http://dx.doi.org/10.15813/kmr.2018.19.3.009

Influence of R&D intensity on Innovation Performance in the Korean Pharmaceutical Industry: Focusing on the Moderating Effects of R&D Collaboration

김 대 중 (Dae-Joong Kim) (주)이노진 상무이사
엄 기 용 (Kiyong Om) 한국기술교육대학교 산업경영학부 교수[2]

ABSTRACT

This paper examined the effect of innovation networks comprising research and development (R&D) collaboration on innovation performance of Korean pharmaceutical firms. As co-assigned patents and co-affiliated publications are common technical outcomes of successful R&D collaboration in the pharmaceutical industry, social network analysis technique was applied for analyzing innovation networks through patent and publication data. Results of Social network analysis indicated that a small set of highly innovative firms in the Korean pharmaceutical industry were actively involved in patenting and publishing. And the analysis of structural equation model found the followings: (1) R&D intensity significantly affected patenting, publication and new drug development, (2) the activity of patenting and publishing was positively related with the innovation performance measured by new drug development, and (3) R&D collaboration in terms of degree centrality of co-patent network played significant moderating roles on the relationships among R&D intensity, patenting, and new drug development. These findings are expected to be helpful to researchers as well as policy-makers to devise innovation-promoting policies in the Korean pharmaceutical industry. Discussions and limitations of the study are provided in the last part.

Keywords: Innovation network, centrality, sources of innovation, pharmaceutical industry

---

[1] This paper was financially supported by 2017 KOREATECH Sabbatical Program.
논문접수일: 2018년 6월 30일; 1차 수정: 2018년 8월 7일; 게재확정일: 2018년 8월 13일.
[2] 교신저자 (kyom@koreatech.ac.kr)

1. Introduction

Questions on sources of innovation have long been at the heart of innovation studies. Traditionally, talented individuals such as inventors, scientists, or designers were recognized as being at the core of innovation process. Since Thomas Edison's first industrial research laboratory in Menlo Park, United States, the importance of research and development (R&D) laboratories of entrepreneurial entities has been emphasized in the study of innovation (Rosenberg 1990).

Beyond the boundary line of R&D laboratories, innovation can originate from (1) any part of business firms, (2) research and scientific activities of universities, private non-profit organization, and government-funded institutions, (3) collaborations and interactions with suppliers of equipment/materials/components, users/clients/customers, competitors, and consultancy firms, and (4) various information sources as patents disclosures, internets/books/newspapers/journals, conferences/seminars/exhibitions/trade fairs, and informal conversation and meeting with colleagues (Bommer and Jalajas 2004; OECD 2005; Salter and Gann 2003). An increasing attention has been paid to the significance of collaborative R&D networks for successful innovation, which has brought about the surge of research on innovation networks (Cantner et al. 2010; Soh and Roberts 2003) and regional, national, or industrial innovation system (Cooke et al. 1997; Freeman 1995; Hsu 2005).

The outcomes of R&D collaboration are materialized into co-assigned patents (the assignees of a patent are two or more different organizations), co-affiliated publications (the affiliations of authors of a paper are two or more different organization), or co-developments of new products and processes. Co-assigned patents divide the right of appropriation into each of assignees according to a pre-agreed right-sharing ratio. Therefore, formal and strong relationships between co-assignees are needed for successful exploitation of co-assigned patents. Co-assignees of a patent would be determined at the time of patent application according to the patent application process in general, which means the researchers of each assignee should participate in the invention of the patent. Therefore, co-assignees of a patent in the patent application should make a R&D collaboration before the time of applying the patent. If a firm wishes to acquire a license for the patent after a patent application, the company can receive technology transfers and be a licensor but can not be a co-assignees of the patent. Publications of R&D collaboration results in academic journals may bring reputation to co-authors, but not be directly related with commercial profits of affiliations of the authors. In addition, highly respected journals in the bio-pharmaceutical sector are more inclined to basic research and breakthroughs than application of pre-existing science and technology. Accordingly, comparative analysis of co-assigned patents and co-affiliated publications may provide more comprehensive understanding of R&D

collaboration in the pharmaceutical industry. Since patents and publications apply different criteria to determine inventorship and authorship and play different roles in new drug development process, they would be treated as separate variables. Patents and publications by a firm may be the results of R&D activities of the firm and at the same time may be the causal variables exerting significant effects on the innovation performance in pharmaceutical industry. Thus, patents and publications are considered as mediating variable in our research models.

The pharmaceutical industry was chosen as a model system to study the effects of innovation network of co-assigned patents and co-affiliated publication on innovation performance, because (1) pharmaceutical industry is a science and technology intensive sector characterized by high-levels of patenting propensity and R&D intensity (Comanor and Scherer 1969; Wang and Hagedoorn 2014), (2) patents provide strong appropriation in the pharmaceutical industry and pharmaceutical firms may be granted for new products and new manufacturing processes (Comanor 1964), and (3) pharmaceutical firms may publish clinical trial results of new products in peer-reviewed scientific journals in order to inform and disclose the efficacy and safety of the new products (Sykes 1998; Wager et al. 2003). This study focuses on Korean pharmaceutical companies, for there is few empirical innovation research with the Korean pharmaceutical industry.

The pharmaceutical industry is a science-based business where science and technology is highly complicated and fast growing, and cooperation between diverse innovators is very important as a source of innovation (Chesbrough 2003; Pisano 2006). In the last several decades, many firms in biotechnology fields have done basic research with the hope of first-mover advantages, and active research programs in the pharmaceutical industry are conducted by large firms such as Merck, Pfizer, etc., especially in their own research institutions. As universities, hospitals and public research organizations have become primary sources of scientific development and technological breakthroughs in drug discovery (Owen-Smith et al. 2002), R&D collaborations between bio-pharmaceutical companies and other research organizations have played pivotal roles in this science-based business (Powell et al. 1996).

This paper examines the moderating effects of R&D collaboration in the Korean pharmaceutical industry on innovation performance by analysing data of co-assigned patents and co-affiliated publication from 2006 to 2014. Centrality was adopted as a measure of the degree of R&D collaboration. The more R&D collaboration a firm has done, the higher the centrality of the firm. Degree centrality is used for the basic analysis of R&D collaboration network and Eigenvector centrality represents the network patterns and sum of weighted contacts of a firm.

The remainder of the paper is organized into five chapters. In Chapter 2, previous studies on the research topics are reviewed: sources of innovation, and innovation network. The hypotheses and research methodologies are

detailed in Chapter 3. Data collection and empirical results and conclusions are presented in Chapter 4 and Chapter 5 respectively.

2. Literature Review

2.1 Innovation

As the term 'innovation' is adapted and utilized in diverse and various disciplines, 'innovation' has been discussed, studied, and defined from different perspectives, which causes the ambiguity and dearth of unanimity on the definition of innovation (Baregheh et al. 2009; Cooper 1998). As the analysis unit of this paper is firm-level innovation, the origin, history, and variation of the definition of innovation on firm-level over time is reviewed.

Joseph A. Schumpeter has debated innovation in his many works and divided the concepts of innovation into five cases: 'the introduction of a new good, the introduction of a new method of production, the opening of a new market, the conquest of a new sources of supply of raw materials and the carrying out of the new organization'. (Schumpeter 1934, p. 66).

After Schumpeter, many researchers have defined innovation in various ways. Among them, Godin (2008) defines 12 concepts of innovation.

As various researchers define and study innovation in different ways and meanings to suit their research fields, each researcher needs to define and study innovation in accordance with one's research field and purpose.

Since this study is focusing on the R&D collaboration in the development of new drugs by Korean pharmaceutical companies, we define innovation as the development of new drugs, adapting and modifying the concept of product innovation from Schumpeter's works.

Although the measurement of innovation is a very important topic in innovation research, it is very difficult to find a reasonable tool for measuring innovation because of the various definitions and characteristics of innovation. Following Rogers' research (Rogers 1998), innovation activities may be divided into input and output. Output measures of innovation activities include the introduction of new or improved products or processes, percentage of sales from new or improved products or processes, intellectual property statistics, and firm performance. Input measures encompass R&D activities and investment, acquisition of technology, facility investment, intangible assets, and intellectual property statistics. It is noted that intellectual property statistics are located in both input and output measures of innovation. Intellectual property is composed of patent, trademark and design application. Rogers (1998) pointed out that drawback of the intellectual property statistics is the lack of representing a commercialization of ideas.

Oslo Manual (OECD 2005) provides an innovation measurement framework from the perspective of the firm for guiding innovation survey design. The main characteristics of the framework in Oslo Manual are "innovation in the

firm, linkages with other firms and public research institutions, the institutional framework in which firms operate and the role of demand." (OECD 2005, pp. 33-34)

Drucker (1997) emphasized the "innovation opportunities" which are found in seven situations. Four internal opportunities are unexpected occurrences, incongruities, process needs, and industry and market changes. Three external opportunities are demographic changes, changes in perception, and new knowledge. Internal opportunities exist within a company or industry, while external opportunities exist outside a company.

2.2 Innovation Network

The innovation networks of science and technology have been studied based on such different theoretical backgrounds as transaction costs (Williamson 1979, 1989), industry structure view (Porter 1998), resource based view (Barney 1991; Penrose 1995), relational view (Borgatti and Cross 2003; Dyer and Singh 1998), and knowledge based view (Grant 1996). In this study, 'innovation networks' are defined as "a relatively loosely tied group of organizations that may comprise of members from government, university and industry continuously collaborating to achieve common innovation goals (Rampersad et al. 2010)."

The R&D collaboration networks of science and technology have been growing in importance. Crane (1969) studied informal network called the 'invisible college' and stressed the importance of the academic community; A group of people who share similar scientific interests communicate with each other more frequently than outsider of the group, exchange each other's ideas and scientific results, and have more changes to collaborate in future research. Newman (2004) discussed the structure of three networks of scientific collaborations (biomedical research, physics, and mathematics), as deduced from the pattern of co-authorships of papers. The study showed that the distribution of the number of co-authors is very broad; most individuals have only a few co-authors, whereas a few have hundreds or even thousands; these collaboration networks form "small worlds." Merton (1968, 1988) pointed out that eminent scientists tend to get more credit than relatively unknown researchers. This 'Matthew effect' is one of the reasons of why a handful of papers in any particular field of science are cited so many times more than other papers with similar contents.

