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A Study of a Patent Network with Respect to Structural Density and Diversity

- Sector, Firm and Country Level Exploration-

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Abstract

A Study of a Patent Network with Respect to Structural Density and Diversity

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Innovation academics have been interested in the systematic perspective on innovation, which emphasizes the interaction between agents such as firms, universities, and governments. In recent years, to improve the understanding of the structural properties of knowledge through this interaction, and its effect on innovation performance, many studies have applied network analysis to the documents that codify knowledge, such as patents and papers. Many comparison studies using network analysis have focused on the effect of network position among comparable agents or its organizational structure. However, considering the resources that agents have developed and possessed such as technology and human resources, it is of primary importance for making strategies or policies for technology management. For this reason, many studies examine

diversification, specialization, and the depth and breadth of the technology and the products that agents possess.

However, the interactions and effects of the diversity and density of technology during its combination and convergence processes have not been examined thoroughly, despite their importance recently skyrocketing. In the digital economy, it is not just important for agents to construct a technology portfolio, but also to have the ability to converge existing technologies into their own technology pool. Therefore, this dissertation discusses the structural characteristics of the technology pool that an agent owns and technology network that reflects the technology convergence tendency for inventions. Moreover, the effect of the characteristics of the technology pool and network of innovation will be examined.

Three kinds of patent co-classification networks are constructed at three levels (technology sector, firm, and country) using the International Patent Classification (IPC). To investigate the characteristics of technology convergence that has occurred in other industries, Korea's patent application data is used. To examine the relationship between technology structure and innovation performance at a firm and country level, patent data, innovation surveys, and economic data were merged. Examinations are conducted by focusing on the effect of the structural density and diversity of the patent network and pool.

The comparison of the characteristics of technology convergence is based on the ICT that has led to Korea's growth. The result shows that ICT contributed to Korea's co-

evolution, which is more likely to pivot on related technology convergence than unrelated technology convergence.

The Relationship between the characteristics of the technology pool and network and innovation shows that diversity in the technology capability pool and the technology usage experience are positively related to the R&D expenditure and innovation output for both firm and country level studies, except for the effect on innovation output in the firm-level study. In contrast to technology pool indices, the technology network indices show different effects for firms and countries. The network density of a firm has a positive relationship with the R&D intensity and innovation output. However, a country's network density does not significantly affect either variable. The network diversity shows a contrary result for innovation output. Firms' network diversity has a negative relationship with innovation output, while a country's network diversity has a positive relationship. Such findings and approaches based on the technology network shed light on policies and strategies for promoting innovation and the performance for different organizations.

Keywords: Knowledge Network, National Innovation System, Patent Analysis, Structural Equation Model, Nonparametric Estimation

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Chapter 1. Introduction

1.1 Motivation

Innovation studies have been interested in developing a systematic perspective for innovation, which emphasizes interaction among agents such as firms, universities, and governments. From this perspective, innovation is conducted by agents who collaborate and interact with one another to learn, reuse, and recombine knowledge (Freeman, 1987; Lundvall, 1992; Nelson, 1993; Edquist, 1996).

The knowledge created during this process is now used for the economic activity of agents, i.e. giving them financial benefits, then that benefit is invested back into their innovation. As a result, knowledge is accumulated, and the amount of knowledge increases. The overall knowledge an agent requires becomes more complex; to be specific, an agent must understand the shape of the overall knowledge they possess for knowledge management, because their accumulated knowledge has a strong inference on the creation of new knowledge (Malerba & Orsenigo, 1996; Joo & Kim, 2009).

Previous studies have applied network analysis to documents to codify the knowledge that agents create such as patent and papers, for understanding the structural properties of knowledge systems and their effects on innovation performance. These studies have implemented their research with the definition of knowledge network in two levels.

One is defining the network of agents such as inventors, authors, firms, and countries

that are linked with each other, and examining whether they have any interaction through the media to facilitate knowledge sharing, such as academic collaboration, technological alliance, etc. (Giuliani, 2013; He & Hosein Fallah, 2009; Hidalgo & Hausmann, 2009; Sternitzke et al., 2008; Wagner & Leydesdorff, 2005). The other is the network of documents that are linked with each other when they share keywords, and when one refers to another (Choi & Hwang, 2013; Curran & Leker, 2011; Lee et al., 2008). According to their analyses with a variety of networks, previous studies found the characteristics of innovative societies such as the node position in a network that improves agent performance and the topology of society that makes it sustainable.

Previous comparison studies using network analysis have focused on the effect of network position among comparable agents such as firms and countries and their organizational structure (Burt, 2004; Corrocher, Malerba, & Montobbio, 2007; Everard & Henry, 2002; Jin, Park, & Pyon, 2011; Tsai, 2001). However, considering the resources agents have developed and possessed such as technology and human resources, it is of primary importance for making strategies or policies for the technology management. For this reason, there are many research studies about the diversification, specialization, depth, and breadth of technology and products that firms possess (Garcia-Vega, 2006; Fleming, 2002; Özman, 2007; Suzuki and Kodama, 2004). However, interaction and the effect of the diversity and density of technology during combination and convergence processes have not been examined thoroughly, despite its importance recently skyrocketing. In the digital economy, it is not only important to construct a technology portfolio, but also to be

able to incorporate existing technologies into their own technology pool or technology market for the creation of new technology.

Therefore, this dissertation discusses the structural characteristics of the technology pool that a firm owns and the technology network that reflects the technological convergence tendency of invention. Moreover, the effect of the characteristics of the technology pool and network of innovation will be examined by focusing on the structural density and diversity of the patent network.

1.2 The objectives

There are always limitations in technology prediction. However, if the influence of the characteristics of technology themselves can be understood, then technology prediction, promotion strategy, and the relationships that technological shape affects in the creation of new technologies or economic results, then more effective technologies or economic plans can be achieved.

Eventually, if our goal is the achievement of technological innovation and economic growth, it is necessary to reward the achievement of optimal technological structures and to develop our understanding of particular technology compositions and promotions are required to make these kinds of structures.

For this purpose, this dissertation looks over R&D, technology, and economic growth through their interactions and learning in between agents under organization's rule by

reinterpreting the technological perspective. In addition, dissertations connect the gaps between studies by considering the system of innovation and the study of technology's structure and evolution.

By this process, we are able to make a universal comparative study with a technology index of homogeneous results from different agents. The former approach was more about the interactions between agents such as firms, universities, and governments, with dominate rules and infrastructure, but if an actor-based approach and technology-centered approach are applied simultaneously, more feasible policy plans can be made.

1.3 Outline

This study is composed of six chapters. The following chapter is a literature review about network analysis to understand innovation systems and technological characteristics and structure. The overall structure of the thesis is shown in Figure 1.

In chapter 3, this dissertation will identify the technology characteristics and technology structure during combination and convergence processes. To do so, this dissertation has composed an accumulated patent network with all of Korea's annual patent application data from 1970 to 2009. In this patent network, the characteristics of five different technology sectors are divided into two periods to make a comparative study. Chapters 4 and 5 compare the effects of technology network characteristics on innovation and economic results at both a firm and country level. For this, this

dissertation composed an individual patent network of firms and countries, and used diversity and the density-clustering index, which represents the characteristics of the patent network. Figure 1 shows the overall structure of the thesis.

Chapter 6 summarizes the comparison results, and addresses the implications, contributions, and limitations of this thesis.

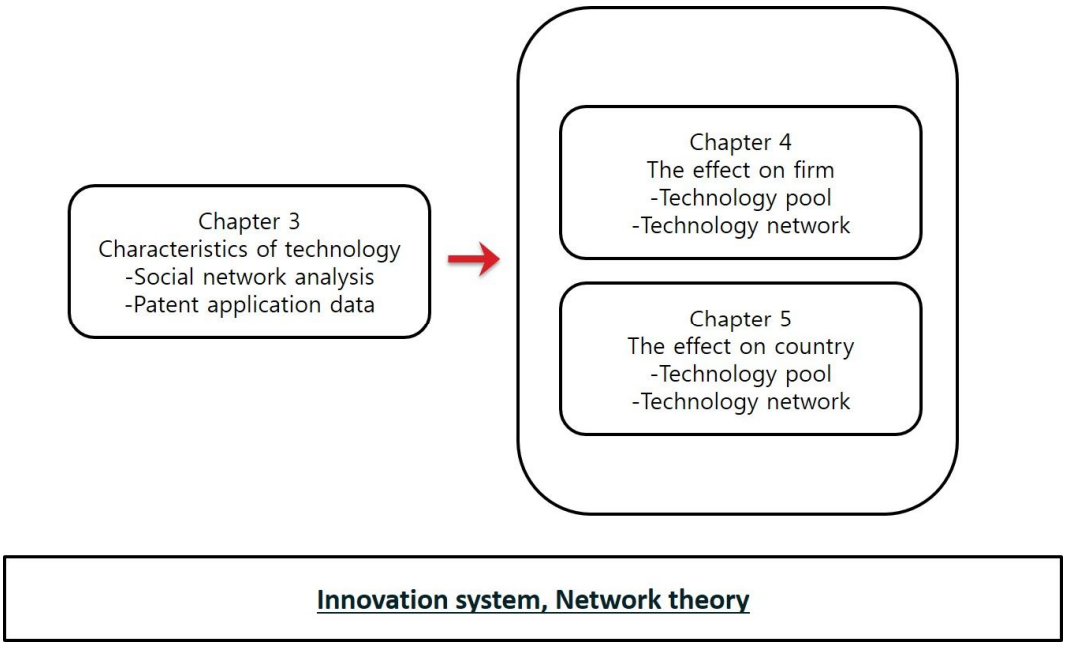


Figure 1. The overall structure of the thesis

Chapter 2. Literature review

This dissertation examines the characteristics of the technology sector in the convergence process, the relationship between the technology structure of firms and countries, and innovation. For this, it is required to consider various existing frameworks and theories. Therefore, this chapter summarizes previous theories, methodologies, and empirical studies to make a new framework by linking existing frameworks. In this dissertation, two research frameworks are used. One is the national innovation system, and the other is network analysis to understand the technology structure that agents possess better. The core concern of the national innovation system is the systematic perspective. To explain the relationship between innovation and economic performance, the various elements that affect innovation process and performance must be considered systemically. Network analysis is useful to investigate the interactions between and within these elements. Among these elements, the knowledge accumulated in agents is one of the most important resources for innovation. Therefore, it is necessary for understanding the nature of knowledge, including technology.

In summary, this chapter describes the nature of knowledge, innovation theories, and the network analysis of knowledge and empirical studies about the relationship between network structure and innovation. This summary will allow us to get clues about the configuration of new frameworks such as a technology network setup.

2.1 Nature of knowledge

Knowledge is an evolving system. In the microscopic perspective, people exchange knowledge, and compromise their perspective, and knowledge is synthesized through their interactions in the environment surrounding people, even if they are scientists well-known for working in laboratories for creating the most objective knowledge in the world (Krohn, Latour, & Woolgar, 1981). In a wider context, knowledge is organized into nations through interactions for finding problems and solutions among people in a variety of ranges from scientists to consumers of goods under the support of institutions such as R&D foundations, commercial law, and traditional culture (Nelson, 2000). In this system, knowledge evolves by responding to current societal issues where they are developing, while also interacting with the organizations creating and demanding the knowledge (Nelson, 1994). Sometimes, knowledge evolution seems revolutionary rather than the result of gradual changes when the theory, methodology, and perspective shift between scientists at the end of efforts to support the current paradigm against abnormalities.

Based on of the theory that knowledge evolves as a system, an abundance of research has investigated the structure of innovation systems (Fagerberg & Verspagen, 2009; Girvan & Newman, 2002; Manning, 2013; Newman, 2001b), systems' evolution patterns (Ávila-Robinson & Miyazaki, 2013; Stolwijk, Ortt, & Hartigh, 2013), and systems' effect on the performance of innovation agents (Everard & Henry, 2002; Hansen, 1999; Krackhardt & Stern, 1988; Tsai, 2001; Walter, Lechner, & Kellermanns, 2007).

However, previous studies on knowledge as an evolving system miss three important points in the perspective of knowledge evolution. First, they focus on the agents of innovation rather than knowledge with the assumption that knowledge flows through agents. If the structure of an innovative society is important because innovation is a social activity, as achieved in (Fagerberg & Verspagen, 2009; Girvan & Newman, 2002; Hosei & Fallah, 2009; Stolwijk, Ortt, & Hartigh, 2013; Wagner & Leydesdorff, 2005), then the knowledge structure organized by society is also worth investigating, because it is the result of social processes. Next, previous studies usually consider the static properties of an evolving system, as they depict a snapshot of innovation networks (Granstrand, Fagerberg, Mowery, & Nelson, 2006; Newman, 2001a; Wagner & Leydesdorff, 2005), and explain the effect of a static network structure and position on innovation (Burt, 2004; Everard & Henry, 2002; Tsai, 2001).

Finally, the previous studies are far from the dynamics of knowledge evolution, even if they consider the changing system of knowledge. Though some previous studies have described the changing pattern of knowledge as achieved in (Barberá-Tomás, Jiménez-Sáez, & Castelló-Molina, 2011; Cantwell & Vertova, 2004; Epicoco, 2013; Lemarchand, 2012), it is hard to say if they are in the evolutionary perspective if they do not consider the rules of evolution such as isolation and inheritance, as outlined in Darwinism (Darwin, 1859).

2.2 Innovation studies in systematic and evolutionary perspective

The neoclassical economist describes economic phenomenon pricing mechanisms based on the market. They assume that the utility and cost functions of agents have homogeneous characteristics. The model is easy to understand because of its simplicity and linearity. However, this model overlooks agent diversity and the social system, which can also affect agents' decisions and interactions. As with the complexity of the social structure, including the market structure increases, the neoclassical model shows the limitations in explaining current economic phenomena such as a two-side market and zero pricing.

