technology on innovation

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Abstract This study 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, we address 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 2074 patents granted to US 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, we find that the organization's scientific capacity, regional scientific knowledge spillover, and knowledge maturity positively moderate the relationship between convergence and innovation impact. Our findings 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.

Keywords Convergence · Knowledge · Science · Technology · R&D · Innovation

JEL Classification O31 · O32 · O38 · O39

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Published online: 18 April 2016

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; 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, we define 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, we investigate 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, we analyze 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, we 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.

Our work has several implications. First, we identify multiple factors which affect innovation by empirically examining convergence effects of science and technology which were largely ignored by existing literature. In addition, we point 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, we examine the regional aspects of scientific knowledge spillover and formulate recommendations for policy to boost convergence or the interaction of science and technology.

This paper is organized as follows. In Sect. 2, we define convergence and examine the roles and characteristics of science and technology in R&D. Next, in Sect. 3, we develop hypotheses describing factors influencing the relationship of convergence of science and technology and innovation. In Sect. 4, we introduce the methodology, data set and variables used for verifying our hypotheses. In Sects. 5 and 6, we present the results of our empirical tests and, in Sect. 7, we discuss the implications and limitations of this study.

2 Research background

2.1 The convergence of science and technology and its role in the invention process

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 Factors influencing the relationship between convergence of science and technology and innovation impact

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 a 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 determinants 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.

3 Hypotheses

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

3.2 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 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.

3.3 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, we 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 The regional scientific knowledge spillover positively moderates the relationship between the proportion of science in the convergence of science and technology and innovation impact.

3.4 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 demands 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

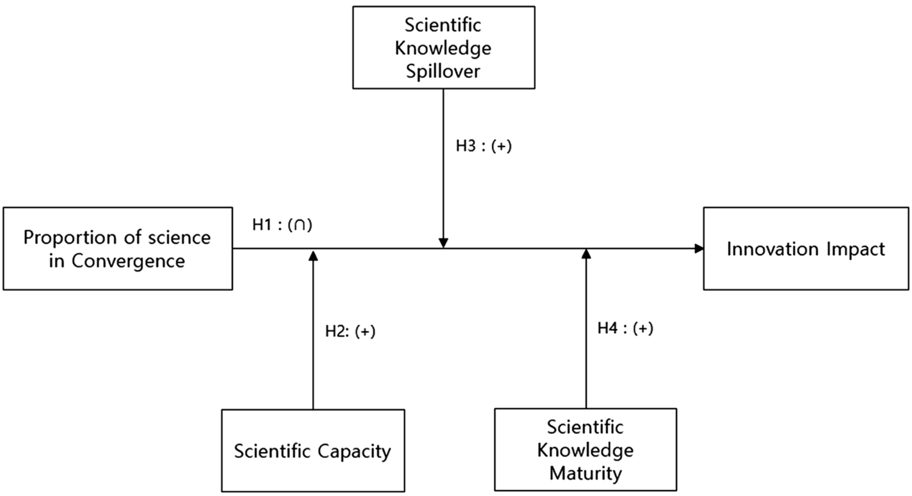

Fig. 1 The conceptual diagram

technology. Ultimately, at each proportion of scientific knowledge, a more mature knowledge allows the organization to produce more impactful innovation.

Hypothesis 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. The conceptual diagram in Fig. 1 shows the relationships between the suggested hypotheses.

4 Methods

4.1 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. We selected patents containing pharmaceutical technology by following the United States Patent

Classification (USPC) used by the USPTO. Specifically, we 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 our research focuses on the organizational level, we excluded patents assigned to individual inventors. Our final dataset included 2074 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 4989 forward citations.

4.2 Variables

4.2.1 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, we 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).

4.2.2 Independent variables

Convergence ratio To calculate convergence of science and technology, this research adopts a measurement which was suggested by Trajtenberg et al. (1997). Our variable 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 We 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, we 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, we 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), we identified the total scientific publications instead of patents due to this research focusing on scientific knowledge spillover rather than technologic knowledge spillover. Specifically, we obtained the total number of scientific publications listed on SCI for each state in the US during the 2003–2007 period. Thereafter, we 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 We identified the year of publication for each journal paper from the non-patent reference information of the patents. We 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.