Stuart et al. (2007) indicated that young biotechnology firms act as intermediaries between universities and large pharmaceutical companies. The results of their study showed that the more biotechnology firms make in-licensing agreements, the more likely they attract revenue-generating alliances with pharmaceutical partners. Gay and Dousset (2005) studied alliance networks of the biotechnology industry and demonstrated that the network is scale-free, follows the fitter-get-richer model of network growth, and shows a small-world effect, using samples of 739 alliances carried out by 557 firms (privately held and publicly

traded) and institutions over the 1987 to February 2004 period.

3. Hypotheses and Research Methodology

3.1 Hypotheses

3.1.1 R&D Intensity and Innovation Performance

On a firm level, R&D intensity is generally defined as a firm's R&D expenditures divided by the firm's sales (Cohen et al. 1987; Hughes 1988). Measures of R&D intensity are used to compare innovation activity of firm-to-firm, industry-to-industry, or even country-to-country basis (Nunes et al. 2012).

Firm's R&D is generally accepted to be fundamental for innovation performance and economic growth. For example, by analysing a database comprising manufacturing firms of 330 non-high-tech small and medium-sized enterprises (SME) and 133 high-tech SMEs in Iberian peninsula through the period 1999 - 2006, Nunes et al. (2012) found that the growth of high-tech SMEs is accelerated at higher levels of R&D intensity, and decelerated at lower levels. Internal R&D intensity and technological sophistication are positively correlated with both the number and intensity of strategic alliances. Several studies have looked at the relationship between R&D spending, productivity returns and firm performance (Comanor 1965; Cohen and Levinthal 1990). Because of the high cost and time involved in the development of new drugs, pharmaceutical companies need to make strategic decisions about R&D investments to develop new products. Taken together, it is anticipated that firms with high R&D intensity and focusing R&D activity have better innovation performance and the above arguments lead to the first hypothesis:

Hypothesis 1a. R&D intensity has a positive effect on innovation performance.

Many studies have provided evidence that patent statistics have very strong positive correlation with R&D investment (Griliches 1994; Pakes and Griliches 1980; Sohn et al. 2010). By analysing a seven-year panel data set comprising 1,176 firms with Korean government's venture certification, Sohn et al. (2010) demonstrate that although R&D investment and patent stock did not have a significant positive effect on financial performance, R&D is an important facilitator of patenting activity. This study thus presents the following hypothesis:

Hypothesis 1b. R&D intensity has a positive effect on patent filing.

Scientific publications are thought to be an indicator of academic superiority and achievement, and publication data can be used as a measure of technological competence of an individual, a firm or a country. Garfield and Welljams-Dorof (1992) employed publication and citation data to develop quantitative and objective indicators of science and technology performance of authors, affiliations, and nations.

In pharmaceutical industry, publication is not an option, but a necessity to demonstrate new product's efficacy and safety to potential users and regulatory entities (Wager et al. 2003). Research on 10 major pharmaceutical companies showed that firms which regard publication records as an important criterion for promotion were more productive than their rivals, located close to important medical research centres, and deeply involved with academic medical establishments (Cockburn and Henderson 1998; Henderson and Cockburn 1994). Academic inventors in Belgium, including medicine and pharmaceuticals discipline, published significantly more than their colleagues (non-inventors) working within similar fields of research (Van Looy et al. 2006). Accordingly, it is expected that firms with high R&D intensity publish more scientific papers.

Hypothesis 1c. R&D intensity has a positive effect on scientific publication.

3.1.2 Technical Performance and Innovation Performance

Before the era of biotechnology in the pharmaceutical industry, drugs were usually chemically synthesized compounds or natural products extracted from raw botanical or animal materials (Galambos and Sturchio 1998). As a drug with simple chemical structure would be very vulnerable to be copied and the manufacturing process for drug production would be easily imitated by competitors or followers, pharmaceutical firms should pay great attention to protect its intellectual property rights (Scherer 2010). A number of studies have found that patents are more important to pharmaceutical firms in appropriating the benefits from innovation than other high-tech industries (Comanor 1964; Grabowski 2002; Levin et al. 1987).

Drug discovery and development process is highly related with patent filing (Ko and Lee 2013) and scientific publication. Based on the analysis of patents and publication data of the U.S. FDA-approved drugs, in total, 154 new chemical entities (including 28 orphan drugs), and 306 updates (including eleven orphan drugs) for the period 1999–2004, Sternitzke (2010) found that during the process of developing each drug, about 19 journal publications and 23 additional patents were produced on average, and interpreted that basic science is pivotal for radical innovation in U.S. pharmaceutical firms.

With the end of patent protection period, for most new drugs, a potential imitator could spend just a few million dollars on process engineering and enter the market with a generic copy (Scherer 2010). As generic imitators are spending less for copying the same efficacy drug to the market, the drug price of imitators can be much lower, without hampering financial performance of copy drug, than original developers. Generic competition, along with R&D costs and price controls, is dramatically undermining the profitability of big pharmaceutical firms (Juliano 2013).

For a sample of 57 pharmaceutical firms from 1955 through 1960, Comanor and Scherer (1969) examined the correlation between a simple count

of the number of patents and the number of new chemical entities and incrementally modified products with each new product weighted by its sales during the first two years following introduction, and found that the association is statistically significant. For 17 U.S. pharmaceutical companies, Narin (1987) examined the relationship between several variables, such as corporate patent, patent citation data, and corporate performance which was measured by changes in sales and profits, research and development budgets, scientific productivity, and expert opinions of company technological strength, and found that the patent data had positive relation with technological strength of a firm with increases in company profits and sales. Using the data of 565 patents owned, as of November 1991, by the 20 largest biotechnology firms (by market value as of December 1988), Austin (1993) tried to estimate the private values of patent based on event-study methodology, and presented that the product-linked patent events were valued considerably more highly than the non-linked ones and that patents readily identifiable with end products tended to be more valuable than the average patent.

The use of patent data as an index of inventive output began with Scherer (1965) and Schmookler (1966). Based on the sample consisted of 448 firms on Fortune 500 list in 1955, Scherer found three conclusions: (1) the number of patent of a firm increase with firm sales, (2) Differences in technological opportunity are a major factor responsible for the differences in the number of patent among industries, and (3) Market power, prior profitability, liquidity, or degree of product line diversification is not systematically related to the number of patent. Scherer and Schmookler relied exclusively on patent counts as an index of innovative output. As Scherer has pointed out, the use of patent counts has two serious limitations: (1) interfirm and interindustry differences in the propensity to patent, and (2) the variation in the quality of patents. The propensity to patent an invention may vary according to a firm's strategic decision or the characteristics of an industry where a firm operates its activities. For example, a firm designing and manufacturing commodities in the fashion industry would not pay much attention to patenting its products, whereas a pharmaceutical company may have great interests in patenting its newly developed drugs and manufacturing processes for the drugs. The technological and economic significance or value, which may be called as the quality, of a patent may vary enormously, and the value distribution may be extremely biased. A patent of platform technology, which is used as a base for diverse application and considered as a breakthrough in technological advances, may produce much more tremendous technological and economic value than a small, incremental patent, but the patent count would not recognize this quality differences. In an intention to overcome the limitation of patent count data, patent renewal data (Pakes et al. 1989) and patent citation data (Trajtenberg 1990) were introduced in the innovation research.

Another line of research is going on the

properties of networks of cooperative invention exploiting information contained in patent data. Several important results are drawn from these studies: social proximity among inventors in collaboration networks is a fundamental driver of knowledge flows (Singh 2005); patent statistics have strong positive correlation with R&D investments (Griliches 1994); and the cooperative invention network does not seem to exhibit the structural properties of a small world graph (Fleming et al. 2007).

Considering the characteristics of the pharmaceutical industry depending on new drug development for company growth and the importance of patent filing for protecting appropriation of new products, the following hypothesis is thus proposed:

Hypothesis 2a. Patent filing positively affects innovation performance.

One of the main issues to address is whether a firm's involvement in scientific publication enhances its innovation performance in the pharmaceutical industry. Academic institutions such as universities and research laboratories are mainly focused on studying scientific breakthroughs, and top-class journals in science fields prefer fancy and up-to-date issues. It is generally accepted that industry publishes relatively few scientific papers (Godin 1996), and basic science has been considered as a public good (Pavitt 1991). In the pharmaceutical industry, however, basic science is strongly related with new opportunity to pursue novel target and new medicine (Galambos and Sturchio 1998). Based on the data of UK therapeutic biotechnology industry, Jong and Slovova (2014) argued that publication of valuable R&D work in high quality scholarly journals and collaborations with academic partners positively affect firm's product innovation performance.

The information on co-authored publication of academic papers has long been used to analyze knowledge exchange among researchers and to investigate social networks of academic scientists (Melin and Persson 1996; Uddin et al. 2013). Uddin et al. (2013) discovered that authors' network positions in co-authorship networks influence the performance and formation of scientific collaborations. The scientific co-authorship network is characterized by the structural properties of small world networks (Newman 2001, 2004). In this kind of research, impact factors of a journal are often used as a measure of expressing the quality of a publication in the journal. Consistent with past work, high impact factors of a journal are regarded as a proxy for the high quality of publication by a firm's scientists. In addition to the measure of impact factor, simple count variable for the number of publication of a firm is widely used for a proxy of a firm's scientific expertise. Accordingly, it is expected that firms with high publication activity have more chance to find competitive position in drug development and the next hypothesis is the following:

Hypothesis 2b. Scientific publication positively affects

innovation performance.

3.1.3 Moderating Effects of R&D Collaboration on technical and innovation performance

The pharmaceutical industry is suffering from continuous R & D productivity deterioration. Development of new drugs requires scientific knowledge in various fields, including biology, chemistry, pharmacology, clinical medicine, and statistics. Because the knowledge base related to new drug development is so vast and diverse, it is almost impossible for a single pharmaceutical company to independently develop all the knowledge needed for new drug development, no matter how big a company it is. In this industrial environment, the importance of R & D collaboration in new drug development is increasing day by day. This led us to infer the hypotheses that the R&D collaboration would represent the moderating effects in the development of new drugs.

There are a lot of prior research stressing the importance of network position and the relationship between network position and firm's innovation performance. Based on the characteristics of network, Burt (1995) demonstrated that an individual in a favoured network position of structural holes gets the opportunity to gain a competitive advantage of information access and performs better than competitors. He insisted that as the structural holes of a player in the network enhance the proportion of relationships, the player's investments on building relationships are more likely to yield a higher aggregate rate of return on investments.