To develop alternative frameworks for standard economics, new theoretical frameworks have appeared such as institutional economics, evolutionary economics, and national innovation systems. Institutional economics interpret economic development as the result of co-evolution among technology, heterogeneous agents, and institutions. Institutional economics are focused on the interaction of various institutions, including markets (Lundvall, 2007). They interpret resource allocation as determined by the form of an institution and organization structure. National innovation systems emphasize the systemic perspective, learning process, institutions, and heterogeneous agents.

The systematic perspective is a core concern in national innovation systems, to explain the relationship between innovation and economic performance. It is necessary

for understanding the various elements that affect the innovation process and performance. Innovation systems do not regard reactions among R&D, innovation, and economic growth as linear and sequential. Beside economic factors such as the market concentration, social, institutional, and organization factors are concerned. These features can be found from the abundance of previous empirical studies about national innovations. They reflect the diversity of innovation sources such as customers, national institutions, and universities. Moreover, they apply education systems, human capital, and infrastructure. Table 1 shows a summary of previous empirical innovation studies.

Along with the systematic perspective, the evolutionary perspective also plays an important role as a frame to explain the innovation process. After the work of Joseph Schumpeter, claiming innovation as the driving force of economic development, an abundance of studies on innovation has been conducted. They have investigated the determinants, effects, processes, and patterns of innovation. Evolved technologies elevate economic growth by improving the labor and capital efficiencies of production (Freeman and Soete, 1999). An abundance of studies on innovation has investigated the evolution patterns and processes of innovation systems (Chandler, 1992; Dosi, Marsili, Orsenigo, & Salvatore, 1995; F. Malerba & Orsenigo, 1997; Franco, Malerba & Orsenigo, 1996; Metcalfe, 1994; Ziman, 2000). Some studies have examined the relationship between and effectiveness of technologies using patent analysis (Hanel, 1994; Hu & Jaffe, 2003; Karvonen & Kassi, 2011), and have identified and forecasted core technologies (Choi, Im, Kim, & Hwang, 2012; Watts & Porter, 1997).

Table 1. Previous empirical innovation studies

Data scope	Reference	data	variable
Within county	Crepon et al.(1998)	France 1986-1990	R&D, patent (or share of innovative sales), labor productivity, diverification, demand condition and technological opportunities
	Galia and Legros (2002)	France 1994–1996	innovation, TFP growth, R&D, innovation output, training, quality, profitability
	Loof and Heshmati (2002)	Sweden	Innovation cost. per employee, innovative sales per employee, and value added per employee
	Parisi et al. (2002)	Italy(1992–1994, 1997–1995)	Product and process innovations estimated by logit or conditional logit, product. growth estimated by IV
Across county	Castellacci et al.(2010)	Norway(1998–2000, 2002-2006)	labor productivity, R&D, market competition(HHI), External sources of opportunities, technological opportunities
	Hashi et al.(2013)	Central and Eastern European Countries, Western Europe (2002-2004)	labor productivity , Source of innovation, market orientation, industry, Marketing /Organisational innovation
	Crespi and Zuniga(2011)	Six Latin American Countries(1998-01,2004-08)	R&D, product or process innovation, export, co-operation, Importance of innovation source
	Bogliacinoa and Pianta(2011)	Eight major EU countries(CIS2-4:1994–1996, 1998-2000,2002-2004)	Technological Innovation, R&D, labor productivity distance, Rate of growth of value added, Human capital
	Griffith et al.(2006)	the four European countries France, Germany, Spain and the UK(1998-2000)	R&D, Product and process innovations, Share of sales with new products, Labor productivity, funding, Demand Pull, Sources of information

2.3 Network analysis of knowledge

Network analysis defines the elements and relationships of communities as nodes and links. A node can be individual, group, or organization where links can be friendships, communications, or collaboration. After constructing the network, the interactions between these nodes are analyzed. Each community within a network can be understood as a social group with cutting interest and characteristics (Brandes & Erlebach, 2005; Choi & Hwang, 2013).

Because network analysis can set the kind of agent and interaction rule, it is suitable for describing innovation activity; network analysis can be good alternative methodology for analyzing technology and knowledge, and examining their effect on innovation.

If a network is a set of technology classifications from a patent application pool applied by a certain firm and technology classifications are linked when they co-occur in the same patent, communities are regarded as showing a complementary relationship for inventions (Pavitt, 1984). A network's configuration can be changed by the characteristics of the relationship, as one of a set of directed and non-directed networks. If there is concept of relation directions, such as sending and receiving between nodes, it can direct a network such as a patent citation network. However, if there is no concept like this in a network, it is an undirected network, such as a patent classification co-occurrence network. Another important network variable is whether it is weighted (valued) or unweighted (binary). A weighted network is one in which the ties among nodes have

weights assigned to them. In an unweighted network, the ties between nodes do not count for the relationship (Wasserman & Faust, 1994). The selection of network configurations in the analysis depends on the characteristics of the data and research objectives.

To measure the performance of universities and countries network analysis is considered using academic articles. References and keywords are useful information in academic articles compared to patents, and knowledge and technology of the measure coverage is different. Academic article is useful for analyzing basic science and patent is useful for the technology of firm and certain region including country.

This dissertation has adopted a weighted and undirected patent network using IPC co-occurrence for the same patents as the linkage rule. Therefore, descriptions of networks on the condition of using patent data are in the following subsection.

2.3.1 Types of relation

2.3.1.1 Citation network

Like science citations, patent citations are defined by the count of citations per patent in subsequent patents (Yoon & Park, 2004). The value of citations per patent is positive correlation with quality of paper (Albert, Avery, Narin, & McAllister, 1991). In addition to the evaluation of patents, patent citation information has been widely used, much like science citations, patent citations are defined as the number of citations per patent in subsequent patents (Yoon & Park, 2004).

2.3.1.2 Co-occurrence network

In a patent network, co-occurrence means when two different elements such as technology classifications are assigned to the same patent. If this element is classified like an IPC and the network is defined by this element as a node and co-occurrence as rule of linkage, then this is a co-classification patent network. If the element type is keyword, then it is a keyword co-occurrence network.

In classification co-occurrence, since the same patent may be classified as several technology classes, the relationships between technologies in a patent network can be analyzed, while a citation network can be grouped by patent level (Kim & Kim, 2012).

Besides classification co-occurrence, the co-inventor network is openly examined to identify organizations' interaction mechanisms in innovation study. Moreover, with text mining, keyword co-occurrence analysis can be conducted to find the relationships between various levels and dimensions.

An abundance of studies use co-occurrence networks. Using keyword co-occurrence, Lee & Su (2010) analyzed the publication trend of regional innovation system research. Tseng, Lin, & Lin (2007) proposed text mining techniques for co-word patent analysis, Curran & Leker (2011) examined technological convergence in nutraceuticals, functional foods, electronics, and telecommunications (ICT) using IPC co-classification

2.3.2 Sources of networks

2.3.2.1 Bibliometric information

Many of the patent analyses used bibliographic information in patent documentation such as the inventor, applicant, classification code, filing date, citation information, and country code, because this terminology in patents is common and invariant over the time and between countries. The result of using this information is comparability over time and area.

Technology classification codes such as the International Patent Classification (IPC) are key information with which to group or identify the industry area of a patent. To match a technology code to an industry, classification technology concordance can be used (Johnson, 2002). Many studies use technology classification; (Lee, Kim, Cho, & Park, 2009; Lee, Yoon & Park, 2009) identified the core technologies in the telecommunication area. Franco & Orsenigo (1996) explored patterns of innovation such as Schumpeterian patterns. Breschi, Lissoni, & Malerba (2003) examined the relationship between knowledge relatedness and technological diversification. To measure relatedness, they use IPC and a concordance table.

Innovation research about mobility open uses the patent inventor and applicant information (Almeida & Kogut, 1999; Møen, 2005; Kerr, 2008). Kwon (2012) and Becheikh, Landry, & Amara (2006) used the nationalty of the inventor and appicant to conduct a national comparison

Using bibliographic information can be convenient for researchers; however, raw

patent data entries are sometimes missing or duplicated. Removing and identifying duplicate entries is a complicated and time-consuming task when researchers make country-level comparisons.

2.3.2.2 Keyword information

The information from patent document text is also useful when used in addition to the bibliographic Information. Such keyword-based patent analysis is useful for understanding core technology information in patent documentation (Choi & Hwang, 2013). Through data mining or surveying from industry experts, some keywords for certain research areas such as emerging technologies can be extracted, then that keyword can be applied to the patent database again to extract more keyword vectors for other patents or to gather other kinds of information such as the number of patents that include the keyword (Yoon & Park, 2004).

It is possible to establish a patent network based on a keyword using this method, or via morphological analysis. There is no typical method such as scientometrics using the bibliography in patent analysis for data mining. Therefore, one of the most important choices is the selection of which part to extract

2.4 Relation between network structure and innovation

Previous social science studies have investigated the network properties of innovation systems to understand innovation from a systematic perspective (Burt 1992; Hansen

1999; Tsai , 2001). In these studies, researchers found that a society consists of subgroups in which the members are connected more densely than the members of other subgroups, and innovation performance is related to the position over the subgroups in the network; a node that connects several subgroups has better performance than the other nodes (Burt, 1992). The effect of innovation performance depends on the context of the innovation in the networks. Hansen (1999) found the different effect of an agent's location in a network on innovation. While innovation performance that involves simple knowledge is more closely related with node location at a bridge, the core location in a network is better in the case of complex knowledge.

The complex network achieved in statistical physics turns the research interest of innovation network studies from network position to network structure. One described the topology of large complex networks such as “Small World” (Watts and Strogatz, 1998) and “scale-free” networks (Albert, Jeong, & Barabasi, 1999), and the researchers in this area proposed models of network evolution such as the random rewiring model (Watts and Strogatz, 1998) and the preferential attachment rule (Albert et al., 1999). Previous studies revealed random connections among nodes in clustered subgroups (Watts and Strogatz, 1998) and the existence of few hubs (Albert et al., 1999) makes large networks small, equivalent to empirical analysis (Milgram, 1967). Succeeding in the research paradigm, innovation studies investigated the network structure of innovation systems (Wagner & Leydesdorff, 2005). Academic collaboration networks have the scale-free property, and show that the network position depends on the scholar’s academic

experience (Wagner & Leydesdorff, 2005)

Recently, the innovation network studies have redirected their focus from stable mechanical structures to the varying network position of nodes during network evolution (Hwang, Altmann, and Kim, 2009; Kim, Altmann, and Lee , 2013). A series of studies on the network of Software-as-a-Service (SaaS) found that the SaaS network maintains its scale-free structure (Kim et al., 2013). However, the network position of each node varies: A hub approaches the network center after entering the network and moves out after prosperity, and a new hub then emerges while the former hub declines (Kim et al., 2013).

Changing the network position of nodes implies that nodes are on the move in the network according to their life cycle, as though technologies have a life cycle in a market (Bass, 1969). The transition of network position from the periphery to the core is affected by the changing innovation environment (Jin, Park, and Pyon, 2011) and innovators' shifting interest (Gloor, Krauss, Nann, Fischbach, & Schoder, 2009)

Chapter 3. Technology characteristics in the process of convergence

3.1 Introduction

Many industries have faced the dynamic environments caused by rapid changes in market forces and technology changes and the feedback effect on firms (Teece, Pisano, & Shuen, 1997). Single services and products are no longer sufficient to satisfy the increasingly diverse customer needs. Under this situation, concepts of service packages and integrated product and service offerings have appeared to cope with market demand (Geum, Lee, Kang, & Park, 2011).

To deal with such dynamic environments, firms should consider possessing and managing a rich amount of responsible resources. Particularly in the manufacturing industry, the technology pool should be abundant, and agents must obtain the ability to produce goods for market by combining or converging technologies. Therefore, the ability to perform effective technology management such as by maintaining a technology portfolio, convergence strategy formulation, and technology convergence is becoming more important.

The design of technological strategies in response to this type of market is not limited to firms. As we can see from the Korean case, strategic technology plans that consider

domestic resources and the global market brought rapid growth to Korea. Despite the lack of technology and resources, Korea was able to grow by imitating mature technology and learning about machinery and instrument technologies.

However, as Korea has achieved recent economic and technological growth, there have been changes to domestic technology competitiveness and their technological and economic position in the global market, and Korea is now in the position where they have to become an innovator, not an imitator, and pursue qualitative growth. In other words, developing the new technology sector is necessary for new growth. Examples include the recent national technology plans for information technology (IT), biotechnology (BT) nanotechnology (NT) (OECD, 2014).

To promote and choose these strategic technologies, agents such as firms and governments must understand the characteristics of their own accumulated technologies, their relationship with existing technologies, and the characteristics of new technologies. Much of new knowledge is based on existing knowledge; namely, accumulated knowledge can be converted into new knowledge via interactions between various agents (Nonaka, 1994). BT is developed using IT, chemistry, and NT (Geum, Kim, Lee, & Kim, 2012). NT also requires knowledge of material engineering and electronic engineering (Ávila-Robinson & Miyazaki, 2013).

The technologies and knowledge created during the previous development process are used for agents' economic activity, i.e. gives them financial benefits, and that benefit is then reinvested in their innovation. As a result, knowledge is accumulated. As the amount

of knowledge increases, the overall knowledge that an agent has becomes complex, so that agent is required to understand the shape of the overall knowledge they possess for knowledge management.