4.2.3 Control variables

Research capacity To capture the research and development capacity of the R&D organization, we 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, we 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, we measure 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, we 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. We obtained the list of the entire patents which were granted to each organization and adopted the Herfindahl index as following

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

Table 1 Descriptive statistics and pairwise correlations (n = 2074)

	Mean	SD	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[a]	4.2114	2.8925	−.0870	.2517	1							
4. Knowledge spillover[a]	8.7646	.9061	.0938	−.0130	−.0712	1						
5. Knowledge maturity (Sci)	13.6050	6.2580	.0338	−.0910	−.0221	.0066	1					
6. Innovation experience[a]	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

[a] Transposed to log scale. Dummy variables were excluded

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, we 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, we identified the granted year of the cited patents of the focal innovations. After that, we calculated the average time lag between the granted year of the cited patents and the focal year (2008) for each innovation.

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

Pharma-related technology type In this research, we 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, we included a dummy variable distinguishing both patent classes in our empirical models.

4.3 Model

The dependent variable of this research, the number of forward citations received, is a nonnegative count variable. Generally, nonnegative count variables are supposed to follow a Poisson or negative binomial distribution. Before adopting the Poisson model, we must confirm that the variance equals the average value. However, in the case of our dependent variable, the variance exceeds the average and the performed likelihood-ratio test confirmed an over-dispersion problem. Consequently, for our 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 we do not consider citations received after five years. We 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 we also decided on using a zero inflated negative binomial model to test our hypotheses.

5 Results

Table 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 1214 patents within the

Table 2 Results of the zero inflated negative binomial regression

Dependent variable (Number of forward citations)	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Control variable						
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 variable						
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 × Scientific capacity			.143* (.117)			.210* (.169)
Convergence ratio^2 × Scientific capacity			−.130** (.120)			−.169* (.155)
Knowledge spillover				.0021 (.0793)		.0094 (.116)
Convergence ratio × Knowledge spillover				.815** (.378)		.730 (.499)
Convergence ratio^2 × Knowledge spillover				−.970** (.383)		−.864* (.469)
Knowledge maturity (Sci)					−.0194* (.0114)	−.0167 (.0114)
Convergence ratio × Knowledge maturity (Sci)					.206*** (.0625)	.189*** (.0627)
Convergence ratio^2 × 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

Table 2 continued

Dependent variable (Number of forward citations)	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Chi square	47.59***	52.08***	55.22***	66.01***	63.32***	78.05***

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; two-tailed tests

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 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–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 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, we constructed both interaction variables of our moderation variables and the linear and square terms of the convergence ratio to test Hypotheses 2–4.

First of all, the linear variable of convergence ratio was found to be positively significant in both Model 2 (coefficient: .354, $p < 0.01$) and Model 6 (coefficient: 10.03, $p < 0.01$). Similarly, the square term of the convergence ratio was negatively significant in both Model 2 (coefficient: −.188, $p < 0.01$) and Model 6 (coefficient: −11.76, $p < 0.001$). 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 our Hypothesis 1. To be specific, the relationship between the convergence ratio and innovation impact, as seen in Fig. 2a, 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, we 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 (Coefficient: −.130, $p < 0.01$) and Model 6 (Coefficient: −.169, $p < 0.05$). As the organizations' scientific capacity increases, it positively moderates the relationship between innovation impact and convergence as can be seen in Fig. 2b. 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 our Hypothesis 2.