Degree centrality and closeness centrality are positively correlated with a firm's innovation performance or information dissemination. Tsai (2001) argues that degree centrality enhances business units' innovation performance measured by the number of new product. Soh and Roberts (2003) argue that a company located in the centre position of knowledge network is more advantageous in information acquisition and product development than a company located in the periphery.

From the patent data of 89 pharmaceutical firms (32 U.S., 33 Japanese, and 24 European firms) during the period 1988–1994, Kim and Park (2010) suggest the moderating role of network position (in terms of network efficiency, measured by the normalized difference of the number of R&D alliances of a focal firm and the average number of R&D alliances of the focal firm's partner by the number of the focal firm's R&D alliances) in the relationship between the firm's science intensity (measured by the average number of science references on the front page of the firm's patents) and the impact of its innovation (defined by the number of citations the patent received from the other firms in the five years following patent-granted year). The results showed that high network efficiency group in R&D network strengthens the positive relationship between a firm's science intensity and its innovation impact.

Hypothesis 3a. A firm's R&D collaboration in co-

assigned patents network positively moderates the effect of R&D intensity on patent filing.

Hypothesis 3b. A firm's R&D collaboration in co-assigned patents network positively moderates the effect of patent filing on clinical trials.

In the pharmaceutical industry, the drug discovery and development process is a science-based, complex and multidisciplinary process requiring intensive knowledge in various fields from biology to chemistry to pharmacology to medicine. However, it is unrealistic to expect a single company to have all of this knowledge and capabilities. Due to the limited resource constraints of a firm, individual firms are focusing on their own unique, specific applications. Therefore, pharmaceutical firms are trying to make an access to the complementary knowledge in drug development process (Teece 1986). External knowledge not only helps projects in drug development progress, but also provides ideas for new drug development projects. Pharmaceutical firms are actively collaborating with academic communities, and this collaboration may enhance its innovative performance in terms of new products in development.

At an individual level, network position of a person may affect directly on the performance of job search (Granovetter 1973), promotion (Kim 2002), and knowledge intensive works such as engineering projects and consulting studies (Cross and Cummings 2004). At a firm level, however, firm's network position may enhance the effect of R&D activities on innovation performance.

Prior research has shown that various network properties and position of a firm exert moderating effects on innovation performance. For example, by analysing 977 German biotechnology firms between 1996 and 2012, Oehme and Bort (2015) revealed the impact of network-enabled imitation processes on the internationalization of young small- and medium-sized enterprises and the moderation effects of a firm's network position and its experiential knowledge on imitative behaviour in internationalization modes, arguing that a firm's imitation propensity depends on network position and past experience.

Using data covering the period 1995-98 pertaining to U.S. venture capital firms and their holdings in initial public offerings (IPOs), Echols and Tsai (2005) showed that both product niche and process niche, defined by the extent to which a firm offers distinctive products and has distinctive operational processes, interact with network embeddedness to determine firm performance (defined by the number of successful IPOs), and the effect of each niche on firm performance is contingent upon network embeddedness.

Mazzola et al. (2015) explored the moderating role of open innovation flow in the network embeddedness and new product development using the BioWorld database comprising the 554 public bio-pharmaceutical companies and data from 1758 agreements among 1890 bio-pharmaceutical firms through the period 2006–2010. Open innovation flow is defined as "the attitude of a firm of balancing inflow of

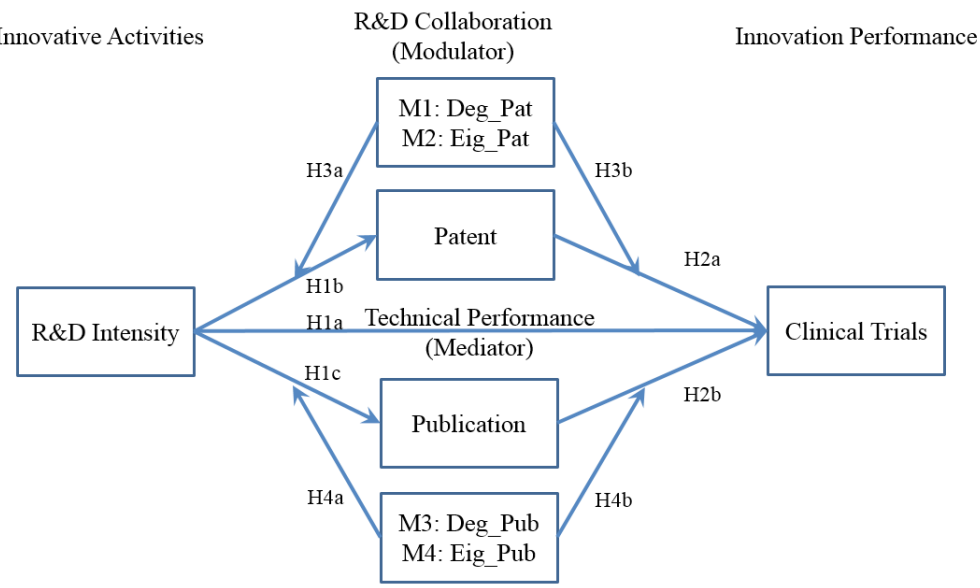
knowledge and outflow of knowledge through the prevalence of inbound and outbound practices; it is positive when inflow of knowledge is greater than outflow of knowledge and vice versa." (Mazzola 2007, p. 109) The results showed that a net positive knowledge flow, i.e. positive open innovation flow, significantly amplifies the positive effect of structural embeddedness positions (centrality and structural holes) on the process of new product development.

McKelvey and Rake (2012) studied the effects of the collaboration with different types of partners and the position in terms of eigenvector centrality within a research network (the scientific co-publications network) on a firm's innovative performance (the number of new pharmaceuticals approved by the FDA) in terms of product innovations in the biotechnology and pharmaceutical industry, and observed that collaboration with academic partners and the network position in terms of eigenvector centrality are positively related to product innovation.

Hypothesis 4a. A firm's R&D collaboration in co-affiliated publication network positively moderates the effect of R&D intensity on scientific publication.

Hypothesis 4b. A firm's R&D collaboration in co-affiliated publication network positively moderates the effect of scientific publication on clinical trials.

The hypotheses in this study are depicted in <Figure 1>. Basic research model is composed of R&D effort, technical performance (patent and publication), and innovation performance. Alternatives to basic research models, whether direct effect of R&D effort to innovation performance is included or not, is tested before assessing the network effects on innovation performance.



<Figure 1> Research models of the study

3.2 Measures

3.2.1 Dependent Variables

The dependent variable in this study is product innovation performance and measured as the accumulated number of clinical trials of a firm over the period of 2007-2015, approved by Korea Ministry of Food and Drug Safety (KMFDS, formerly Korea Food and Drug Administration). The number of new drug is well recognized as the measure of new product introduction. For example, Comanor and Scherer (1969) used as the measure of new products the number of new chemical entities and generic products including combination of active ingredients, new dosage forms and copy products.

The distinction of clinical trials in this study consists of three phases: Phase I, Phase II and Phase III. If a new drug passed successfully Phase I or Phase II study, the drug would enter the next Phase of clinical trials. Whereas innovative new chemical entities should enter into Phase I as a starting point of clinical trials, incrementally modified drugs, especially those with modification of formulation using previously approved material and the same active pharmaceutical ingredients as approved drugs, could start Phase II without taking Phase I trials. Therefore, for the most successful drugs, the number of clinical trials would be more than one.

KMFDS does not provide information about the original developer of a drug during its approval process. There is no significant difference in the clinical trial process between in-house developed and in-licensed drugs. The dependent variable in this study, therefore, includes all the number of clinical trials of a firm regardless of the originality of drug developer.

For a successful, previously approved drug, a firm would exert its best efforts to expand the indication of the drug. An example of an indication expansion would be Gleevec (Novartis International AG, Basel, Swiss) that was first approved for chronic myelogenous leukemia, and later entered clinical trials to gain approval for use in the treatment of gastrointestinal stromal tumours (GISTs) and a number of other malignancies. In order to expand the indication of a drug, a firm should enter into new clinical trials of Phase II or Phase III. The indication expansion of a drug would increase the total number of clinical trials of a firm in the dependent variable.

Although many researchers have been studying innovation performance measures of a firm, it is still very difficult to select the appropriate innovation performance measures suitable for individual studies (Zeng et al, 2010). For the study of pharmaceutical industry, product innovation performance may be measured as the number of new drugs in development that enter a firm's product development pipeline in clinical or preclinical trials (Jong and Slavova 2014).

3.2.2 Independent Variables

The first independent variable of interest is R&D intensity. The simple static model of R&D intensity was employed by Nunes et al. (2012) where

R&D intensity is defined as a firm's yearly R&D expenditure divided by sales in the same year. In this paper, average value of the ratio of R&D expenditures to sales over the period of 2004-2011 is used to represent R&D intensity of a firm.

It should be noted that there is a time lag of 3 years between dependent and independent variables. Before entering clinical phases, a sequence of research and development should be performed, including target identification, target validation, screening, optimization and pre-clinical tests. Pharmaceutical firms tend to apply patents of new drugs immediately before clinical phase in order to secure longest patent period during their marketing of the drugs. The lag structure of the patents-R&D relationship has been repeatedly examined (Hall et al. 1984; Lee and Choi 2015; Wang and Hagedoorn 2014). Prior studies have usually studied the lag structure by using panel data. For example, Lee and Choi (2015) studied the influence of the R&D intensity on firm value in the pharmaceutical industry in Korea, and found that only the R&D intensities of previous years 2 and 5 were statistically significant. According to the results of Comanor and Scherer (1969) on the study of patents and new product introduction in pharmaceutical firms, the median lag from patent application and commercial introduction in the United States from 1955 through 1960 was 3 years.

However, if it is considered that the commercialization of R&D results in the pharmaceutical industry requires a lot of knowledge accumulation over long period of time, it would be very difficult to acknowledge the assertion that the investment on R&D only in particular year will be able to influence any specific future year's performance. Therefore, the R&D intensity is assumed in this study to influence the performance of a firm in a cumulative manner, and the time lag of 3 years is adopted considering the required time for pre-clinical tests and application for clinical trials. Considering the required time for documentation and application for clinical trials after the R&D activities in a firm, additional 1 year of dependent variable is added to the end year of independent variable.