Due to these situations, studies have examined the characteristics of and predictions regarding technology and the relationships between technologies. Lee, Kim & Park (2009) investigated the interactive nature of the relationships between ICT in terms of their technological innovations and diffusion. Lee & Su (2010) examined the structure of regional innovation systems research through keyword co-occurrence and social network analysis. Moreover, Antonelli, Krafft, & Quatraro (2010) evaluated the economics of recombinant knowledge by analyzing the co-occurrence of technological classes on patent applications.

For new technology creation, it is necessary to understand the interrelations between technologies. Creating new technology is impossible if they are not consistent with existing technology, and if the rate of technological development is not harmonized with neighboring technologies. Therefore, it is valuable for agents to understand relativeness, convergence, and the co-evolution of technology. Technological relativity is defined as the similarity between technologies, using the distance between the various elemental vectors of the technology field and products. Rosenberg (1976) defined technological convergence as the process by which different industries come to share a similar technological base. The combination and convergence of existing knowledge is the most representative type of knowledge creation. However, different technology groups have

different patterns and properties in the process of convergence. Gambardella & Torrisi (1998) insisted that technological convergence is caused by the emergence of generic technologies, which implies, by definition, that these technologies can be applied to many different products. Namely, while not all technology engages in technological convergence, there are some characteristics for convergence. Greater convergence will occur frequently among related technologies. Therefore, we need to understand the distance between technologies to promote innovation through technological convergence.

We have to observe the role of ICT, especially in Korea, in the characteristics of technology and the process of convergence. Korea is viewed as an advanced country, due to its successful ICT diffusion and country-level policies that have led to economic growth (Choudrie, Papazafeiropoulou, & Lee, 2003). What was also revealed is that in the last decade, when considering Korea's Gross Domestic Product (GDP), ICT development and exports have considerably increased with the ICT growth that led to improvements in the innovation system, such that labor productivity and economic growth have experienced significant increases (Jung et al., 2013). This is why ICT is a representative GPT, which can be used for a diverse range of technologies and economic activities, and has inherent potential for improvement and dynamism (Shin & Park, 2007)

Understanding technologies and attempting to forecast them does not guarantee their success. Since technological direction is determined by numerous factors, agents cannot consider all domestic and international risks such as finance, technologies, human resources, etc., so there is always exists uncertainties in technology plans. Hence,

countries and firms with those particular resources compose a technology portfolio. Typical examples are the synchronous and asynchronous standards of Korea's IMT-2000, and the double standard strategy for telecommunication firms' LTE and WiBRO.

However, if one can understand the influence of technological characteristics themselves, technology predictions and promotion strategies, and the relationship that technological shape has on new technology creation or economic results, then technologies and economic plans that are more effective can be achieved. Over the past two decades, ICT has been considered the most innovative area. Furthermore, by viewing IT as key to socio-economic changes, a review of innovation literature can reveal that there have been investigations into the evolutionary patterns of innovation systems (Ávila-Robinson & Miyazaki, 2013), and the effect of systems on the performance of innovation agents (Burt, 2004). However, previous studies have only emphasized the agents of innovation rather than technological evolution, and have assumed that knowledge flows from agents; thereby overlooking the structure of the technology itself and its pattern of self-organization and coevolution. Moreover, previous studies have paid attention to the static mechanical properties of evolving systems, and explained the effect of a static network structure and position on innovation. Therefore, the methodologies of the preceding research studies are inappropriate for understanding the actual process of occurrence from policies to the national economy aspect; i.e. the response of innovation systems to the political and economic environment, and the effect of the response on the national economy. This provided motivation for this study to conduct further research into

investigating and recommending the role and properties of the ICT sector on the construction of technology networks that can be understood using real life, empirical data based on the development of both Korea's ICT and all other sectors.

For this purpose, this dissertation suggests that a novel research frame is required for the study of innovation in ICT to examine the following research questions: What is the role of ICT when the knowledge network grows dramatically? Did ICT lead innovation in Korea's knowledge system, and if so, how? Did ICT combine with anything other than the technology in other categories to create new knowledge? Is ICT more likely to attach to other ICT, or with technologies in other categories? Does ICT promote convergence among distant technologies? For this, this dissertation has analyzed a knowledge network by applying social network theories to Korean patent applications collected from the European Patent Organization. A knowledge network consists of nodes that represent technology sectors identified by their International Patent Classification (IPC) codes (European Patent Office 2011). This dissertation assumes that a pair of nodes is linked if a patent is described by both, i.e. IPC codes. The technologies are categorized into five sectors and 35 fields according to WIPO IPC-Technology Concordance Table" (Schmoch, 2008). With this knowledge network, this dissertation has implemented three sets of analysis, including two sets of non-parametric hypothesis tests to determine whether ICT played an extraordinary role in the network coevolution compared to the other technology categories.

The following section introduces the theoretical background for the hypotheses on the

role of ICT in the Korean network evolution. Sections 3 and 4 depict the procedure of our analysis and its results, respectively. Section 5 discusses findings. Finally, section 6 summarizes the research and its contributions, and lays out plans for future research.

3.2 Theoretical background

3.2.1 Innovation and ICT

Since the 1990s, the emergence of ICT has greatly impacted changes in technology, industry, and the economy. The OECD (2009) noticed the role of ICT as a GPT. Thus, the ICT sector has attracted interest among researchers (Colombo & Grilli, 2007). Accordingly, there are an abundance of studies on the relationship between ICT and innovation. These studies can be divided into two parts: 1) ICT's contribution to productivity improvement and economic growth, 2) ICT's innovation and diffusion pattern.

Many researchers have paid attention to the role of ICT on economic growth; it has a positive effect on economic growth through the growth of the ICT industry itself, and the increase in overall efficiency for neighboring industries. Jung, Na, & Yoon (2013) examined both ICT-using and ICT-producing sectors' contributions to increasing the overall efficiency of economic growth in Korea. They used growth accounting, and estimated the direct and indirect impacts of ICT capital on TFP growth between the 1990s and 2000s, As a result, they found a positive impact for ICT on industrial total factor productivity (TFP). Oliner & Sichel (2000) showed that ICT contributed to the growth of

labor productivity in the second half of the 1990s in the U.S. economy using a standard neoclassical growth accounting framework. Bakhshi & Larsen (2005) showed the positive impact of technological progress in ICT-related sectors on economic growth in the United Kingdom. They decomposed labor productivity growth using aggregate data over the sample period (1976–1988) and found that ICT investment-specific technological progress could explain as much as 20–30% of labor productivity growth.

Along with the study of the role of ICT on promoting the efficiency of neighboring industries, the study of the pattern of ICT diffusion and co-evolution with other technologies was also conducted. Vicente & López (2006) showed the pattern and determinants of ICT diffusion, such as the Internet, computers, and mobile telephony. The result showed that the determinants of ICT adoption are increased incomes, education, and prices. Corrocher, Malerba, & Montobbio (2007) and Malerba & Orsenigob (1997) showed Schumpeterian patterns of innovation for activities in the ICT field. They found two main groups that showed clear distinction in the growth of patents, the structure of innovative activities, technological pervasiveness, and the variety of knowledge sources. Shin and Park (2007) drew a map of the national ICT frontier using centralities and brokerage. In the analysis, they found that the Korean technology network is organized into six large clusters, and the pattern of technology network evolution is heterogeneous over these clusters.

3.2.2 Convergence and role of ICT

Hacklin, Marxt, & Fahrni (2009) and Karvonen & Kassi (2011) mentioned technological convergence as a sign of the transition of knowledge convergence into potential for technological innovation. Technological convergence allows inter-industry knowledge spillovers to facilitate a new mixture of technologies. Similar to technological convergence, technology fusion, as stated by Kodama (1993), is the fusion of existing technologies, Kodama (1986) examined how one of the important factors of Japan's success in the 1980's was due to the fusion of science and mechanical engineering. No & Park (2010) examined the evolutionary path of technological fusion in nanotechnology and biotechnology using a patent citation network. They found that six different patterns of fusion and patterns had changed over time. Technologies that could not converge with other technologies were removed during the technology evolution process. It is valuable work for its examination of the characteristics of technology in convergence with other technology and within similar technologies for forecasting its effects and development.

Because ICT can be regarded as a GPT, great interest in the ICT sector has followed by the study of convergence among ICT and other technology applications in the chemical, pharmaceutical, food, and bioengineering industries. These studies used different methodologies and perspectives to examine the convergence of ICT such as supply/demand, product/process, and technology classification.

Xing, Ye, & Kui (2011) measured the convergence of ICT sectors based on China's 2002 input–output (IO) table, and they distinguished a two-dimension taxonomy of

convergence based on supply/demand and complementation/substitution. Hacklin et al. (2009) proposed a conceptual framework to understand the coevolution of actors and patterns of innovation in a converging environment and its development process. They found that while ICT convergence is facilitated as a form of a functionally integrated product, the convergence of nanotechnology and biotechnology involves scientific advances and processes such as manufacturing at the nanoscale. By using an IPC co-classification–based approach, Curran & Leker (2011) examined technological convergence in ICT-related areas with areas such as Nutraceuticals and Functional Foods (NFF) and Cosmeceutical-related areas. Results found convergence tendencies among telecommunication and computers, music and computers, and navigation and computers in ICT.

Moreover, there are studies about the characteristics of ICT itself; Lee et al.,(2009) investigated the interactive nature of the relationship between ICT in terms of technological innovation and diffusion. They classified the interaction patterns among ICT sectors as pure competition, mutualism, predator and prey, commensalism, amensalism, and neutralism, using positive and negative interactions and the level of patenting activities between technologies. Salavisa, Sousa, & Fontes (2012) compared the nature of the knowledge required for innovation and its organization between molecular biotechnology and software for telecommunication. The results showed that the differences between the two factors affected the architecture formation for the innovation networks of each sector.

As mentioned above, many studies have used I/O tables, patent network analysis, and case studies to investigate ICT convergence and co-evolution. In addition to the previous study, this study provides useful insights for understanding the convergence of ICT and comparing the characteristics of each technology, including ICT, using these different approaches. However, each study has limited scope for certain technology categories or industries such as ICT (Lee, Kim, & Park, Y. 2009; Shin & Park, 2010), Bio (Salavisa et al., 2012), and Energy (Kajikawa, Yoshikawa, Takeda, & Matsushima, 2008)–focused studies from the perspective of the firm's manager and policymakers in certain industries.

Few previous research studies have analyzed technology networks using national levels for all micro-level data. Because most technologies are connected to others, it is important to observe the overall technology set (Barabasi et al., 2002). Analyzing all technological structures, links, and nodes' properties in a network will help make national-level policies.

After analyzing the overall features of technology structures, it is important to find the role of key technologies such as ICT in co-evolution of technology's structure. For this purpose, a novel research frame in the study of innovation for national-level technology is needed to examine the structure and properties of all individual technologies simultaneously: Thus, this dissertation proposes a new analysis framework for technology convergence and co-evolution using the national-level's micro-level technology data.

3.3 Methodology

3.3.1 Analysis framework and hypotheses

3.3.1.1 Measuring convergence

Hacklin (2008) proposed that the convergence process consisted of four stages: Knowledge, technology, application (products or services), and industry convergence. To understand the convergence process, it is important to analyze the overall process across both academia and industry. Even though Hacklin et al. (2009) conducted research that considered this convergence process, it is has limitations, in that it lacks quantitative analysis and a systematic method of comparison. The ambiguous boundaries of each convergence stage, and the heterogeneity of observable data and its availability make it difficult to analyze the overall convergence process quantitatively.

Overall, studies that measure convergence can be divided into two streams of literature. One is studies about convergence that are related to science and technology, and the other is about convergence related to applications and industry. The former generally measures the degree of convergence using classifications and citation information from bibliographic references in academic literature and the patent database (Breschi, Lissoni, & Malerba, 2003; Joo & Kim, 2009; Makri, Hitt, & Lane, 2010). The latter typically adopts input/output analysis using I/O tables and case studies using interviews and surveys (Fan, Lang, Journal, & Oct, 2007; Teece & Winter, 1994). It measures the degree of convergence using the value of variables classified from the Standard Industry Classification (SIC) system, and it uses patents for analysis to apply

concordance between patent classes and SIC industrial classes (Johnson, 2002; Gambardella & Torrisi, 1998)). Similarly, studies that rely on SIC and classifications in academic literature and patents, have adopted the Herfindahl index, entropy, and concentric measures in their measures design.

Many recent studies using these indices have also adopted social network analysis for quantitative analysis. Kim & Kim (2012) proposed a patent network analysis method for technological convergence based on citation, co-classification, and portfolio analysis. Kim et al. (2012) also applied this analysis method to measure the convergence of IT and BT. This research uses convergence intensity, the rate of intensity, and coverage. Intensity is the number of patents with co-classification into two technologies, which means the level of relevance between two technologies. Coverage is the number of classes with co-classification, which means the amount of converged area with a certain technology. To identify the nature of the technology involved in the convergence process, it is necessary to observe the phenomenon over a long time, and the analyzer must consider the feasibility of comparison among samples and measurement across different periods. Patent data and IPC meet these conditions. Choi, Kim, & Park (2007) and Joo & Kim (2009) mentioned that because the classification of patents has been updated and applied to all accumulated patents periodically and IPC is assigned using strict guidelines, it is a reasonable source for technology comparison and forecasting over time. Therefore, this dissertation improves upon Kim & Kim (2012)'s convergence analysis using patent data at the micro-level, so that we can consider the nature of the technology that clusters

around the initial technology to accelerate convergence.