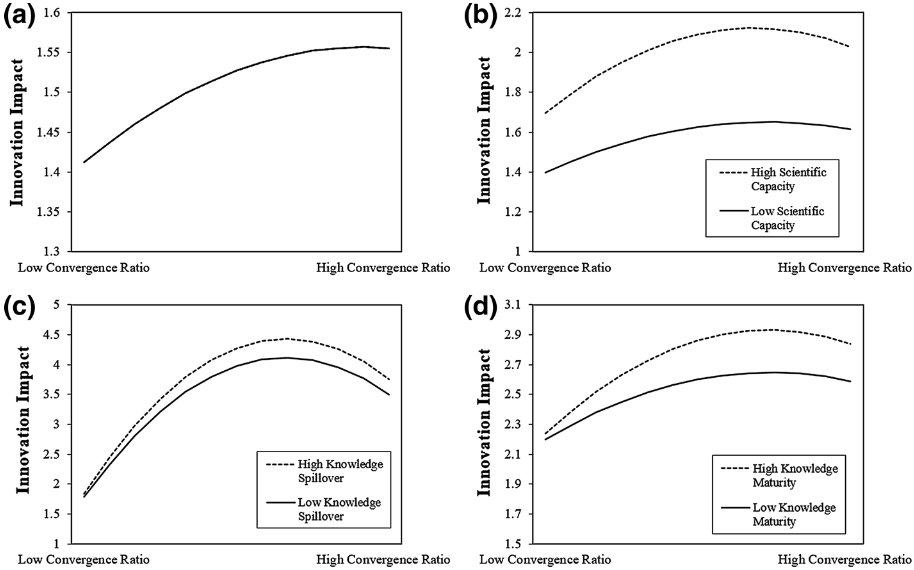

Fig. 2 The relationship between the (**a**) dependent variable (number of forward citation received) and convergence of science and technology and the moderation effects of **b** scientific capacity, **c** scientific knowledge spillover, and **d** scientific knowledge maturity with convergence

Following Hypothesis 3, we 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 (Coefficient: $-.970$, $p < 0.01$ and Coefficient: $-.864$, $p < 0.05$, 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 Fig. 2c. These result support our Hypotheses 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, we 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 (Coefficient: $-.252$, $p < 0.001$ and Coefficient: $-.237$, $p < 0.001$, 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 2d. 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, we 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. 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, we found that technological knowledge maturity negatively affects innovation impact.

6 Conclusion

This research empirically analyzes the impact of convergence of science and technology on innovation impact. We analyze the relationship between convergence and innovation impact by using patent data from the U.S. pharmaceutical industry, moreover we test our hypotheses considering possible moderation effects of organization's capabilities, knowledge spillover, and characteristic of knowledge. To begin with, we address how the organization's scientific capacity influences the impact of innovation from convergence. Moreover, we consider the scientific knowledge maturity used in innovation, while following the knowledge spillover, we investigate and consider a research environment in which personal contacts among researchers easily occur. We 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 we operationalize innovation impact by the number of forward citations received. Applying the zero inflated negative binomial regression model, we obtain a number of key results.

First, we 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). Our 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, we 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, we provide 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.

7 Discussion

The results of this research have academic, managerial and policy implications. From the academic perspective of innovation research, we empirically analyze 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). Our results show how different knowledge sources influence innovation and highlights the importance of converging effects at the knowledge level for pursuing impactful innovation. We also elucidate 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, we expect more future research on the significant relationship of innovation and convergence.

For managers of organizations, the results of this study present a suitable research strategy for their R&D activities. At first, results of this research 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). These 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 policymakers, the results of this study provides 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).

Despite delivering a range of implications as described above, our research has limitations, mainly based on two reasons. First, our data is based on patents, meaning that innovation which was not patented cannot be analyzed. 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. Moreover, other non-patent research output such as research documents is often not open to the public. This study derives significant result by measuring innovation through patent data, however, we expect future research to extend this work by including other sources of information on innovation. Second, in analyzing the organizations scientific capacity, we are 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. We believe future research can deliver more detailed results by including such indexes to proxy organizations scientific capacity.

Acknowledgments We are grateful to Donald S. Siegel, Editor of Journal of Technology Transfer, for his insightful and perceptive editorship. We would also like to thank Klaus Marhold, and two anonymous reviewers for their helpful comments and suggestions. The Institute of Engineering Research at Seoul National University provided research facilities for this work.

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