3.2.3 Mediating Variables

The unit of analysis in co-affiliated publication and co-assigned patents is usually an individual scholar or inventor. However, owing to the complexity of science and technology in the pharmaceutical industry, it is very common that several scientists or groups of scientists in different organizations cooperate and publish a single paper or patent. In this line of view, the affiliations rather than authors of a published article and the assignees rather than inventors of a patent would provide organization level of understanding for R&D collaboration (Chan et al. 2005; Gorraiz et al. 2012).

The mediating variables are the accumulated number of patents or publications of a firm over the period of 2006-2014. Considering that the application of a patent is generally made before the relevant study is open to public to maintain the novelty requirement of the patent, the time

period of mediating and moderating variables is set to 1 year before that of clinical trials (dependent variable). The origins of studies on the relevance of innovation and patents can be traced back to the pioneering works of Schmookler and his colleagues in 1960's (Comanor and Scherer 1969; Schmookler and Brownlee 1962; Schmookler 1966). Measures that can be derived from patent data include a simple count of the number of patents, citation information of a patent, and network properties obtained from the social network analysis of patent networks (Breschi and Catalini 2010; Goetze 2010).

Publication counts are widely used as a measure for the research activity performed by firms (Jong and Slavova 2014). In more specialized researches, a publication count weighted by the impact factor of the journal is used as a proxy for the quality of publications by a firm (Wang and Guan 2005). Although publishing in prominent scholarly journals may bring reputation for the authors of publication, it should be emphasized that the most prominent journals in pharmaceutical and biotechnology fields tend to put a higher value on breakthrough basic researches than application research and commercialization of product innovation. The impact factors of scientific journals in biotechnology and pharmaceutical fields are continuously changing according to contemporary research topic trends. Considering these facts, the validity of impact factors of journals as a predictor of the innovation performance of a firm is highly questionable.

3.2.4 Moderating Variables

The R&D collaboration variables as measures of firm's network position are the degree centrality and Eigenvector centrality (or Bonacich centrality) of a firm's patent or publication networks. Deg-Pat and Eig-Pat respectively stand for degree and Eigenvector centrality of a firm's patent network based on the accumulated data of co-patents from 2006 to 2014. In a similar manner, Deg-Pub and Eig-Pub is used to note degree and Eigenvector centrality of a firm's publication network based on the accumulated data of co-publications from 2006 to 2014.

Centrality is a measure of how well connected or active a firm is in the overall network (Powell et al. 1996). The central actor with the most ties to others must be the most active one in the network (Freeman 1979). Two approaches to centrality – degree and Eigenvector – at the firm level is considered. Degree centrality measures only the number of other companies connected to a firm but ignores how well the partners are connected to each other. Eigenvector centrality measures not only the connectivity of a specific actor but also the connectivity of its collaboration partners (McKelvey and Rake 2012). Unlike degree centrality, which weights every contact equally, eigenvector centrality, suggested by Bonacich (1972), weights contacts according to their centralities and is a measure for the weighted sum of direct and indirect connections of the contacts (Bonacich 2007). Therefore, eigenvector centrality can give an information about the entire pattern in the network and the positional importance of a

firm in the R&D collaboration network.

Significant associations between a firm's network position and performance were reported in studies of start-ups. In a study of new companies in the semiconductor industry, Walker et al. (1997) found that the network position and collaborative relationships were related to innovative output. In a study of the international chemical industry, Ahuja (2000) showed that both direct and indirect ties had a positive impact on innovation but their roles were different.

In another study, Powell (1996) found that the centrality in the inter-firm learning networks of biotechnology start-ups was positively related to firm growth. He postulated that the central connection in a network generates access to resources and shapes the reputation of the firm. In addition, he found positive associations of a firm's network centrality with company growth and the number of R&D collaborations. These studies suggested that a firm at the central position of the network can advance innovative and economic performance largely due to better accessibility to critical knowledge and flow of resources.

(1) Degree centrality

Degree of a point is defined by "the number of other points to which a given point is adjacent" (Freeman, 1979. p. 218). In other words, degree of a point is the number of direct connections that an actor (a node) has with other actors.

Actor-level degree centrality of a point P_k (Freeman, 1979) is defined by

$$C_D(P_k) = \sum_{i=1}^{n} a(P_i, P_k)$$

where

C_D = a degree centrality measure, which will be a function of a specific actor P_k,

$a(P_i,P_k)$ = 1 if and only if P_i and P_k are connected by a line

0 otherwise

Degree centrality measures take into account only an actor's direct ties, or the ties between the actor and the actor's neighbors, rather than indirect ties to all others in a network.

(2) Eigenvector centralit

Eigenvector centrality is introduced by Bonacich (1972). Bonacich suggested that a good network centrality can be measured by the eigenvector of an adjacency matrix.

The main difference between degree centrality and eigenvector centrality is the weight of contacts of a point. Degree centrality assumes the weight of every contact of a point is equal, while eigenvector centrality weights contacts according to the centrality of the contacts (Bonacich, 2007). Eigenvector centrality of a point is determined by the centrality of the contacts of the point.

Eigenvector centrality $\boldsymbol{x}$ is defined by as follows (Bonacich, 2007. p. 556):

Let be the adjacency matrix; a_{ij} = 1 if points i and j are connected by line and a_{ij} = 0 if they are not.

$\boldsymbol{\lambda}$ is the largest eigenvalue of A and n is the number of points:

$$Ax = \lambda x,\ \lambda x_i = \sum_{j=1}^{n} a_{ij}x_j,\quad i = 1,\ldots,\ n$$

3.2.5 Control variables

For control variables, firm size and total salary are included that are routinely used as adjusters in a wide range of organizational studies on economics and management. Firm size is defined as the average number of employees between 2004 and 2011 and salary as the average of the total amount of salary paid to all employees between 2004 and 2011.

<Table 1> Operational definition of the variables in the regression model

Variables	Definition
Dependent variable: innovation performance	
Clinical Trials	Accumulated number of clinical trials of a firm over the period of 2007-2015
Independent variables	
R&D Intensity	Average value of the ratio of R&D expenditures to sales over the period of 2004-2011
Mediating variables	
Patents	Accumulated Number of patents over the period of 2006-2014
Publications	Accumulated Number of publication over the period of 2006-2014
Moderating variables	
Deg-Pat	Degree centrality of patent network based on the accumulated data of co-patents from 2006 to 2014
Eig-Pat	Eigenvector centrality of patent network based on the accumulated data of co-patents from 2006 to 2014
Deg-Pub	Degree centrality of publication network based on the accumulated data of co-publications from 2006 to 2014
Eig-Pub	Eigenvector centrality of publication network based on the accumulated data of co-publications from 2006 to 2014
Control variables	
Size	Average number of employees between 2004 - 2011
LogSalary	Logarithm (base 10) of the average of total amount of salary paid to all employees between 2004-2011

3.3 Analytical Methodology

This study has the characteristic and contribution of combining two methodologies, social network analysis and structural equation modeling, in studying moderating effects of R&D collaboration on innovation performance in pharmaceutical industry. Moderating variables of centralities was derived from and calculated by social network analysis method and the explanatory power of a research models was analyzed by structural equation modeling.

Path analysis was developed by Sewall Wright in 1918 and a method to relate "the correlation coefficients between variables in a multiple system to the functional relations among them" (Wright 1934, p. 161). Path analysis has been used in explaining causal relationship among variables in a model. Structural Equation Modeling (SEM) evolved from path modeling of Sewall Wright. Several statistical packages have been developed for the SEM, including LISREL, EQS, and Amos. Based on graphics, Amos is easy to use compared to LISREL. In this study, IBM SPSS Amos v.22 was used to analyze research models.

If two alternative models use the same data set, they are referred to as nested models (Schumacker and Lomax 2010). The assessment of comparative fit in the nested-model approach involves Chi square testing and path coefficients. For the comparison of the non-nested models, the models "may be compared on the basis of descriptive goodness-of-fit measures that take parsimony as well as fit into account (Schermelleh-Engel 2003, p. 35)."

Social network analysis is an analytical methodology to determine the structure of a particular network and the relationship between actors in the network in the social sciences. It enables the interpretation of the relationship of actors in networks by quantifying, statistically processing and making a graph of the networks. Social network analysis variables can be divided into three types, depending on the interests of researcher. Density and size of a network and measures of centralization represent the characteristics of entire network topology. The measures of degree, centrality and structural holes are indicators of a specific actor in a given network. These measures are critical variables for the research where the unit of analysis is individual actor or firm. The characteristics of relation between actors in a given network are measured by indicators of strength and direction.

A social network consists of a finite set or sets of actors and the relation or relations defined on them. The presence of relational information is a critical and defining feature of a social network (Wasserman and Faust 1994). In social network analysis, indicators of centrality are used to identify the most important actors within a network. The underlying concept on importance is that important actors are "extensively involved in relationships with other actors" (Wasserman and Faust 1994, p. 173).

Much attention should have been paid in comparing data of patents and papers, because they have different norms of issuing and publishing. Some scientific facts published

in scientific journals may not be granted as patentable unless other conditions such as novelty, inventive step, and industrial applicability are met. The requirement of inventorship is generally much more rigorous than authorship. In one example, a person who performed experiments according to supervisor's directions without one's own idea may be included as an author, but not an inventor.

The R&D collaboration variables in this study are degree and Eigenvector centralities of patent and publication networks. The social network analysis software UCINET v.6.625 was used to compute the degree and Eigenvector centralities.

4. Empirical Results

4.1 Data Collection

The research setting of this study is the Korean pharmaceutical industry. The main criteria to select sample pharmaceutical firms were set by the availability of financial information, the ownership of the firm, and the firm's foundation date. The first consideration was the availability of financial information from reliable sources. This criterion restricted sample firms to the listed on Korea Exchange (KRX) or Korean Securities Dealers Automated Quotations (KOSDAQ) for stock trading, and their financial information is available from Data Analysis, Retrieval and Transfer System (DART) of Financial Supervisory Service. The second consideration was the ownership of the firm in order to exclude foreign companies or the subsidiary of multinational pharmaceutical companies. The date of incorporation was also considered in order to ensure the full coverage of financial information over the period 2004–2011. Data on financial information and R&D investment of these firms were obtained from DART.