Drawing on a network perspective for technology coevolution, I examined three important concepts: Ease of convergence, diversification of convergence, and acceleration of convergence. These characteristics of entities in a network have an effect on the growth and evolution of a network. Ease of convergence, the degree of connectedness to other technologies, means how easily certain technologies can be applied or used with others. Diversification of convergence, a variety of link combinations for convergence, means how various technologies converge with particular technologies. Diversification in convergence is an important factor for innovation. The acceleration of convergence, the tendency of technology to promote the clustering of technologies around it, mean that certain technologies play a pivotal role when convergence happens between different technologies .

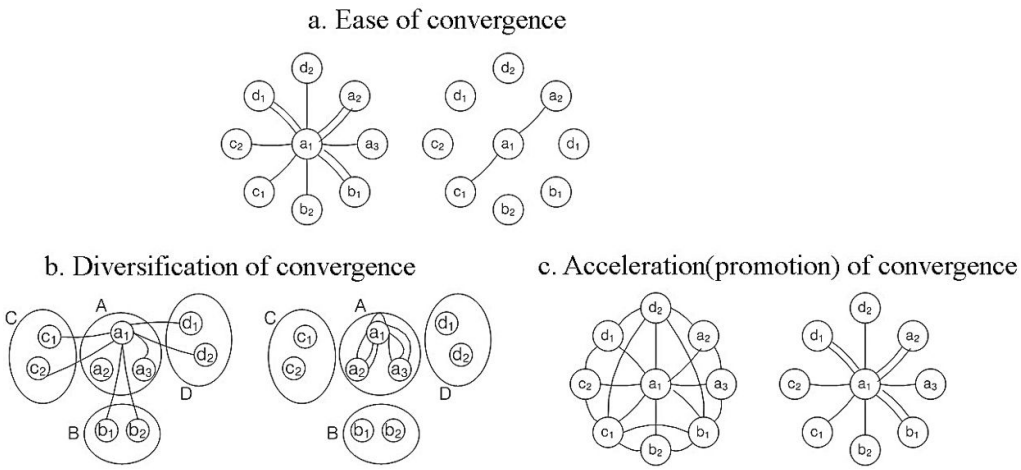


Figure 2. EDA framework

3.3.1.2 Hypotheses

If technology has the characteristic "ease of convergence," then that technology can be well used and applied with other technologies when an inventor creates an invention. Most of all, it has most important characteristics for technological co-evolution via convergence. Kodama (1993) and Miyazaki (1994) paid attention to technologies such as ICT, which have diffused through various different industries. These are general purpose technologies whose main characteristics are their pervasiveness and role as innovation-enablers across the entire economy. Björkdahl (2009) and Corrocher et al. (2007) also mentioned that ICT is a GPT, since it can be combined with a multitude of other technologies. It has been shown that firms that create patents outside their core technical domain increasingly do so within the ICT field. In fact, this field attracts more patents than any other, and has therefore increasingly dispersed across different sectors (Mendonc, 2002).

In this respect, ICT has allowed the emergence of an increasing number of technologies and applications. This can be measured as the degree of technological co-occurrence for the same innovation outputs such as patents, products, and the relative positions of technology on a technological network. As Tsai (2001) said, agents' central network positions are important for ease of access to new knowledge. Technology's central network positions are also the same as this, it already tells us that technology in central network positions is used with other technologies and can be applied for the development of similar but new technologies.

After the introduction of a method of adopting the degree of co-occurrence of classes in 1960, quantitative analysis can be made for convergence between technologies (D, 1989). There are many studies that use the degree of co-occurrence as an index to measure the degree of technology convergence (Kim & Kim, 2012; Choi & Hwang, 2013; Curran & Leker, 2011). Therefore, this dissertation proposes the following hypothesis:

Hypothesis 1: ICT is more likely to be attached to other technologies for invention than other technology groups.

This hypothesis can be tested using the technology classification's degree of centrality.

Previous studies have also shown the effect of technology diversification on innovation activity, including R&D expenditure and innovation output. (Becheikh et al., 2006). Technologically diverse firms are found to be more innovative and survive longer (Breschi et al., 2003; Suzuki & Kodama, 2004; Garcia-Vega, 2006). Fleming (2002) suggested that technologically diversified firms consciously mix their technologies, because diversity in technologies increases the possibility that a previously untried combination will be attempted. Quintana-García & Benavides-Velasco (2008) compared the effect of technological diversification for exploratory innovation capacity and for exploitative innovation capacity, and showed that technological diversification has a stronger effect on exploratory innovation capacity. Technological diversity creates cross-

fertilization and spillovers between related knowledge bases, which positively affect firms' innovative competencies (Granstrand, 1998; Quintana-García & Benavides-Velasco, 2008). Thus, firms that have different types of technology and technologies for which their characteristic is to converge with a variety of technologies are considered competitive.

Representative indices for measuring the diversification of convergence are the EI index and the entropy index. The former can measure the flow and homophily of technologies that compose the result of convergence such as patents and products using the criterion of their internal and external links. Meanwhile, the latter can measure the concentration of technologies. Han & Park (2006) and No & Park (2010) used the concept of the E-I index to measure the inflow and outflow degree and the homophily of convergence. Han & Park (2006) analyzed the process by which technological knowledge spreads through research spillover using a disembodied patent citation network. The results showed that there is a tight knowledge link between the IT-based sector and scale-intensive sectors such as metal working, motors, and power systems in both in and out flow. However, the link between the IT-based sector and the BT-based sector is not tight. The entropy index is also used to measure the degree of technological diversification. Palepu (1985) used the entropy index to examine whether the growth rate of related diversification firms is better than that of unrelated diversification firms. Ávila-Robinson & Miyazaki (2013) measured the variety of knowledge bases in scientific areas using the Thomson Reuters/ISI Science Citation Index Expanded database, by employing the case

of micro/nanoelectromechanical systems technologies (MEMS/NEMS), which is a promising technology in the ICT field. By using the entropy index, Ko et al. (2014) also presented a procedural method for analyzing the trends of industry-wide technology fusion. Their results showed that electrical machinery and apparatus, and both computer hardware and software, have a high external impact. This means that cross-boundary technology fusion happens briskly. As in the above discussion, the following hypothesis is established:

Hypothesis 2. ICT is more likely to be attached to a diversity of technologies in other categories than technologies in other categories

The characteristics of clustering various technologies through bridging neighborhood technologies are also important, along with the mixing of a variety of technologies. Through the development of bridges and general purpose technology, innovative technologies and inventions can emerge through the convergence of existing and new knowledge. For example, the development of nanorobots for the treatment of various medical problems is the result of convergence among technologies related to image processing and mechanical control, and technologies related to medical and bioscience through the benefit of nanotechnology such as micro electro mechanical systems (MEMS). In other words, miniaturization using MEMS has stimulated the convergence of many existing technologies.

Nodes located at a bridge are more innovative when they have access to simple knowledge, whereas nodes at the core are better when able to access complex knowledge (Hansen, 1999). If the innovation capacity of the former is high, then its central position leads to improved innovation, whereas nodes with low capacity do not correlate with their position (Tsai, 2001)

Some previous studies have handled the role of ICT as a bridge for innovation. Lee et al. (2009) showed the evolving pattern of Korean ICT with the Patent Interaction Network (PIN), based on Lotka-Volterra equations. With their results, they recommended that promoting broadband and home-network technologies would be important for developing Korea's whole ICT industry. García-Muñiz & Vicente (2014) analyzed the capacity of ICT as bridge for knowledge flow using Burt's approach (1992) on structural holes. They used indicators of redundancy and the constraint index to measure sectorial efficiency and constraint dependency. Their results showed that the ICT sector plays an important role as an intermediary in the flow of information across economic networks, and it can access a variety of information from other sectors.

The betweenness centrality of technology on a network can be good measurement for identifying the characteristics of technology as a bridge, as mentioned above. However, because betweenness centrality is defined as the number of shortest paths that pass through a particular node among all possible shortest paths, it cannot give enough information about the degree of a certain technology's involvement in convergence with others, or the degree of a particular technology's clustering with neighbor technologies.

Burt's approach (1992) on structural holes assumes that because information from connected nodes is similar, the net amount of information can be small. However, it can be interpreted differently if each node is an already classified technology base by an exclusive property such as functionality, product, or service. This means that the technology base has the characteristic of accelerating convergence, and that certain technologies are well clustered with other technologies, i.e., they stimulate convergence between heterogeneous technologies.

Therefore, this dissertation proposes the following hypothesis

Hypothesis 3. ICT clusters other technologies around itself more easily than non-ICT technologies.

3.3.2 Data

This dissertation has gathered patent applications from Worldwide Patent Statistical Database version 4.31 provided by The European Patent Office (EPO) for which the release date is 11-10-2011 (European Patent Office, 2011). The EPO is one of the most famous organizations that provides patent data and cooperates with the United States Patent and Trademark Office, or USPTO (http://www.uspto.gov/). The Worldwide Patent Statistical Database of the EPO provides bibliographic information on patents around the world, extracted from the EPO master documentation database, i.e. the DOCDB and INPADOC Worldwide Legal Status database. The database contains the title, applicants' names, inventors' names, their address, references, and the classifications of patent

applications from about 90 countries, including Korea (European Patent Office, 2011).

The patents are classified by IPC, which was agreed in Strasbourg in 1971 and enforced in 7 October 1975 for the standardization of the patent classification system across the world (World Intellectual Property Office, 2013: http://www.wipo.int/). Figure 3 describes the four hierarchical levels of IPC codes. Level 1 consists of eight sections, represented by capitalized letters of the alphabet (i.e. A, B, …, and H). For example, Section A is technologies for human necessities and Section B is for transport technology. Each section involves classes expressed by two digits (Level 2), each of which is divided into subclasses (Level 3) and then groups (Level 4).

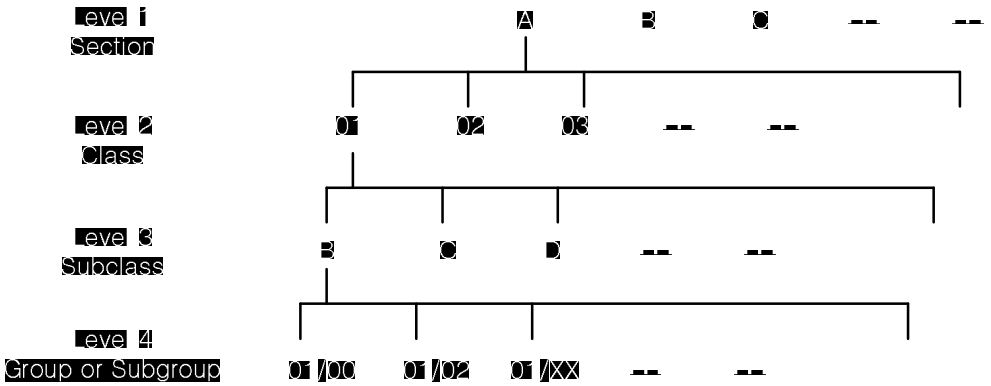


Figure 3. Hierarchy of IPC

In total, 2,357,891 patent applications filed from 1970 to 2009 were used for analysis, and 10,476,896 IPC co-occurrences from 1,197,948 applications that involved two or more IPC codes were extracted.

Since the 1990s, a tendency towards convergence has emerged for the ICT field. It has been extended to various other technologies from the chemical, pharmaceutical, food, and bioengineering industries (Geum et al., 2012; Xing et al., 2011), and around the 1990s, a radical growth of the degree centrality in IPCs related to ICT was found (Kim et al., 2013). Thus, the test process is conducted using two period data groups, which are divided into 1970–1989 and 1990–2009.

3.3.3 Knowledge network

A technology network is defined as a set of nodes and links between the nodes, in which nodes correspond to IPC codes, and a link is detected between two nodes when two IPC codes appear concurrently in a patent. Figure 4 describes an example of a technology network extracted from the patent data. In Figure 4, there are four patents (i.e. A, B, C, and D). Patent A is classified with IPC 1 and IPC 2, Patent B with IPC 2, IPC 3, and IPC 4, and so on. Because Patent A involves IPC 1 and IPC 2, a link appears between those two nodes to represent these two IPCs. Likewise, three links appear between IPC 2, IPC 3, and IPC 4 for Patent B; therefore, the patent data in Figure 4 leads to a technology network with four nodes. The technology network is a weighted graph in which the weight means the number of connections between any two nodes. That is, the weight between IPC 3 and IPC 4 is two. IPC 5 is isolated, because there are no new IPC codes in Patent D, which is the only patent involving IPC 5. In our analysis, two technology networks are established for all patents applied for during the two analysis periods: 1970–

1989 and 1990–2009.

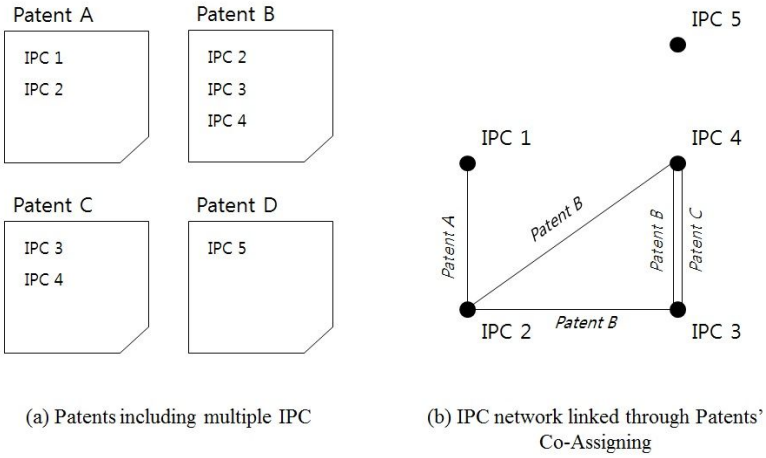


Figure 4. Example of a Technology Network

After forming a technology network using subgroup-level IPCs, the result is reported using five sectors of technology according to WIPO IPC-Technology Concordance Table (Schmoch, 2008). The sectors are sub-divided into 35 fields of technology. They cover all technology domains, thus all the types of IPC code are assigned to the 35 fields of technology (see Table A1)

3.3.4 Indicators

To examine three hypotheses, four indices (degree centrality, E-I index, entropy index, and clustering coefficient) are calculated from the patent co-classification network described in the previous subsection. In the subchapter, these indices will be described,

and then the next subchapter flows for testing the hypothesis will follow.