Firm-level patent data are obtained from Korea Intellectual Property Rights Information Service (KIPRIS) established by Korean Intellectual Property Office, the governmental authority in charge of intellectual property in Korea. The patents filed by each firms in Korea were collected from 2006 to 2014 and used for network analysis based on co-assignees. Korean pharmaceutical companies have diverse range of business units, including functional foods and cosmetics. In order to exclude non-pharmaceutical patents, International Patent Classification (IPC) symbols are considered in the patent search process. Three IPC symbols are selected relevant to drug development: A61K, C07C, and C07D. The search operator combination is

IPC=[A61K+C07C+C07D]*AD=[20060101~20141231]*AP=[/company name],

where AD is an operator for application date and AP is for applicant.

The first set of search of patents was performed using the firm name of sample companies in the field of applicant of patents. This first set of search provides the information about the patent network where each firm plays a role of central node or agent and the network density is low. In order to expand the network and apprehend the comprehensive patent network, the second set

of search was performed using the name of co-assignees of the first set of search as an applicant of patents. As universities have diverse research fields and apply patents of other academic disciplines than pharmaceutical research, the second set of search excludes the co-assignees of university.

Publication data during the period of 2006 and 2014 were extracted from Scopus database of Elsevier B.V. and Medline of U.S. National Library of Medicine. Medline contains journal citations and abstracts for biomedical literature from around the world. The papers published by Korean pharmaceutical companies, identified by the affiliation information of the papers, were searched in journals of Scopus database and Medline which have little information on Korean journals published in Korea and written in Korean. 773 papers that met the sampling criteria were found.

Information on clinical trials and new drug development by Korean pharmaceutical companies from 2007 to 2015 were obtained from the official website of KFMDS. 867 clinical trials met the sampling criteria.

4.2 Descriptive Analysis

Descriptive statistics of the samples in <Table 2> tell us that there is a wide range of diversity among the sample firms. For example, the largest firm in the set has 36 times more employees than the smallest.

4.3 Correlation Analysis of Variables

Prior to the hypothesis testing, the correlation analysis between variables used in verifying hypotheses was conducted. The results of the Pearson correlation analysis are tabulated in <Table 3>. Overall, there is a statistically significant correlation between the variables.

<Table 2> Descriptive Statistics

Variables	Min	Max	Total	Mean	Std.Dev.
ClinicalTrials	0	101	869	17.38	23.173
RnDIntensity	.002471455	.215283864	2.581532143	.05163064286	.034450092638
Patents	0	160	1534	30.68	36.312
Publications	0	160	773	15.46	35.031
Size	83.8333	2983.1667	32861.9000	657.238000	568.5627410
LogSalary	3.50	5.03	213.36	4.2671	.36713
Deg_Pat	.0000	.7330	8.0760	.161520	.1882587
Eig_Pat	.0000	.6820	1.4740	0.29480	.0999874
Deg_Pub	.0000	1.227	5.4470	.123795	.2719084
Eig_Pub	.0000	.6190	1.4320	.028640	.0954232

There is high correlation among network properties of patent and publication. These also have very strong correlation with size of a firm. Degree centrality seems to have positive effects on the number of new drug development in a simple regression analysis. However, when firm size is controlled, this positive effect of degree centrality on innovation performance of Korean pharmaceutical companies is diminished to the level of no significance.

The correlation coefficients between independent and control variables are not so high. Multicollinearity analysis was performed and confirmed that most independent and control variables have a significant correlation, but the variance inflating factor (VIF) is not greater than 3, indicating that there is no problem in the multicollinearity between independent and control variables.

<Table 3> Correlation coefficients

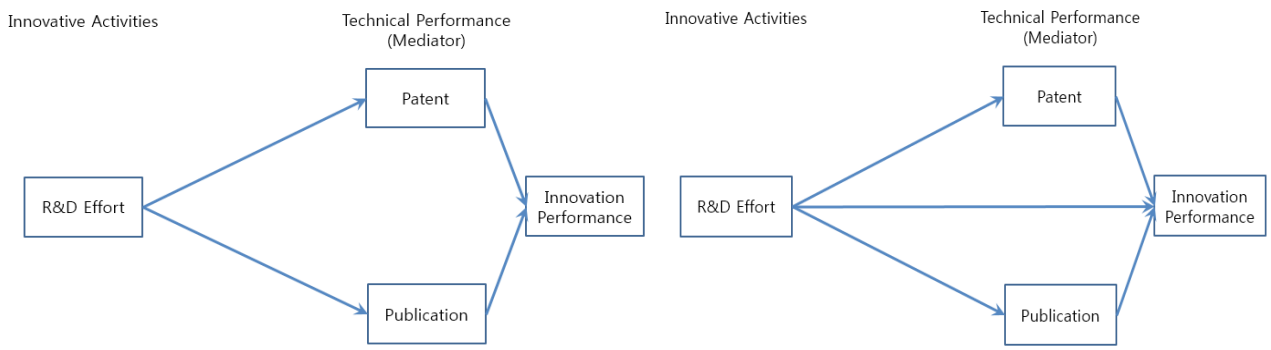
Variables	1	2	3	4	5	6	7	8	9	10
1. ClinicalTrials	1									
2. RnDIntensity	.644**	1								
3. Patents	.827**	.657**	1							
4. Publications	.720**	.331*	.701**	1						
5. Size	.666**	.347*	.548**	.580*	1					
6. LogSalary	.791**	.484**	.662**	.621**	.726**	1				
7. Deg_Pat	.319*	.155	.497**	.487**	.393**	.456**	1			
8. Eig_Pat	.225	.108	.264	.357*	.284*	.358*	.549**	1		
9. Deg_Pub	.660**	.257	.506**	.905**	.574**	.604**	.346*	.388*	1	
10. Eig_Pub	.488**	.188	.468**	.767**	.540**	.503**	.401**	.506**	.836**	1

Note: *p < 0.05, **p < 0.01.

4.4 Development of the Basic Research Model

The basic research model of this study consisted of four indicators: R&D Effort, patent, publication and innovation performance. R&D effort is measured by R&D intensity of Korean pharmaceutical firms. Based on the previous literature of R&D intensity, the direct effect of R&D effort on innovation performance was considered in Alternative Model 2, as shown in <Figure 2>.

As Alternative Model 1 is nested in Alternative Model 2, the fit of models can be evaluated by comparing χ^2 scores of the models (Hooper et al. 2008). From the table of χ^2 distribution statistics,

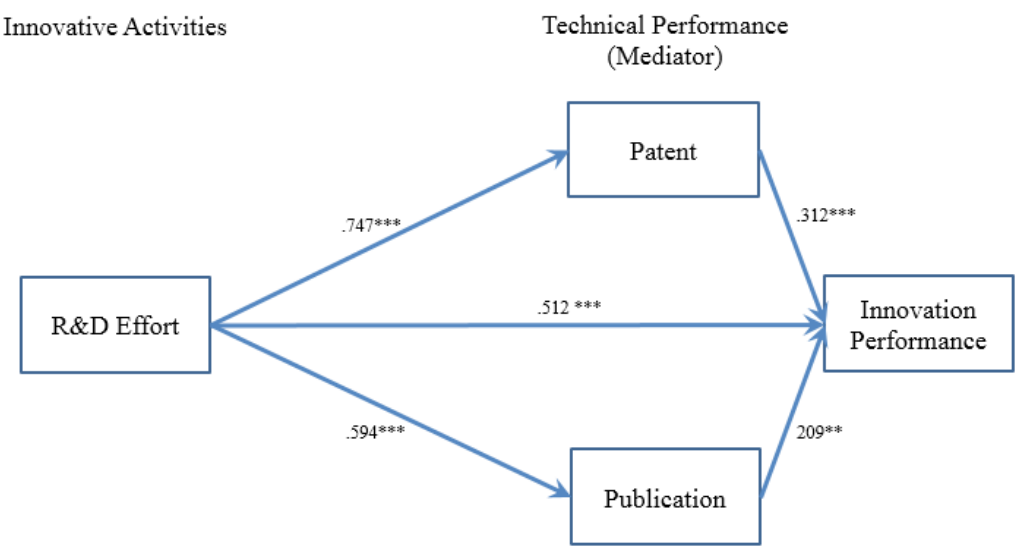


a. Alternative Model 1 b. Alternative Model 2

<Figure 2> Alternative models

it is found that at the .05 level of significance, χ^2 value for 1 degree of freedom is 3.84. Based on this Chi square tests of the models, Alternative Model 2 is selected as the further research model, because the difference of χ^2 of the two alternative models, i.e. 37.592-12.913 = 24.679, is much larger than 3.84. From the Chi square tests, patent and publication account for partial mediation effects rather than full or complete mediation.

The next step to compare alternative models is to examine path coefficients of the two models. As the coefficient of added path in Alternative Model 2 is statistically significant and other path coefficients of Alternative Model 2 are more statistically significant than those of Alternative Model 1, Alternative Model 2 is selected as the basic research model for further analysis. The path coefficients of Alternative Model 2 are depicted in <Figure 3>.



<Figure 3> Path coefficients of basic research model

4.5 Moderating Effects of R&D Collaboration

Parsimony serves as a criterion for choosing between non-nested alternative models (Schermelleh-Engel 2003). Several fit indices, including the Parsimony Goodness-of-Fit Index (PGFI), the Parsimony Normed Fit Index (PNFI), the Parsimony Comparative Fit Index (PCFI), the Akaike Information Criterion (AIC), the Consistent AIC (CAIC), and the Expected Cross-Validation Index (ECVI) are used for assessing the fit of structural equation models. Parsimony fit indices for four research models are shown in <Table 4>.

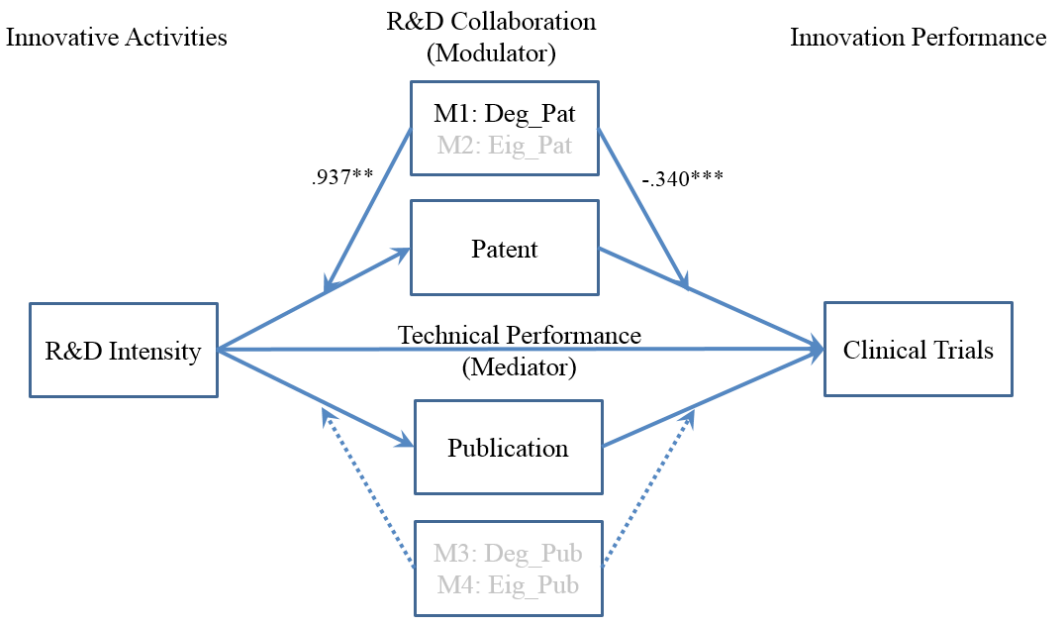
As shown in <Figure 2>, R&D collaboration variables are not included in the basic research model. Therefore, research models with network effects are non-nested alternative models for the basic research model. In order for the model to be adopted, three criteria must be met: First, parsimony fit indices of research models with R&D collaboration variables should be greater than those of basic model. Second, statistical significance of standardized regression should less than .05. And, third, $\Delta\chi^2$ of a model should be greater than χ^2.05(D.F.), i.e. 7.81473 in these models.

The path coefficients and their significances of research models with network effects are depicted in <Figure 4>. The standardized regression weights of two research models are statistically significant: one shows positive moderating effect on patent application, and the other shows negative moderating effect on clinical trials.

<Table 4> Parsimony Fit Indices for research models

Variables	Basic	H3a-M1		H3a-M2		H3b-M1		H3b-M2		H4a-M3		H4a-4		H4b-M3		H4b-M4	
		Free	RES	Free	RES	Free	RES	Free	RES	Free	RES	Free	RES	Free	RES	Free	RES
Parsimony Fit Indices																	
PGFI	.070	.094	.120	.094	.122	.090	.109	.091	.108	.093	.114	.099	.120	.082	.109	.086	.115
PNFI	.104	.126	.161	.126	.164	.125	.149	.126	.150	.128	.158	.134	.164	.103	.141	.117	.157
PCFI	.104	.126	.162	.126	.165	.125	.149	.127	.151	.128	.159	.135	.165	.101	.140	.117	.158
AIC	30.913	81.100	104.361	80.811	97.283	82.624	118.398	80.016	121.325	84.702	120.207	67.864	101.157	142.617	159.081	100.049	112.155
Standardized Regression																	
Std.Est.	-	.274	.937	.206	.847	-.188	-.340	-.171	-.208	.848	-.167	656	.137	.338	-.566	-.025	-.638
P	-	.006	.005	.048	.043	.005	***	.012	.112	***	.541	***	.772	***	***	.744	.005
Model Fit																	
χ^2	12.913	31.100	42.361	30.811	35.283	32.624	56.398	30.016	59.325	34.702	58.207	17.864	39.157	92.617	97.081	50.049	50.155
D.F.	1	3	5	3	5	3	5	3	5	3	5	3	5	3	5	3	5
$\Delta\chi^2$			11.261		4.472		23.774		29.309		23.505		21.293		4.464		0.106

χ^2.05(2) = 7.81473



<Figure 4> Path coefficients of research models with network effects

The results of hypotheses testing are shown in <Table 5>.

<Table 5> Summary of hypotheses testing

Hypotheses	Adoption
1a. R&D intensity has a positive effect on innovation performance.	Yes
1b. R&D intensity has a positive effect on patent filing.	Yes
1c. R&D intensity has a positive effect on scientific publication.	Yes
2a. Patent filing positively affects innovation performance.	Yes
2b. Scientific publication positively affects innovation performance.	Yes
3a-M1. A firm's R&D collaboration (Deg_Pat) in co-assigned patents network positively moderates the effect of R&D intensity on patent filing.	Yes
3a-M2. A firm's R&D collaboration (Eig_Pat) in co-assigned patents network positively moderates the effect of R&D intensity on patent filing.	No
3b-M1. A firm's R&D collaboration (Deg_Pat) in co-assigned patents network positively moderates the effect of patent filing on clinical trials.	Yes
3b-M2. A firm's R&D collaboration (Eig_Pat) in co-assigned patents network positively moderates the effect of patent filing on clinical trials.	No
4a-M3. A firm's R&D collaboration (Deg_Pub) in co-affiliated publication network positively moderates the effect of R&D intensity on scientific publication.	No
4a-M4. A firm's R&D collaboration (Eig_Pub) in co-affiliated publication network positively moderates the effect of R&D intensity on scientific publication.	No
4b-M3. A firm's R&D collaboration (Deg_Pub) in co-affiliated publication network positively moderates the effect of scientific publication on clinical trials.	No
4b-M4. A firm's R&D collaboration (Eig_Pub) in co-affiliated publication network positively moderates the effect of scientific publication on clinical trials.	No

Hypotheses 1a, 1b, 1c, 2a, and 2b are tested in the basic research model. R&D intensity is an independent variable in the basic research model and has positive effects on the innovation performance, which is measured by the number of clinical trials of Korean pharmaceutical companies. With regards to patent filing and scientific publications, R&D intensity has a positive effect on the number of patents and publications. Patent and publication are partial mediators in this research model. R&D intensity has both direct and indirect effects on innovation performance of a firm. Patent and publication have respectively a positive effect on innovation performance.

Hypotheses 3a, 3b, 4a, and 4b are tested using the research models with R&D collaboration variables. Degree and Eigenvector centrality of co-assigned patent network are the R&D collaboration variables for research model 1 and 2 respectively. Degree centrality of co-patent network has a positive moderating effect on patent filing and a negative moderating effect on clinical trials. The moderating effects of Eigenvector centrality are not statistically significant. In the same manner, degree and Eigenvector centrality of co-affiliated publication network are the R&D collaboration variables for research model 3 and 4 respectively. The moderating effects of degree and Eigenvector centrality of co-affiliated publication network are not statistically significant.

The moderating effects of R&D collaboration variables of the patent network and the publication network are different from each other. These differences are believed to be due to the fundamental nature of patent and publication networks. In addition, as shown in <Table 2>, the total number of publications was only half of the number of patents during the study period. In the same period, only 3 firms had zero patents, while 30 firms had zero publications. This low incidence of publication may contribute to the statistical insignificance of R&D collaboration variable of the publication network.

Eigenvector centrality is higher as the contacts of an actor have more connections, whereas degree centrality is an indicator of the number of partners directly connected to an actor. Degree centrality increases with the number of directly connected actors, whereas Eigenvector centrality shows a higher value when the actor's partner has more connections. In order for Eigenvector centrality to be positively correlated with drug development, pharmaceutical companies should conduct joint research with partners who actively collaborate with other pharmaceutical companies. The table 2 of this study for the Korean pharmaceutical industry shows that mean values of degree and Eigenvector centrality are very low, which means that there is a lack of research institutes, i.e. Research Hub, that actively promote joint research with pharmaceutical companies to facilitate drug development.

In the patent network, the moderating effects of the R&D collaboration variable have a positive relationship with the increase in the number of patents, but a negative relationship with the increase in the number of new drug development. This may imply that patents applied as a result of

R & D collaboration are either more focused on basic scientific breakthroughs or not yet directly relevant to the development of new drugs.

5. Discussions and Conclusions

One of the most important features of this study is that the patent and the paper are considered simultaneously as mediating variables that directly affect the innovation performance in terms of clinical trials of the Korean pharmaceutical industry. Patents and publications have their own unique characteristics and occupy different positions in innovation research. Since patents are closely linked to commercialization and appropriation, a more formal and stronger relationship with partners is required from the perspective of the pharmaceutical company. Before starting a joint research which may result in patent filing, it is common to sign a contract between a partner and a pharmaceutical company that clearly defines the right-sharing ratio for the patent filing between each other. If a pharmaceutical company pursues the monopoly of patent rights in a strategic way, it may choose to pay financial compensation, such as research grants and subscription of partner's stocks, to the partner instead of co-assigned patent filing with the partner.

In view of innovation performance, patent data are very tricky because it contains a wide range of individual patents with a variety of characteristics. For example, most patents are simple improved inventions, while a few are innovative, platform technological breakthroughs. In addition, the value of registered patents would be different from that of applied but failed patents. Some researchers have tried to find positive relations between the number of patents and innovation performance, but could not find statistically significant positive results (for example, Sohn et al. 2010).

Collaboration with university scientists and publishing quality articles in prominent journals is related to innovation performance of companies in the pharmaceutical industry (Jong and Slavova 2014). It is common for a variety of papers to be published about the development and clinical trials of an innovative drug before it is launched on the market. Because universities and hospitals need to participate as partners in the development and clinical trials of new drugs, companies that are active in drug development activities have more collaboration with universities and hospitals, and joint research will become more common in publishing the results of new drug development.

The publication activity of the Korean pharmaceutical industry on the development of new drugs is very weak compared to the countries where R&D for drug development is active and fruitful. The Korean pharmaceutical companies are publishing fewer than two papers per year on average during the period of this study. Considering the maximum number of publication of a company is 160 as shown in <Table 2>, most Korean pharmaceutical companies are publishing less than one paper per year. The low publication activity is linked to weak drug development

performance of Korean pharmaceutical companies. Therefore, for the advancement of the Korean pharmaceutical industry, it is necessary to establish an incentive system for promoting the co-affiliated publication of pharmaceutical companies.