3.3.4.1 Degree centrality

The degree centrality of each technology is used to test Hypothesis 1. The degree centrality for weighted graphs according to the definitions of Opsahl et al. (2010) is applied.

Let w_{ij} be the weight of the link between nodes i and j in weighted graph G that has size g. w_{ij} is 0 when i and j are disconnected nodes. Then, the degree of node i is defined as the sum of the weight of the links between node i and its neighbors, i.e. $\sum_{j \epsilon G} w_{ij}$. Degree centrality, as defined above, is likely influenced by network size; therefore, the degree centrality of a node in one network can be normalized by the network size when it is compared to the degree centrality of a node in another network that has a different size. The normalized degree centrality of node i can therefore be defined as the degree centrality divided by the maximum possible number of links to the node in the network with size g:

$$k_i = \sum_{j \epsilon G} w_{ij} / (g-1). \qquad \text{Eq. (1)}$$

3.3.4.2 E-I and entropy index

Hypothesis 2 examines whether IPC codes in the category of ICT are more likely to be attached to IPC codes in other categories by comparing the IPC codes in the same

category to those in other categories. To test this, the E-I and the entropy indices are used as diversification measurements for each technology node. The E-I index was proposed by Krackhardt & Stern (1988), and is defined as follows:

$$\text{E-I index} = \frac{E - I}{E + I} \qquad \text{Eq. (2)}$$

where E = the number of external links (between-group), I = the number of internal links (within-group).

Not only can this index be applied to a whole network, such as in (Krackhardt & Stern, 1988), but also to groups and individual nodes (Everett & Borgatti, 2012). The index has a range of -1 to +1; the index of a group that has only internal links is -1, and one that has only external links is +1. Because this index is not just a measure of external links but is the ratio of the difference between external and internal links to all links, node homophily can be measured for individual groups and for the whole network.

In measuring diversification in technology convergence, many previous studies exist that examine the index, such as the Shannon entropy index and Herfindahl index. However, this dissertation uses the entropy index as diversification measurement rather than the Herfindahl index, because Gemba & Kodama (2001), Hoskisson, Hitt, Johnson & Moesel (1993), and Raghunathan (1995) proved that the entropy index is more effective than the Herfindahl index.

Shannon entropy (ε_i) (Eagle, Macy, & Claxton, 2010; Jacquemin & Berry, 1979) is defined as:

Entropy index:

$$\varepsilon_i = -[\sum_{j=1}^{m_i} P_{ij} \log(P_{ij})] \qquad \text{Eq. (3)}$$

P_{ij} is the proportion of *i*'s degree with node j over the total degree of node *i*, m is the number of nodes with links to node *i*, and the index has range of 0–1. The index of a node that has an equal number of links with various nodes is 1, and that of a node linked with only one node is 0.

3.3.4.3 The clustering coefficient

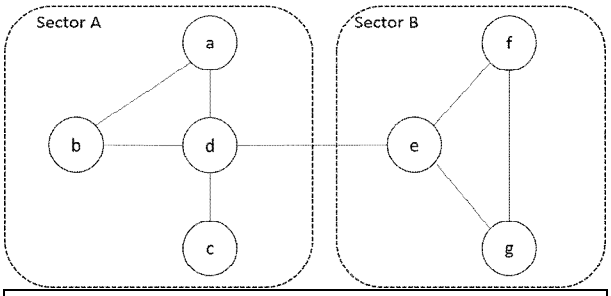
The difference in the clustering coefficient among the IPC nodes for each technology sector was tested in Hypothesis 3. In other words, it tested whether the clustering coefficients for IPC codes in the category of ICT were higher than those in non-ICT categories. The node level clustering coefficient is defined as

$$C = \frac{3 \times (\text{number of trianges on the graph})}{(\text{number of connected triples of vertices})} \qquad \text{Eq. (4)}$$

By definition, connected triples are trios in which at least one is connected to another,

and triangles mean trios of vertices that are connected to another two vertexes. In other words, this is the ratio of the number of links between nodes and their neighbors to the number of possible links between them. A higher coefficient means that nodes are either more likely to be influenced by their neighbors or have a higher influence on their neighbors. Thus, the IPC co-occurrence network's average coefficient indicates the tendency for analytical units to form "local" clusters (Genet, Errabi, & Gauthier, 2012).

Two technology bases (IPC) that co-occur in same invention will have a greater probability of converging with one another than two chosen at random from the population. The clustering coefficient for measuring this probability has range of 0 to 1. The coefficient of a fully connected graph is 1 and that of a star network is 0. Many real-world networks typically have values in the range 0.1–0.5 (Girvan & Newman, 2002)



Degree centrality: d > e > a=b=f=g>c
E-I and entropy index: e > d > a=b=c=f=g
Entropy index: e > d > a=b=c=f=g
Clustering coefficient: a=b=f=g>e>f

Figure 5. Sample network for measurement

3.3.5 Process

To identify the structure of a technology network, degree distribution analysis is conducted. Degree distribution P(k) is the relationship between a degree and the number of nodes that have the same degree. Previous studies of empirical network analysis show that the degree distribution decreases by a power function for many real networks, and a defined network with this degree distribution forms a scale-free network (Albert et al., 1999). However, because the frequency of nodes with a high degree (i.e. hubs) is too low in a scale-free network, the degree distribution function fluctuates considerably in this area for many real networks. The serious fluctuation for hubs makes it difficult to identify the scale-free property of real networks. To resolve this fluctuation problem, Newman (2004) proposed using cumulative degree distribution. Cumulative degree distribution P(k>) is the correspondence between a degree and the number of nodes with at least that degree. Measuring the cumulative degree distribution reduces fluctuation at hub areas without losing scale-free identification, due to the property of the power function. An integration of the power function k-γ is also a power function with an exponent that increases by 1: k-(γ-1). The cumulative degree distribution P(k>) of a scale-free network whose degree distribution is k-(γ-1) for an arbitrary exponent γ fits to a linear function in log–log scales:

$$\log P(k_{>}) \sim -(\gamma-1) \log k. \qquad \text{Eq. (5)}$$

Likewise, if the degree distribution is an exponential function rather than a power function, the cumulative degree distribution should be exponential due to the property of integration of an exponential function. Therefore, the cumulative degree distribution $P(k_{>})$ of a network whose degree distribution is $\exp\{-\gamma k\}$ for arbitrary coefficient γ is transformed to a linear function in log-linear scales:

$$\log P(k_{>}) \sim -(\gamma-1)\, k. \qquad \text{Eq. (6)}$$

To identify whether a sample is derived from power law distribution, least-squares fitting is applied using the cumulative degree centrality data. In addition, this dissertation proves it using the statistical framework presented by Clauset, Shalizi, & Newman (2009), which is based on Kolmogorov–Smirnov (KS) statistics and likelihood ratios. This method is also used to identify the degree distribution for each technology sector before comparing the convergence preference of the ICT sector to that of the others.

To prove Hypothesis 1, the IPC code in the category of ICT is tested for whether it is more likely to attach to other IPC codes than those in other categories. It is investigated through three steps as follows.

First, the degree distribution of each sector is examined using the approach of (Clauset et al., 2009). Then the comparison of the convergence strength with other technologies including both related and unrelated technologies among five technology sectors is conducted. For this comparison, a Kruskal–Wallis test is applied for two

reasons: Normality cannot be assumed, and it consists of five sample groups, not two. Because normality cannot be assumed and it there are five sample groups rather than two, though Mood's median test can be an alternative, it is not as effective as the Kruskal–Wallis test. This is because it just uses the number by which it is larger or smaller than the median value of a sample, in contrast to Kruskal–Wallis's use of the sum of the difference between the mean ranks of these samples as a statistic. The Kruskal–Wallis test statistic is given by:

$$KW = \frac{12}{N/(N+1)} \sum_{j=1}^{k} n_j (\overline{R}_j - \overline{R})^2 \qquad \text{Eq. (7)}$$

Where k = number of samples or groups

n_j = The number of cases in the *j*th sample

N = The number of cases in the combined sample (the sum of the n_j's)

$\overline{R}_j$ = The average of the ranks in the jth sample or group

$\overline{R}$ = (N+1)/2 = The average rank in the combined sample (the grand mean)

Lastly, if Kruskal–Wallis shows a significant effect, a *post hoc* test follows for pairwise comparison to determine which pair has the difference. This dissertation uses differences $\left|\overline{R}_u - \overline{R}_v\right|$ for all pairs of five sectors, i.e., 10 pairs. For this test, the following inequality is used (Siegel, S., & Castellan, 1988).

$$\left|\overline{R}_u - \overline{R}_v\right| \geq z_{\alpha/k(k-1)}\sqrt{\frac{N(N+1)}{12}\left(\frac{1}{n_u}+\frac{1}{n_v}\right)} \qquad \text{Eq. (8)}$$

$z_{\alpha/k(k-1)}$ represents the mean abscissa values from the unit normal distribution above for $\alpha / k(k-1)$. If the inequality (8) is true, then the hypothesis H_0: $\theta_u = \theta_v$ is rejected, and the conclusion is reached that $\theta_u \neq \theta_v$. In other words, these medians are different.

In cases of Hypothesis 2, for the calculation of the E-I index, an undirected binary network is constructed. It does not have the direction of the edge between nodes, and all edge weights are set to 1. This network adopts a subgroup level (4 level) IPC of applications as nodes. Then, IPC nodes are classified as sector level technologies using an IPC-technology concordance table (Schmoch, 2008). To calculate the E-I index, analysis distinguishes the relationship between external and internal nodes and the relationship within the same group in five sector technology classification. IPC pairs in which the two nodes are in different technology sectors is defined as a pair in an external relationship. Using the two numbers E and I, the E-I index of each group is calculated as in Eq (2) (Krackhardt & Stern, 1988). As Krackhardt and Stern pointed out, this dissertation uses this rather than the normalized one by the maximum possible relation, because many relationships are created among internal groups, so a positive E-I value is rarely observed. Moreover, though it can be normalized by dividing by the large number of maximum external edges, because it is already a small number, this normalized index is too small to interpret the relationship

For the calculation of the entropy index, a weighted undirected network is constructed instead of a binary network in the E-I index. The entropy index is calculated for 35 field levels using the IPC-Technology-Concordance Table A1, then the result is summarized at the sector level to compare it with the E-I index. Because the average number of nodes in the IPC level per sector is 11524.4, if this were applied as a node, then the entropy of all nodes would be high and the difference in index value between nodes would be little. Thus, it makes comparing this index between sectors difficult. Moreover, the degree distribution of networks composed at this level IPC node follows the power-law. It means that there is a large difference in the number of observations for each node to calculate the entropy index. Therefore, this dissertation uses 35 fields as nodes.

For hypothesis 3, after constructing an undirected binary network as in hypothesis 2, and calculating the clustering coefficient for the IPC node level, IPCs are then classified by technology sector, as in hypothesis 2. Unlike the E-I index, the clustering coefficient is not a group index but a node index.

The distribution of each sector's clustering coefficient is examined using a histogram. Unlike using the degree centrality as a measurement for Hypothesis 1, it is difficult to find previous studies that provide evidence that the clustering coefficient shows a power-law distribution, and the Kruskal–Wallis test and pairwise comparison are conducted, like for Hypothesis 1, to compare the convergence ability among five different technology sectors using the clustering coefficients.

3.4 Analysis Result

3.4.1 Descriptive Analysis

It is important to understand the distribution of index values before group comparisons. The degree distribution of a whole network and the degree distribution of each sector in a network were examined. Even though the result of the tests presented by (Clauset et al., 2009) rejects samples drawn from the fitted power-law distribution, Figure A. 2 and result of testing by OLS signifies that the cumulative degree distribution of technology network for 1970–2009 approximately follows the power-law distribution rather than either the exponential or normal distribution. In addition, as shown in Table A2, the degree distributions of all sectors during the two periods follow the power-law distribution.

The clustering coefficient distribution of each sector is also examined using histograms and the cumulative histogram of the coefficient, i.e., the number of nodes that have a given coefficient. As shown in Figures A. 5 and A. 6, the clustering coefficient distribution of a network during the two periods is skewed to the right (positive skew) and has a sharp peak around coefficient 1. Therefore, we cannot say that the clustering coefficient distribution follows a particular distribution like the power-law and the normal distribution. Thus, it is appropriate to apply the Kruskal–Wallis test rather than ANOVA to compare the indices among technology sectors. Moreover, because the degree distributions follow the power-distribution, the median and maximum values of the indices give valuable information about the average.

Descriptive statistics for degree centrality of network, which mean their co-occurrence

with other technologies in patent applications, are shown in Table 2. From these statistics, it is possible to find the change of degree between two periods, which are 1970–1989 and 1990–2009, and several differences among five sectors. For 20 years, in contrast to the small growth of nodes, there has been rapid growth in links, which is equal to the number of patent applications that contain a node's IPC code, as shown in Figure A.1. In particular, the growth rate of sector 1 is more than 25 times greater during this period. Sector 1's number of links was the third largest before this period, and about one sixth of that of Sector 3. However, it later became the second largest, and there was little difference between Sectors 1 and 3. The nodes in Sector 1 have a median link of 96 and an average link of 851.51 in the later period, which is the largest value among the five sectors. Sector 1 has the biggest hub with 65,835 degrees. Through the differences between the median, mean, and maximum, it can be inferred that Sector 1's network structure is scale-free and highly centralized with a big hub.