The most significant feature and contribution of this study was shown to be the mediating effect of two types of centrality variables derived from social network analysis. This study has originality in presenting a new research model combining mediating effects of patent and publication and moderating effects of R&D collaboration. In addition, this study paved a way to investigate innovation performance in Korean pharmaceutical industry using patent and publication data and has implications for future research extending the scope by considering limitations: a short history of innovative activity and a meagre stock of innovation performance of new drug development of Korean pharmaceutical companies, the difficulty of access to patent licensing information which may complement firm's weak pipeline of in-house research, incomplete Scopus database which has insufficient information on the Korean journals where the Korean pharmaceutical companies may have published papers, and small set of sample companies which met research criteria. In addition, although the dependent variable in this study is the number of clinical trials, this research models may be extended and modified to adapt economic indicators as dependent variable (Park and Choo 2010).

This study also has significance in the aspect of empirical research on Korean pharmaceutical companies. Mediating effects of R&D collaboration in this study has small explanatory power, due to the relatively short research period, comparing to global pharmaceutical companies, and weak international competitiveness of Korean pharmaceutical companies. It is expected that the academic significance and contribution of this research model will increase as Korean pharmaceutical companies become more competitive, and new drug development activities become more active in the future and more empirical data can be obtained.

Since the patent data of this study are limited to Korean patents, it is expected that it will be able to gain expanded explanatory power by including the patents of US, Europe, PCT, and so on. Also, considering the easiness of data acquisition, the publication data of this research have fully depended on the foreign databases (SCOPUS, PUBMED), thus it was not possible to utilize the social network analysis through the papers published in the Korean language. It is necessary to acquire a suitable Korean publication database and expand the research. This study was conducted only for Korean pharmaceutical companies. However, if comparative studies including overseas pharmaceutical companies are conducted, it would be possible to improve generalizability of the research results.

References

1. Ahuja, G. 2000. "Collaboration networks, structural holes, and innovation: A longitudinal study," *Administrative Science Quarterly* (45:3), pp. 425-455.
2. Austin, D. H. 1993. "An event-study approach to measuring innovative output: The case of biotechnology," *The American Economic Review* (83:2), pp. 253-258.
3. Baregheh, A., Rowley, J. and Sambrook, S. 2009. "Towards a multidisciplinary definition of innovation," *Management Decision* (47), pp. 1323-1339.
4. Barney, J. 1991. "Firm resources and sustained competitive advantage," *Journal of management* (17:1), pp. 99-120.
5. Belleflamme, P. and Peitz, M. 2015. *Industrial organization: markets and strategies,* New York: Cambridge University Press.
6. Bommer, M. and Jalajas, D. S. 2004. "Innovation sources of large and small technology-based firms," *IEEE Transactions on Engineering Management* (51:1), pp. 13-18.
7. Bonacich, P. 1972. "Factoring and weighting approaches to status scores and clique identification," *Journal of Mathematical Sociology* (2), pp. 113-120.
8. Bonacich, P. 2007. "Some unique properties of eigenvector centrality," *Social Networks* (29), pp. 555-564.
9. Borgatti, S. P. and Cross, R. 2003. "A relational view of information seeking and learning in social networks," *Management Science* (49:4), pp. 432-445.
10. Breschi, S. and Catalini, C. 2010. "Tracing the links between science and technology: An exploratory analysis of scientists' and inventors' networks," *Research Policy* (39:1), pp. 14-26.
11. Burt, R. S. 1995. *Structural Holes: The Social Structure of Competition*. Cambridge, Massachusetts: Harvard University Press.
12. Cantner, U., Meder, A. and Ter Wal, A. L. 2010. "Innovator networks and regional knowledge base," *Technovation* (30:9), pp. 496-507.
13. Chan, K. C., Chen, C. R. and Cheng, L. T. 2005. "Ranking research productivity in accounting for Asia-Pacific universities," *Review of Quantitative Finance and Accounting* (24:1), pp. 47-64.
14. Chesbrough, H. 2006. *Open innovation: The new imperative for creating and profiting from technology*, Boston, Massachusetts: Harvard Business School Publishing.
15. Cockburn, I. M. and Henderson, R. M. 1998. "Absorptive capacity, coauthoring behavior, and the organization of research in drug discovery," *The Journal of Industrial Economics* (46:2), pp. 157-182.
16. Cohen, W. M. and Klepper, S. 1996. "Firm Size and the Nature of Innovation within Industries: The Case of Process and Product R&D," *Review of Economics and Statistics* (78), pp. 232-243.

17. Cohen, W. M. and Levin, R. C. 1989. "Empirical studies of innovation and market structure," in *Handbook of Industrial Organization* (Volume 2), R. Schmalensee and R. Willig (eds.), North Holland: Elsevier, pp. 1059-1107.
18. Cohen, W. M., Levin, R. C. and Mowery, D. C. 1987. *Firm size and R&D intensity: A re-examination*, Cambridge, Mass., USA: National Bureau of Economic Research.
19. Comanor, W. S. 1964. "Research and competitive product differentiation in the pharmaceutical industry in the United States" *Economica* (31:124), pp. 372-384.
20. Comanor, W. S. and Scherer, F. M. 1969. "Patent statistics as a measure of technical change," *The Journal of Political Economy* (77:3), pp. 392–398.
21. Cooper, J. R. 1998. "A multidimensional approach to the adoption of innovation," *Management decision* (36:8), pp. 493-502.
22. Crane, D. 1969. "Social structure in a group of scientists: A test of the" invisible college" hypothesis," *American Sociological Review* (34:3), pp. 335-352.
23. Cross, R. and Cummings, J. N. 2004. "Tie and network correlates of individual performance in knowledge-intensive work," *Academy of Management Journal* (47:6), pp. 928-937.
24. Drucker, P. 2002. "The discipline of innovation," *Harvard Business Review* (Aug), pp. 5-10.
25. Dyer, J. H. and Singh, H. 1998. "The relational view: Cooperative strategy and sources of interorganizational competitive advantage," *Academy of management review* (23:4), pp. 660-679.
26. Echols, A. and Tsai, W. 2005. "Niche and Performance: The Moderating Role of Network Embeddedness," *Strategic management journal* (26:3), pp. 219-238.
27. Fleming, L., King, C. and Juda, A. I. 2007. "Small worlds and regional innovation," *Organization Science* (18:6), pp. 938-954.
28. Freeman, L. C. 1979. "Centrality in social networks conceptual clarification," *Social networks* (1:3), pp. 215-239.
29. Galambos, L. and Sturchio, J. L. 1998. "Pharmaceutical firms and the transition to biotechnology: A study in strategic innovation," *Business History Review* (72:2), pp. 250-278.
30. Garfield, E. and Welljams-Dorof, A. 1992. "Citation data: Their use as quantitative indicators for science and technology evaluation and policy-making," *Science and Public Policy* (19:5), pp. 321-327.
31. Gay, B. and Dousset, B. 2005. "Innovation and network structural dynamics: Study of the alliance network of a major sector of the biotechnology industry," *Research Policy* (34:10), pp. 1457-1475.
32. Godin, B. 1996. "Research and the practice of publication in industries," *Research policy* (25:4), pp. 587-606.
33. Goetze, C. 2010. "An empirical enquiry into co-patent networks and their stars: The case of

cardiac pacemaker technology," *Technovation* (30), pp. 436-446.

34. Gorraiz, J., Reimann, R. and Gumpenberger, C. 2012. "Key factors and considerations in the assessment of international collaboration: a case study for Austria and six countries," *Scientometrics* (91:2), pp. 417-433.
35. Grabowski, H. 2002. "Patents, innovation and access to new pharmaceuticals," *Journal of International Economic Law* (5:4), pp. 849-860.
36. Granovetter, M. S. 1973. "The strength of weak ties," *American journal of sociology* (78:6), pp. 1360-1380.
37. Grant, R. M. 1996. "Toward a knowledge-based theory of the firm," *Strategic Management Journal* (17), pp. 109-122.
38. Griliches, Z. 1994. "Productivity, R&D, and the data constraint," *The American Economic Review* (84:1), pp. 1-23.
39. Hall, B. H., Griliches, Z. and Hausman, J. A. 1984. *Patents and R&D: Is There A Lag?*, Cambridge, Mass., USA.: National Bureau of Economic Research.
40. Haynie, D. L. 2001. "Delinquent peers revisited: Does network structure matter?" *American journal of sociology* (106:4), pp. 1013-1057.
41. Henderson, R. and Cockburn, I. 1994. "Measuring competence?: Exploring firm effects in pharmaceutical research," *Strategic management journal* (15:S1), pp. 63-84.
42. Hooper, D., Coughlan, J. and Mullen, M. 2008. "Structural equation modelling: Guidelines for determining model fit," *Electronic Journal of Business Research Methods* (6:1), pp. 53-60.
43. Hughes, K. 1988. "The interpretation and measurement of R&D intensity—A note," *Research Policy* (17:5), pp. 301-307.
44. Jong, S. and Slavova, K. 2014. "When publications lead to products: The open science conundrum in new product development," *Research Policy* (43), pp. 645-654.
45. Juliano, R. 2013. "Pharmaceutical innovation and public policy: The case for a new strategy for drug discovery and development," *Science and Public Policy* (40:3), pp. 393-405.
46. Kim, C. and Park, J. H. 2010. "The global research-and-development network and its effect on innovation," *Journal of International Marketing* (18:4), pp. 43-57.
47. Kim, Y. 2002. "Executive social capital and its impacts on job promotion," *Academy of Management Proceedings:* 2002 (Meeting Abstract Supplement) J1-J6.
48. Ko, Y. H. and Lee, M. H. 2013. "A Study on Properties of Patents in the Applicants and Possibility of Economical Usage-Focused on Pharmaceutical Chemistry Industry Sector," *Knowledge Management Research* (14:1), pp. 39~54.
49. Lee, M. and Choi, M. 2015. "Analysis on Time-Lag Effect of Research and Development Investment in the Pharmaceutical Industry in Korea," *Osong Public Health and Research*

Perspectives (6), pp. 241-248.

50. Levin, R. C., Klevorick, A. K., Nelson, R. R., Winter, S. G., Gilbert, R. and Griliches, Z. 1987. "Appropriating the returns from industrial research and development," *Brookings papers on economic activity* (1987:3), pp. 783-831.
51. Mazzola, E., Perrone, G. and Kamuriwo, D. S. 2015. "Network embeddedness and new product development in the biopharmaceutical industry: The moderating role of open innovation flow," *International Journal of Production Economics* (160), pp. 106-119.
52. McKelvey, M. and Rake, B. 2012. "Research Network Position and Innovative Performance: Evidence from the Pharmaceutical Industry," *Jena Economic Research Papers* (2012-021), pp. 1-34.
53. Melin, G. and Persson, O. 1996. "Studying research collaboration using co-authorships," *Scientometrics* (36:3), pp. 363-377.
54. Merton, R. K. 1968. "The Matthew effect in science," *Science* (159:3810), pp. 56-63.
55. Merton, R. K. 1988. "The Matthew effect in science, II: Cumulative advantage and the symbolism of intellectual property," *Isis* (79:4), pp. 606-623.
56. Narin, F., Noma, E. and Perry, R. 1987. "Patents as indicators of corporate technological strength," *Research policy* (16:2-4), pp. 143-155.
57. Newman, M. E. 2004. "Coauthorship networks and patterns of scientific collaboration," *Proceedings of the National Academy of Sciences of the United States of America* (101:Suppl 1), pp. 5200-5205.
58. Newman, M. E. 2001. "The structure of scientific collaboration networks," *Proceedings of the National Academy of Sciences* (98:2), pp. 404-409.
59. Nunes, P. M., Serrasqueiro, Z. and Leitao, J. 2012. "Is there a linear relationship between R&D intensity and growth? Empirical evidence of non-high-tech vs. high-tech SMEs," *Research policy* (41:1), pp. 36-53.
60. OECD. 2005. *The measurement of scientific and technological activities. Proposed Guidelines for Collecting and Interpreting Technological Innovation Data*, European Commission and Eurostat.
61. Oehme, M. and Bort, S. 2015. "SME internationalization modes in the German biotechnology industry: The influence of imitation, network position, and international experience," *Journal of International Business Studies* (46:6), pp. 629-655.
62. Owen-Smith, J., Riccaboni, M., Pammolli, F. and Powell, W. W. 2002. "A Comparison of U. S. and European University-Industry Relations in the Life Sciences," *Management Science* (48:1), pp. 24-43.
63. Pakes, A. and Griliches, Z. 1980. "Patents and R&D at the firm level: A first report," *Economics Letters* (5:4), pp. 377-381.
64. Pakes, A., Simpson, M., Judd, K. and Mansfield, E. 1989. "Patent renewal data. Brookings papers on economic activity," *Microeconomics*, pp.

331-410.

65. Park, K. H. and Choo, K. 2010. "A Study on the Determinants of the Economic Value of Patents Using Renewal Data," *Knowledge Management Research* (11:1), pp. 65~80.
66. Pavitt, K. 1991. "What makes basic research economically useful?" *Research policy* (20:2), pp. 109-119.
67. Penrose, E. T. 1995. *The Theory of the Growth of the Firm*, New York: Oxford University Press.
68. Pisano, G. P. 2006. *Science business: The promise, the reality, and the future of biotech*, Boston, Massachusetts: Harvard Business Press.
69. Porter, M. E. 1998. *Competitive advantage: Creating and sustaining superior performance*, Free press.
70. Powell, W. W. 1996. "Inter-organizational collaboration in the biotechnology industry," *Journal of Institutional and Theoretical Economics (JITE)/Zeitschrift fur die gesamte Staatswissenschaft (151:1)*, pp. 197-215.
71. Powell, W. W., Koput, K. W. and Smith-Doerr, L. 1996. "Interorganizational collaboration and the locus of innovation: Networks of learning in biotechnology," *Administrative science quarterly* (41:1), pp. 116-145.
72. Powell, W. W., Koput, K. W., Smith-Doerr, L. and Owen-Smith, J. 1999. "Network position and firm performance: Organizational returns to collaboration in the biotechnology industry," *Research in the Sociology of Organizations* (16:1), pp. 129-159.
73. Rampersad, G., Quester, P. and Troshani, I. 2010. "Managing innovation networks: Exploratory evidence from ICT, biotechnology and nanotechnology networks," *Industrial Marketing Management* (39:5), pp. 793-805.
74. Rogers, M. 1998. *The Definition and Measurement of Innovation* (No. 10/98), Melbourne Institute of Applied Economic and Social Research.
75. Rosenberg, N. 1990. "Why do firms do basic research (with their own money)?" *Research policy* (19:2), pp. 165-174.
76. Salter, A. and Gann, D. 2003. "Sources of ideas for innovation in engineering design," *Research policy* (32:8), pp. 1309-1324.
77. Scherer, F. M. 1965. "Firm size, market structure, opportunity, and the output of patented inventions," *The American Economic Review* (55:5), pp. 1097-1125.
78. Scherer, F. M. 2010. "Pharmaceutical innovation," in *Handbook of the Economics of Innovation* (1), B. H. Hall and N. Rosenberg (eds.), North Holland: Elsevier, pp. 539-574.
79. Schermelleh-Engel, K. 2003. "Evaluating the fit of structural equation models: Tests of significance and descriptive goodness-of-fit measures," *Methods of Psychological Research Online* (8:2), pp. 23-74.
80. Schmookler, J. and Brownlee, O. 1962. "Determinants of inventive activity," *The American Economic Review* (52:2), pp. 165-

176.

81. Schmookler, J. 1966. *Invention and economic growth, Cambridge*, Massachusetts.: Harvard University Press.
82. Schumacker, R. and Lomax, R. 2010. *A beginner's guide to structural equation modeling (3rd ed.)*, Routledge.
83. Schumpeter, J. 1942. *Capitalism, socialism and democracy*. New York, NY: HarperCollins.
84. Schumpeter, J. A. 1934 (2012). *The Theory of Economic Development: An Inquiry Into Profits, Capital, Credit, Interest, and the Business Cycle*, translated from the German by Redvers Opie, New Brunswick (U.S.A) and London (U.K.): Transaction Publishers.
85. Scott, J. 2010. *Social network analysis*, London, U.K: SAGE Publications Ltd.
86. Singh, J. 2005. "Collaborative networks as determinants of knowledge diffusion patterns," *Management Science* (51:5), pp. 756-770.
87. Soh, P. H. and Roberts, E. B. 2003. "Networks of innovators: a longitudinal perspective," *Research policy* (32:9), pp. 1569-1588.
88. Sohn, D., Hur, W. and Kim, H. 2010. "Effects of R&D and patents on the financial performance of Korean venture firms," *Asian Journal of Technology Innovation* (18:2), pp. 169-185.
89. Sternitzke, C. 2010. "Knowledge sources, patent protection, and commercialization of pharmaceutical innovations," *Research policy* (39:6), pp. 810-821.
90. Stuart, T. E., Ozdemir, S. Z. and Ding, W. W. 2007. "Vertical alliance networks: The case of university-biotechnology-pharmaceutical alliance chains," *Research Policy* (36:4), pp. 477-498.
91. Sykes, R. 1998. "Being a modern pharmaceutical company involves making information available on clinical trial programmes," *British Medical Journal* (317:7167), pp. 1172-1180.
92. Teece, D. J. 1986. "Profiting from technological innovation: Implications for integration, collaboration, licensing and public policy," *Research Policy* (15:6), pp. 285-305.
93. Trajtenberg, M. 1990. "A penny for your quotes: patent citations and the value of innovations," *The RAND Journal of Economics* (21:1), pp. 172-187.
94. Tsai, W. 2001. "Knowledge transfer in intraorganizational networks: Effects of network position and absorptive capacity on business unit innovation and performance," *Academy of Management Journal* (44:5), pp. 996-1004.
95. Uddin, S., Hossain, L. and Rasmussen, K. 2013. "Network Effects on Scientific Collaborations," *PLoS ONE* (8:2), e57546.
96. Van Looy, B., Callaert, J. and Debackere, K. 2006. "Publication and patent behavior of academic researchers: Conflicting, reinforcing or merely co-existing?" *Research policy* (35:4), pp. 596-608.
97. Uzzi, B. 1996. "The sources and consequences of embeddedness for the economic performance of organizations: The network

effect," *American Sociological Review* (61:4), pp. 674-698.

98. Wager, E., Field, E. A. and Grossman, L. 2003. "Good publication practice for pharmaceutical companies," *Current Medical Research and Opinion* (19:3), pp. 149-154.

99. Walker, G., Kogut, B. and Shan, W. 1997. "Social capital, structural holes and the formation of an industry network," *Organization Science* (8:2), pp. 109-125.

100. Wang, J. and Guan, J. 2005. "The analysis and evaluation of knowledge efficiency in research groups," *Journal of the American Society for Information Science and Technology* (56:11), pp. 1217-1226.

101. Wang, N. and Hagedoorn, J. 2014. "The lag structure of the relationship between patenting and internal R&D revisited," *Research Policy* (43:8), pp. 1275-1285.

102. Wasserman, S. and Faust, K. 1994 (2009). *Social network analysis: Methods and applications*, New York, NY: Cambridge university press.

103. Williamson, O. E. 1979. "Transaction-cost economics: the governance of contractual relations," *Journal of law and economics* (22:2), pp. 233-261.

104. Williamson, O. E. 1989. "Transaction cost economics," *Handbook of industrial organization* (1), pp. 135-182.

105. Wright, S. 1934. "The method of path coefficients," *The Annals of Mathematical Statistics* (5:3), pp. 161-215.

106. Zaheer, A. and Bell, G. G. 2005. "Benefiting from network position: firm capabilities, structural holes, and performance," *Strategic Management Journal* (26:9), pp. 809-825.

107. Zeng, S. X., Xie, X. M., and Tam, C. M. 2010. "Relationship between cooperation networks and innovation performance of SMEs," *Technovation* (30:3), pp. 181-194.

저 자 소 개

김 대 중 (Dae-Joong Kim)

서울대학교 분자생물학과 학사 및 의학과 석사학위를 취득하였고, 한국기술교육대학교 기술경영학 박사학위를 취득하였다. 주요관심분야는 바이오/제약 산업분석, 기술/기업 가치평가, 기술경영 등이다.

엄 기 용 (Kiyong Om)

현재 한국기술교육대학교 산업경영학부 교수로 재직 중이다. 한국과학기술원에서 경영공학 박사 학위를 취득하였고, 한국전자통신연구원 정보통신경영연구소 선임연구원과 영국 Sussex대학교 과학기술정책연구소 방문연구원을 역임하였다. 주요 관심분야는 기술혁신경영, 지식경영, 인적자원개발 등이다. 지금까지 Research Policy, International Journal of Technology Management, Scientometrics 등 주요 학술지에 논문을 발표하였다.