The descriptive statistics for a network's clustering coefficient are shown in Table 3. The difference in the median between sectors is larger than the mean. As Figures A. 5 and A. 6 have shown, a little difference in the median is attributable to many observations having coefficient 1, and many that have coefficient 1 have just 2 or 3 links, as shown in Figure A. 7. Overall, the clustering coefficient has decreased from 0.509 to 0.385, which is the median of the whole network including all sectors. However, the relative coefficient of Sector 1 increased during this time. Sector 1's clustering coefficient was the smallest, but it became the largest. It means that Sector 1 and the technologies around it form a

cluster as a technology basis for identical inventions, and Sector 1 has a central role of clustering.

Table 2. Descriptive statistics for the each sector's degree centrality

	1970-1989						1990-2009					
	Sector1	Sector2	Sector3	Sector4	Sector5	Sector all	Sector1	Sector2	Sector3	Sector4	Sector5	Sector all
Node	5,581	3,328	12,497	12,591	3,285	37282	8,149	5,432	17,093	20,654	6,294	57622
Links	276,568	84,872	1,374,163	280,717	36,402	2052722	6,938,989	1,495,356	7,532,716	2,117,091	606,676	18,690,828
Median	15	10	31	9	5	13	96	47	92	26	24	46
Mean	49.56	25.50	109.96	22.30	11.08	55.06	851.51	275.29	440.69	102.50	96.39	324.37
S.D.	114.53	59.08	328.73	54.09	19.04	202.83	2971.06	1296.77	1455.32	301.81	296.59	1464.27
Minimum	1	1	1	1	1	1	1	1	1	1	1	1
Maximum	2,304	1,145	17,448	1,735	298	17448	65,835	37,216	53,207	13,546	6,976	65,835

Table 3. Descriptive statistics for each sector's clustering coefficient

	1970-1989						1990-2009					
	Sector1	Sector2	Sector3	Sector4	Sector5	Sector all	Sector1	Sector2	Sector3	Sector4	Sector5	Sector all
Node	5,271	3,061	12,104	11,421	2,671	34,528	7,931	5,232	16,807	19,645	5,896	55,511
Median	0.46	0.5	0.531	0.515	0.533	0.509	0.42	0.371	0.418	0.348	0.359	0.385
Mean	0.536	0.58	0.585	0.589	0.592	0.579	0.468	0.438	0.471	0.433	0.44	0.451
S.D.	0.303	0.319	0.289	0.319	0.345	0.309	0.248	0.263	0.249	0.275	0.278	0.263
Minimum	0	0	0	0	0	0	0	0	0	0	0	0
Maximum	1	1	1	1	1	1	1	1	1	1	1	1

Note: all sample- 37282, isolates- 2754 for 1970-1989; all sample- 57622, isolates- 2111 for 1990-2009

3.4.2 Emergence of ICT from Knowledge Base

3.4.2.1 Hypothesis 1:

First, Kruskal–Wallis was tested to examine the difference in the median degree of all five technology sectors. In the test for the two period samples of 1970–1989 and 1990–2009, the test results of the sample during 1970–1989 revealed a significant difference between technology sectors for value ($\chi^2(4)= 5777.057$, $p < 2.2e^{-16}$), and the results of samples for 1990–2009 revealed a significant difference between technology sectors for value ($\chi^2(4)= 5264.07$, $p < 2.2e^{-16}$). It is means that at least one technology sector is different from the others for the median and the distribution from which the sample has come. Thus, to see which pair is different, pairwise comparison is carried out using the rank of samples as Eq (8)

Table 4 is the result of *post hoc* tests. The result showed significant differences between all sectors ($p < 0.05$) except for Sectors 1 and 3 for 1990–2009. As shown in Table 2, Sectors 1 and 3 are similar in the median, maximum, and the difference between the mean and variance are smaller than for the other pairs.

Sector 1 has the highest value for the median for 1990–2009 and second highest for 1970–1989, and a pairwise comparison test showed significant differences; hence, Hypothesis 1 is supported.

오류! 연결이 잘못되었습니다. Note: * Significance at the 5% levels.

3.4.2.2 Hypothesis 2

To inspect diversification (heterogeneity) in the convergence between technologies, the E-I index and entropy index are measured. As shown in Table 5, all of the E-I index values for each sector have increased, and their order has not changed between the two periods. An increased index means that the degree of homophily for all technologies decreases. Among the five sectors, Sector 3 (Chemistry) shows smallest value, followed by Sector 1 (Electrical engineering) for two periods. Sector 2 (Instruments) shows the largest value among all sectors. Sector 2 (Instruments) includes five technology fields: "Optics," "Measurement," "Analysis of biological materials," "Control," and "Medical technology." "Medical technology" is already technology in a converged field, the four other fields are also GPT, which is supposed to converge with other technology fields easily.

Table 6 shows (scaled) Shannon entropy, which is slightly different from the E-I index. All the entropy index values of each sector decreased, and there were changes in terms of their order except for Sector 1 between the two periods. Decreasing the entropy index means increasing a certain few technology fields' concentration in technology convergence. Among the five sectors, Sector 1 (Electrical engineering) showed the smallest value for the two periods, but there was little difference between the others.

The small value of the E-I index and the entropy index in Sector 1 mean the rejection of Hypothesis 2

오류! 연결이 잘못되었습니다. Note: Binary IPC network is used for index
오류! 연결이 잘못되었습니다.

3.4.2.3 Hypothesis3

The Kruskal–Wallis test and *post hoc* test like Hypothesis 1 was performed but by using different index, the clustering coefficients, for Hypothesis 3. The results of a Kruskal–Wallis test revealed a significant difference for technology sectors on clustering coefficient values (χ^2 (4) =139.0655, $p < 2.2e^{-16}$) using a sample from 1970–1989, and (χ^2 (4)= 582.5061, $p < 2.2e^{-16}$) for using a sample from 1990–2009

The *post hoc* test is conducted because you gain a significant effect from Kruskal–Wallis test. Table 7 is the result of *post hoc* tests. The results show significant differences between all sectors ($p < 0.05$) except for two pairs: Sector 2 and 3, and Sector 4 and 5 from the sample 1970–1989.

Though sector 1 has the lowest median value for 1970–1989, it has the highest value for 1990–2009; all pairwise comparison tests with others show significant differences. Hence, Hypothesis 3 is partially supported for the 1990–2009 period.

Table 4. Multiple comparison test after Kruskal-Wallis of Hypothesis 3

sector pair	1970-1989			1990-2009		
	obs.dif	critical.dif	difference	obs.dif	critical.dif	difference
1-2	24,570.31	3,991.81	TRUE	90,715.89	5,465.21	TRUE
1-3	21,290.49	1,933.09	TRUE	164,378.84	2,825.55	TRUE
1-4	32,723.42	2,396.49	TRUE	20,2942.3	3,568.27	TRUE
1-5	33,536.14	5,079.96	TRUE	127,114.56	6,531.48	TRUE
2-3	3,279.82	3,625.89	FALSE	73,662.95	5,067.98	TRUE
2-4	8,153.1	3,892.74	TRUE	11,2226.4	5,516.63	TRUE
2-5	8,965.83	5,934.33	TRUE	36,398.67	7,769.23	TRUE
3-4	11,432.93	1,719.21	TRUE	38,563.46	2,923.77	TRUE
3-5	12,245.65	4,797.76	TRUE	37,264.28	6,202.91	TRUE
4-5	812.73	5,002.48	FALSE	75,827.74	6,574.57	TRUE

Note: * Significance at the 5% levels.

3.5 Discussion

This dissertation has investigated the nature of technology in convergence, focusing on the role of ICT. For this, this dissertation proposes an analysis framework that consists of three important concepts: ease of convergence, diversification of convergence, and acceleration of convergence.

The result of testing the ease of convergence suggests that ICT is more likely to attach to other technologies for new inventions than other technology groups. This result is

consistent with prior research (Björkdahl, 2009; Corrocher et al., 2007). The result of testing the diversification of convergence suggests that ICT is more likely to attach to technologies in the same category (ICT) than other categories. In addition, this dissertation found technology concentration in the convergence of ICT. That is possibly why Korea chose strategic development areas in ICT such as telecommunication, Broadband Internet and semiconductors in the 1990s (OECD, 2005)

In analysis using the E-I index and the entropy index, different classification levels are used, but the results are summarized as the same sector level. Both indices indicate high technology concentration for ICT convergence over all periods. However, it is found that the degree of diversity in convergence increased over time. In other words, for invention, a greater variety of technologies from different boundaries is required. In addition, technology concentration in convergence seems to have increased. These facts imply that convergence between ICT and other areas became extremely progressed, more specialized with related technology, and diversified with more unrelated technologies during 1970–2009.

The result of testing the acceleration of convergence suggests that ICT clusters other technologies around it more easily than non-ICT categories. In contrast to previous studies that use agents and citation information as nodes, because this dissertation uses the co-occurrence of technology classification for the same inventions, patent applications, and technologies that are connected to the same cluster mean that they have a complementary relationship for one invention; In other words, combining them can create

new innovations. If certain technologies frequently engage in many combinations and inventions, it gives other technologies the opportunity to create or promote innovations.

In contrast to a balanced network that is more optimal than Korea's actual technology network, as proposed by Shin, Juneseuk, and Yongtae Park (2010), the results show that the network in Korea has centralized ICT. ICT's increasing returns snowball in a manner described by previous studies. Arthur (1989), David (1985, and 2000), Dosi, Ermoliev & Kaniowski (1994), and Antonelli et al. (2006) suggested some possibilities for path dependency. One is the cumulative technology interpretation. The Korean government and firms made the decision to grow ICT strategically. Over this period, the competitiveness of ICT and ICT-related technologies has improved. After the early stages, because of their finite resources and relative dominance over other technologies, both within Korea and internationally, agents including governments, firms, and research organizations increased their investment in ICT. The second possibility is network externalities and complementary technology. Korea commercialized second-generation wireless Code Division Multiple Access (CDMA) systems, and was considered the leading country in this period for achieving the world's highest penetration rates. These reprehensive wired and wireless services have network externalities properties; each user is strongly interested in ensuring other users have compatible products and services. Moreover, the two technologies are based on technology for developing information and digital contents service such as VoIP, online gaming, IPTV, and e-commerce. For this complementary characteristic of ICT, convergence among related technologies in ICT has

emerged dominantly in Korea.

It is difficult and inefficient to make efforts to developing all kinds of technologies in Korea. However, as Shin & Park (2010) emphasized for the benefit of balanced developed networks, technology diversification is important for the evolution of technology. If one country cannot develop all kinds of technology and must construct a diversified technology environment, It can be a feasible strategy to select GPTs that can be applied in various other technologies and create new technologies.

Recently, one promising technology field is healthcare. The result of this study estimates that Korea has the technological strength and opportunities for innovation in this area, because Korea has abundant technological bases and inventions in Sector 1 (Electrical engineering) and Sector 3 (chemistry) compared to other countries, as shown in Tables 2 and 4. Though convergence coverage of Sector 1 is narrow, Sector 3 has technological characteristics of convergence with various other technologies, as shown in Tables 5 and 6. Moreover, Sector 1 and 3 have strong technological characteristics to promote convergence between different technology foundations, as shown in Table 3. Thus, a high possibility of successful innovation is expected in healthcare, and for the more sophisticated policymaking and strategy establishment, further research is required in more detail for technology levels.

There are some limitations to this study; first, there is a tradeoff between readability for problem detection and usefulness for making policies by adopting different technology classification levels for the analysis. For example, if a researcher uses 35

fields to test Hypotheses 1 and 3 instead of five sectors, then they must compare 595 technology pairs, which is difficult to comprehend. However, this comparison can be effective at the policy implementation stage. Moreover, the values of indices used for the hypotheses test in this paper can be changed by this classification level. Thus, finding the appropriate level and meaningful results may require checking the robustness of the index and comparing the values by using different classification levels.

Second, this dissertation divides the examined period into two, based on the trigger point of Korean ICT development. It cannot be enough to take the effect of time shock and the technology cycle into account. However, most modern technology in Korea has been developed since the 1950s, major innovations have emerged since the 1970s, and the growth rate of the overall new technology base (IPC) has slowed since 1990, as shown in Figure A.1. As the analysis includes all patent applications from the 1970s to 2009, and 1990 is chosen as the split point for period separation, this study has tried to control the effect of the time and technology cycle.

3.6 Conclusion

GPT can be used for a diverse range of technologies, products, and human lives. Thus, it can have a great effect on economic growth and the quality of human life. In the early

1990s, ICT in Korea was a representative example of this. There are many studies about role of ICT on productivity growth and the pattern of ICT evolution. However, none of the previous research has analyzed the nature of technology during technology convergence using national-level data.

This dissertation focuses on the convergence of the technological base. IPC is used as the technological basis; its co-occurrence in the same inventions is analyzed. For convergence analysis, a new framework is proposed, which consists of three important concepts: The ease, diversification, and acceleration of convergence.

The results showed 1) ICT (Sector 1) has a tendency to converge with other kinds of technology more easily than any other sectors. 2) ICT has the tendency to converge with the same kind of technology (ICT) more easily than sector 2 (instruments), 4 (mechanical engineering), and 5 (others), but not 3 (chemistry). 3) ICT gives and receives the greatest influence on technology convergence. In other words, it stimulates convergence. Thus far, it can be concluded that Korea's ICT sector has been more active in its promotion of convergence with neighboring technologies, and ICT has contributed to Korea's technology coevolution after centralizing related convergence rather than convergence with unrelated technology in the 1980s.

This study expected to help understand the structure and interaction mechanisms of technology from a systematic perspective, and improve national-level technology policies. Furthermore, the proposed framework was expected to derive the more fundamental nature of technology-related co-evolution. In the future, it will be valuable to investigate

the relationship between the three variables: Ease, diversification, and the acceleration of convergence for both sectors and countries to facilitate a precise understanding of the relationship between all technologies and their transformation as further study.

Chapter 4. Density and diversity of technology pool and network for firm innovation

4.1 Introduction

In Chapter 3, the different characteristics of the technology involved in different industries influence on convergence were identified by comparing five technology sectors according to their WIPO IPC-Technology Concordance. From the existing studies, it was determined that ICT plays a crucial role in industry and technology development, and its characteristics on the side of convergence with other industries' technology were overviewed in Chapter 3. In other words, the relationships between industrial technologies were examined in their networks by considering all Korean technologies.

Two studies in Chapters 4 and 5 identify the determinants that affect firms' and countries' innovation and economic development with the characteristics of their technological capabilities. In this chapter, this dissertation examines the effect of the diversity and density of the technology pool and network on innovation activities and the performance at a firm level.

From a national innovation perspective, there are many studies about the relationships between R&D investment, innovation, and finance. Comparative studies on several firms in European countries have been conducted by many researchers (Crepon, Duguet, & Mairesse, 1998; Hashi & Stojčić, 2013;Bogliacino & Pianta, 2011; Griffith, Huergo, Mairesse, & Peters, 2006), and Crespi & Zuniga (2012) performed a comparative study for South American countries. Moreover, there are studies about market competition and technological diversity in innovation research that take a systematic view (Castellacci,

2011; Miller, 2006; Suzuki & Kodama, 2004), and most found a positive relationship between R&D, innovation, and performance, though there are differences in the degree of influence.

Along with the research approach that investigates the relationship between R&D, innovation, and performance, the approach based on developing an understanding of the characteristics of resources and relationships between various resources such as structural features will provide valuable insights for improving firm management. In particular, the topic related to the structure of technology and human resources has continuously attracted interest. Many studies have examined the characteristics of organizations and the structure of firms and technologies (Watanabe, Hur, & Matsumoto, 2005; Watanabe, Matsumoto & Hur, 2004; Kim et al., 2009). Their changes and their effect on innovation have previously been carried out (Corrocher et al., 2007; Malerba & Orsenigo, 1997; Shin & Park, 2007; Hacklin et al., 2009; Lee et al., 2008; Lee et al., 2009). As mentioned in the previous chapter, technologically diversified firms show better innovation performance, and a high-density network structure in technology and collaborator promotes the faster growth of innovation outputs. However, disputes occur when firms' resources are limited, which is commonly the case in the real world. In this case, this problem changes to an issue of diversification and specialization strategies at the firm level. The effect of technological diversification and specialization on innovation has been a subject for debate in former literature; but the evidence for the relationship is ambiguous and mixed in its effect on diversification and specialization.

Stirling (1998), Chang & Wang (2007), and Jones & Hill (1988) mentioned that technological diversification has negative aspects. Diversity causes a loss of economies of scale, because firms must share their limited resources for diversification, and high transaction costs are an issue. To handle many types of technology, firms require greater information and infrastructure.

In spite of the negative side of diversity, technologically-diversified firms can gain advantages in markets. The positive side of diversity can be summarized as follows: i) Increasing technology cross-fertilization between different firms (Quintana-García & Benavides-Velasco, 2008), ii) managing the risk of failure in R&D projects (Garcia-Vega, 2006) iii) preventing the negative lock-in effect (Suzuki & Kodama, 2004).

However, most of those studies only focused on the partial or independent relationships related to innovation or finance, and the systematic approach is therefore insufficient. Moreover, previous innovation research has focused on the effects of technological diversification based on technological and industrial classification. The effect of diversity and the density of technology during the technology combination and convergence process is not examined deeply, even though its importance has increased recently. As mentioned in Chapter 3, it is important for firms to possess a rich technology pool in dynamic environments and the ability to converge existing technologies in the technology pool to create technology has proven very important in recent industries, such as those related to ICT. Though increasing the importance of this ability, few studies examine the effect of diversity and density during technology convergence, because the

process of linking heteroscedastic databases has to be done to analyze the relatedness of knowledge, innovation, and finance, and this process requires much manual work. In addition, since the history of the collected innovation research data is not long enough, long-term analysis using panel or time-series data was difficult to collect. Moreover, econometric analysis, which analyzes knowledge itself and its effects systematically, has been conducted. Time-dependent research on innovation that contains technology pool and technology network could not be performed because of its lack of observations. This chapter describes the general relationship between R&D, innovation, patenting, and performance, and the effect of technology structure on these behaviors across firms.

To achieve this, this dissertation proposes developing a systematic innovation model such as the Crepon-Duguet-Mairesse (CDM) model (Crepon et al., 1998) to improve our understanding of the characteristics of the technology pool and network in innovation activities and performance.

This study is conducted with four Korean innovation surveys from 2002–2010 and all data patents of individual firms, which were collected from EPO and its financial material. Through this data, this study expects to identify the influences of Korean firm's technological characteristics on manufacturing innovation and its results. There exist limitations in using the technology index, which is a proxy that consists of limited samples and patents. However, this study will be the cornerstone of the diagnosis of Korean innovation structure.

This study attempts to bridge the gap of innovation study based on CIS and the

network study of knowledge structures by examining the effect of knowledge structure on innovation activity and firms' performance. To accomplish this, the characteristics of a technology pool and network using all patent applications from firms are analyzed. After calculating the density, diversity, and clustering index from the technology pool and network constructed using the IPC of patent applications, the relationships between these indices, R&D investment, innovation output, and labor productivity using econometric analysis are investigated.

The remainder of this chapter is organized as follows: Section 4.2 explains the dataset, the terms technology pool and network, measurements based on the characteristic of the technology pool and network. Section 4.3 provides the results from descriptive and empirical analysis. Section 4.4 and 4.5discuss the results, and then conclude and suggest areas for further study.

4.2 Methodology

4.2.1 Data

This study makes use of samples by merging three kinds of databases between 2001 and 2009 to analyze Korean manufacturing firms: Firms' financial statements, innovation survey data, and patent application information.

Firm's R&D activity related to information such as R&D expenditure and the number of R&D employees was extracted from the Korean Innovation Survey (KIS) data (2002, 2005, 2008, and 2010). The Science and Technology Policy Institute has conducted this

survey in Korea since 2002, following the guidelines in the OECD's Oslo manual.

Two finance and firm information databases are used to extract the number of employees, the firm's age, the Herfindahl index, and the industry classification. One of the databases is the Korea Information Service-Value (KIS-VALUE) database from Korea Investors Service, Inc. Another is the TS2000 database from the Korea listed companies association. To make more accurate and abundant samples, both databases were considered together.

Lastly, The European Patent Office (EPO) Worldwide Patent Statistical Database version 4.31 (11-10-2011) is the main source for patents. Like the finance and firm information databases, patent information from the KIS data is also considered an accurate sample. Using the patent application data, this paper constructs a technology capability pool and network, then calculates six technology-related indices from pool and network.

To connect three kinds of data, all patent application information is first subtracted from the EPO patent database using the firm list of four KISs. There are many same or similar firm names, but they are not identical. To identify the firms between those databases, a corporate registration number is used, as is the applicant's address, industry classification, the date of the firm's establishment and their patent applications. This dissertation omits some observations that cannot be identified by this information and missing core variables such as firms' R&D expenditure and employment. Our final sample consists of 3,772 firms.

Because each KIS refers to several years (KIS2002 to 2000–2001, KIS 2005 to 2002–2004, KIS 2008 to 2005–2007, KIS 2010 to 2007–2009), data from KIS such as the existence of products and process innovation is not yearly data, but two- or three-year period data. However, this dissertation extracts patent and financial data from other databases, and the others have yearly values.

This dissertation primarily collects yearly value except in analysis about product and process innovation. However, I collapsed the panel to four periods that cover the 2000–2009 for analysis of the product and process innovation. Hall, Helmers, Rogers, & Sena (2013) used averaged values or the maximum value for three years. However, this dissertation adopted the final year value for each survey. For example, KIS2010 refers to 2007–2009 data. Therefore, this dissertation uses it as information about 2009. It is why the standard deviation for each variable value within each firm was small. In addition, some variables, such as sales from new products, are only about the last year of KIS.

Because the panel is highly unbalanced, tests were carried by pooling data for Korean firms for 2000–2009. This dissertation describes the general relationship between R&D, innovation, patents, and performance, and the effect of the technology structure on these behaviors across firms.

Table 5. Types of innovation

n=3180	nprd.mk[1]	nprd.firm[2]	nprc.mk[3]	nprs.firm4
All firm	719	420	560	247

R&D	278	149	226	51
R&D.patent	278	149	226	51
Share of sample				
All firm	24.3%	14.2%	18.9%	8.4%
R&D	76.2%	40.8%	61.9%	14.0%
R&D.patent	76.2%	40.8%	61.9%	14.0%

Note

1: Innovators with product new to the market

2: Innovators with process new to the market

3: Innovators with product new to the firm, but not the market

4: Innovators with process new to the firm, but not the market

Table 6. Share of patenting firms by technology intensity and innovation activities

	All Manufacturing Industries			High-technology industry			Medium-high-technology industry			Medium-low-technology industry			Low-technology industry		
	All	Patent	Share*	All	Patent	share	All	Patent	share	All	Patent	share	All	Patent	share
All	2957	517	17.5%	1046	55	5.3%	857	114	13.3%	821	246	30.0%	233	102	43.8%
Does R&D	365	365	100.0%	30	30	100.0%	66	66	100.0%	186	186	100.0%	83	83	100.0%
Innovation	1028	403	39.2%	239	33	13.8%	271	87	32.1%	391	201	51.4%	127	82	64.6%
no R&D or Innovation	1872	57	3.0%	799	14	1.8%	577	18	3.1%	402	17	4.2%	94	8	8.5%
Innovation But no R&D	720	95	13.2%	217	11	5.1%	214	30	14.0%	233	43	18.5%	56	11	19.6%
R&D but no innovation	57	57	100.0%	8	8	100.0%	9	9	100.0%	28	28	100.0%	12	12	100.0%
Does R&D and innovates	308	308	100.0%	22	22	100.0%	57	57	100.0%	158	158	100.0%	71	71	100.0%

Table 7. Characteristics of firm's technology pool and network

	High-technology industry				Medium-high-technology industry				Medium-low-technology industry				Low-technology industry			
Variable	Mean	S.D	Med	Obs	Mean	S.D	Med	Obs	Mean	S.D	Med	Obs	Mean	S.D	Med	Obs
cum tech exp	434.32	851.15	112	47	819.56	3259.73	74	99	1017.17	6252.30	75	244	3057.97	25294.53	79	115
ipc tech scope	199.40	357.16	60	47	187.12	581.39	37	99	132.93	327.28	33	244	194.30	825.88	36	115
diversity in tech	0.81	0.11	0.82	47	0.76	0.12	0.75	99	0.74	0.13	0.75	244	0.74	0.13	0.75	115
network density	0.17	0.22	0.09	47	0.19	0.21	0.12	99	0.18	0.20	0.12	244	0.19	0.18	0.14	115
network diversity	1.56	0.77	1.26	47	1.62	0.62	1.58	97	1.62	0.67	1.41	242	1.89	0.80	1.91	112
network clustering	0.70	0.23	0.70	47	0.69	0.24	0.72	96	0.66	0.23	0.65	242	0.72	0.23	0.76	111

4.2.2 Technology pool and network

This study uses two index groups from the technology pool and technology network. The technological competitiveness of each firm shows the characteristics of individual firms within networks, and this can be discussed through the technology position for country-level technology networks.

However, Gilsing, Nooteboom, Vanhaverbeke, Duysters, & van den Oord (2008) found that position alone does not describe all relationships with new creations and the absorption of knowledge. Moreover, if we compose an IPC co-occurrence network based on the accumulation of Korean patent applications, firms' positions must be compared in a giant network composed of about 60,000 active IPC codes and 10 million links. For instance, if most firms hold less than 100 patents, it is difficult to make effective comparisons between firms. Because of this, most research studies have only dealt with the shape of the technology network, transformation, and firms' position in specific industries and circumstances. However, this type of research cannot identify technology and industry boundaries like ICT and the bioindustry, where technological convergence and industrial boundary corruption arises. Moreover, if analyses are limited to specific standards, they can miss new important technological convergence. In addition, networks that use partial data sometimes make the opposite result in holistic network analysis (Barabasi et al., 2002).

This dissertation composes each firm's technological capability pools and networks, then calculates the index from these characteristics. After this, the comparison and indices

of different firms in similar industries and their influence on innovation have followed. To confirm this, this dissertation uses IPC as a unit of analysis like (Strumskya, Lobob, & Leeuwb, 2012), which used USPC as an indicator of technology capability. Strumskya et al. (2012) supposed that "a patented invention is an instantiated combination of technologies from the defined set of all possible combinations of technologies," referring to the set of technology codes, the United States Patent Classification (USPC).

IPC is assigned by patent examiners, and is Mutually exclusive and collectively exhaustive (MECE). Therefore, the method using IPC could be better than those of text-mining techniques or citation information for identifying firms' technological capabilities, spaces, and complexity, for comparison with others. Moreover, Choi et al. (2007) and Joo & Kim (2009) mentioned that it is a reasonable source for technology comparison and forecasting over time.

Firm applications are classified in terms of the IPC code. In this dissertation, the set of these IPCs is the technology pool. Beside the technology pool, the technology network is defined as the co-occurrence of IPCs in same patent application. In other words, each IPC in a technology network is related to other IPCs. To be specific, the relationship only indicates the technological capacity when used in the same invention and proxied by IPC.

Knowledge and technology are cumulative; due to the nature of technology, a firm's accumulated technological capabilities will affect its ability to create new knowledge. Therefore, when measuring the characteristics of a technology pool and network, the

information of accumulated patent applications is used. The subgroup of indices is detailed in the next section.

4.2.3 Measuring the characteristics of technology pools and networks

Identifying the characteristics of technology pools and networks, as explained in the previous subsection, and measuring them as indices is the first step in examining the impact of technology composition and technology network configuration on firm innovation and performance.

Many previous studies have used patents to analyze the characteristics of technology, the competitiveness of firms, and countries' innovation capabilities. Neuhäusler (2012) used the number of patents and the patent intensity, which is defined as patents per unit of R&D expenditure as a firm, to examine the effects of firms' different characteristics. The number of patents is a simple but important measure of firms' R&D and innovation performance, but has limits when measuring the quality or value of a patent. Therefore, several scholars have proposed other patent quality indicators to measure the value of innovation output and technological competiveness accurately, such as cites per patent, current impact index (CII), and technology strength (TS) (Chen & Chang, 2010).

Furthermore, indices that consider technology diversification, depth, and position on the patent network are designed and applied to many studies. One example of this is (Bekkers & Martinelli, 2012); they used indices based on a firm's position in the patent

citation network to examine the effect of the firms' knowledge positions on technological changes.

The measurement is divided into two groups: (1) Measuring the characteristics of the technology pool (2) measuring the characteristics of the technology network. The technology pool indicates the quantity of technologies that are available for a firm to combine for new inventions such as patent applications. Although those who study open innovation deal with their interaction with other innovation sources or the position of the holistic structure, in reality most of sources of knowledge are one's inner resources. Therefore, for most innovation research, understanding inner source and structure is important. This chapter analyzes each firm's overall technology structure and its effect on innovation.

If a co-occurrence network is composed, then isolated technology capabilities cannot be handled for the analysis. Thus, a similar index is used that can represent the whole technology capabilities pool.

4.2.3.1 Measuring the characteristics of a technology pool

Three characteristics of technology pool are measured: 1) A firm's experience of using technology, 2) the scope of their technology capabilities (Richness of technology capability), and 3) diversity in the technology pool.

4.2.3.1.1 Firm's experience of using technology

A firm's skill-level for technology usage might be proportional to the number of technologies they use. This index does not simply distinguish whether similar or different technologies were used several times, but measures the degree of technology usage experience. Since IPC observation is a technology capability that can be used when creating an invention, this dissertation uses the number of all IPC codes that are assigned to patents to measure a firm's experience with technology applications. There are innovation strategies based on learning by doing, using, and interacting (Jensen, Johnson, Lorenz, & Lundvall, 2007). Measuring the degree of a firm's experience with technology evaluates that firm's learning system.

4.2.3.1.2 Scope of technology capabilities (Richness of technology capabilities)

The scope of technology capabilities measures the breadth of technology capabilities in a firm, and reflects the richness of their technology capabilities. The more different IPC sets a firm has, the broader the technology base a firm can use for new inventions. For this purpose, this dissertation uses the number of a firm's unique active IPC codes. Özman (2007) adopted a direct count of the number of secondary IPC codes in a patent to measure the breadth of the patents themselves, and to measure the average breadth of patents in certain fields.

4.2.3.1.3 Diversity in the technology pool

The diversity index using nodes on the technology network cannot consider isolated nodes, which is when a patent application is categorized into just one IPC. However, the share of solo IPC patent applications is large. In such a situation, using a diversity index from the technology pool is appropriate.

To measure diversity in the technology pool, this dissertation uses the entropy measure employed in the previous chapter.

Entropy index in a technology pool:

$$\varepsilon_i = -\sum_{j=1}^{m_{it}} P_{ij} \ln(P_{ij}), \qquad \text{Eq. (9)}$$

P_{ij} is firm i's share of IPC j over all years, except those where dependent variables are measured; it can be expressed as $Pij = n_{ij}/ N_{i.} m_i$, which is the total number of IPC categories (technological field) into which firm i's patent applications have been classified. n_{ij} is the sum of firm i's patents, classified as IPC code j. N_i is the sum of IPC codes that appear in firm i's patents

4.2.3.2 Measuring the characteristics of technology networks

Indices from a technology network are only measured when each technology has participated in creating an invention as the technological part. Before we move on to the interactions between each technology, indices from the technology pool tell us of the

empirical size, the range of held technology, and the diversity of technology possession.

For instance, the diversity of indices from technology networks represent whether various technologies are combined when each technological base makes several inventions, but the diversity of indices from the technology pool shows how broad a technological experience it has made, in other words, whether firm possesses various technologies which are resource for the new invention. As we can see from this, indices from the technology pool show us what shape firms have that is a necessary technology for invention or innovation, and indices from the technology network tell us how real companies manage technology for inventions .

4.2.3.2.1 The Network Density

Cowan and Jonard (1999) pinpointed the role of networks in the creation and diffusion of knowledge, and showed that high-density network structures allow knowledge to grow more rapidly. This dissertation makes a binary co-occurrence network, then measures the graph density. Using each firm's patent applications, an IPC co-occurrence network is constructed. In contrast to other network measurements that use a weighted network, this dissertation uses a binary network. The purpose of measuring the technology network is to examine the degree of overall connections between technology capabilities. If using a weighted network, the frequency of linkages between certain technology capability pairs is reflected in the index, which in return changes the mean of density. The network density is the ratio of the number of linkages and the number of

possible edges. It is defined as follows:

$$d = \frac{L}{g(g-1)} \qquad \text{Eq. (10)}$$

L refers to the number of linkages in the network, d is the network density, and g is the number of nodes

4.2.3.2.2 The Network Diversity

The network diversity also uses the scaled entropy index instead of the entropy index. The difference between diversity in technology pool and network diversity is the average entropy index of all nodes in the technology network.

The entropy index of the technology network:

$$\varepsilon_i = -\frac{\sum_{k=1}^{n_i} \sum_{j=1}^{m_{ik}} P_{ikj} \ln(P_{ikj}),}{n_i} \qquad \text{Eq. (11)}$$

On firm i's IPC co-occurrence network, P_{jkj} is node k's share of the link with the IPC j; it can be expressed as $P_{ikj} = n_{kj} / m_{ik.}$ m_{ik}, which is the total number of IPC categories (technology scope) in node k. This is identical to the total degree of node k. n_{kj} is the sum of node k's links connected with IPC code j. N_i is the sum of nodes that appear in firm i's patent network. P_{ij} is the proportion of i's degree with node j over the total degree of node

i, *m* is the number of nodes that are linked to node i, and k is the total degree of node i. The index has range of 0–1. If more nodes have a connection with various other IPC nodes in technology networks, it shows a larger value for the entropy index of the technology network.

4.2.3.2.3 Clustering coefficient

To measure the clustering coefficient in technology network, this dissertation uses the global clustering coefficient of a technology network. Unlike the local clustering coefficient used in Chapter 3, the global clustering coefficient measures the degree of clustering in the overall network. The global clustering coefficient is defined as the ratio of the triangles and connected triples in the network. The clustering coefficient for measuring this probability has a range of 0–1, the coefficient of a fully connected graph is 1, and that of a star network is 0. Many real-world networks typically have values in the range 0.1–0.5 (Girvan & Newman, 2002). A fully connected graph is 1 and a star network is 0. many real-world networks typically have values in the range 0.1–0.5 (Girvan & Newman, 2002). The Higher clustering coefficient of a IPC co-occurrence network means that the firm has made more inventions to which multiple technology capabilities can be applied

4.2.4 Empirical model and estimation method

4.2.4.1 Variable

In addition, from the measurements from technology pool and network described in

previous measurement section, this dissertation has categorized variables into three groups: 1) Innovation and performance, 2) characteristics of technology, and 3) controls group. The innovation and performance variables group are measurements related to innovation activities and the output of firms such as R&D engagement, R&D intensity, the sum of patents, the share of new products in sales, labor productivity, and product and process innovation achievements. This dissertation has defined R&D intensity as the annual R&D expenditure per employee for R&D-performing firms. The sum of patents means the annual sum of patent applications for which the firm has applied each year. The number of patents is a representative index of innovative output measurement (Seppä, 2007), but innovative output is not always patented or patentable (Crepon et al., 1998). Therefore, this paper adopts innovative sales variables measured as a share of the new product in sales besides the number of patents.

The characteristics of the technology variables group are indices from the technology pool and network described in the previous section. The test omits the technology scope in this analysis, because of the high correlation (0.822) between the other two indices from the technology pool. These can infer the trend of the technology scope using diversification in the technology pool, because diversity measurement depends on the number of technology classification and the evenness between them (Izsáki & Papp, 1995).

This dissertation uses industry affiliation, market concentration, age, and the size of firms, and the year as control variables. Revilla & Fernández (2012) showed that a firm's size

affects a firm's innovation activity. They examined the effect of firm size by considering the different dimensions of the technological regimes such as appropriability, technological opportunities, and knowledge accumulation. They discovered that small firms had higher innovation performance when technological opportunities and the frequent usage of IPRs were high.

The empirical model includes an industry dummy, and this paper uses the aggregation of the manufacturing industry based on the statistical classification of economic activities in the European Community (NACE) at the two-digit level.[1]

The Herfindahl index (HHI) is used as a market concentration index. The index is calculated according to the two-digit Korean standard industrial classification (KISC) codes and the sales of the sample firm. The number of employees is used as a proxy variable for firm size.

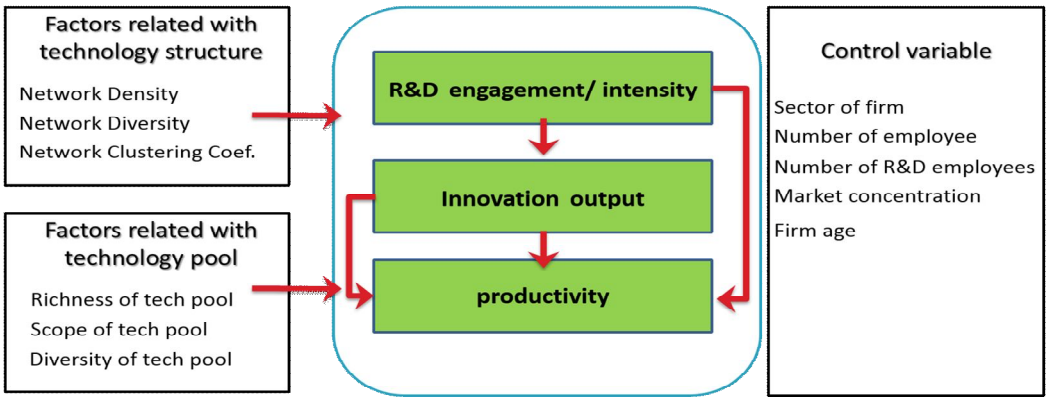


Figure 6. Empirical model in firm level

[1] This classification apply the technological intensity of sectors expressed as R&D expenditure/value added, and classifies the sectors as high, medium or low technology according to the score obtained. To get this classification from dataset, I merge concordance table between International standard industrial classification(ISIC) and Korean standard industrial classification (KISC) and Statistical classification of economic activities in the European Community (NACE)

Table 8. Definition of variables for the country study

Variable	Definition
R&D engagement	Whether firm invests R&D or not
R&D intensity	Amount of R&D expenditure per employees
app_year_sum	Sum of application for one year
nprd	Share of new product in sales
productivity	Labor productivity(value added per employees
cum tech exp	Sum of IPC codes (in log)
ipc tech scope	Sum of unique IPC code (in log)
diversity in tech pool	Entropy of IPC pool
network density	Density of IPC co-occurrence network
network diversity	Average Entropy of IPC nodes in IPC co-occurrence network
network clustering	Clustering coefficient of IPC co-occurrence network
nprd.mk	Whether firm have product innovation new to the market
nprd.firm	Whether firm have product innovation new to the firm
nprc.mk	Whether firm have process innovation new to the market
nprc.firm	Whether firm have process innovation new to the firm
predicted R&D intensity	R&D intensity value fitted from R&D intensity
predicted number of patents	Patents estimated at innovation equation by negative binomial GLS
tech.lvl (dummy)	High-technology industry
tech.lv2 (dummy)	Medium-high-technology industry
tech.lv3 (dummy)	Medium-low-technology industry
tech.lv4 (dummy)	Low-technology industry
R&D emp	Number of R&D employees
emp	Number of employees as firm's size proxy
industry HHI	Industry concentration using the Herfindahl-Hirschman Index
firm age	Firm's age
Exp.yn	Whether the firm exports

4.2.4.2 Model and estimation method

This study modified the conventional CDM model to examine the effect of the knowledge pool and firm networks on firms' innovation and performance behavior. Our model consists of three sub-models; the first sub-model contains two equations for describing firms' R&D behavior, the first of which is a selection equation to specify a firm's R&D engagement. The second equation identifies firm's R&D intensity conditions on a firm's R&D engagement.

To correct for selectivity biases, estimation adopts two equations systemically using a generalized Tobit model. If g^*_{it} is a latent (unobserved) R&D engagement variable and k^*_{it} is a latent R&D intensity variable, the first sub-model, the R&D engagement equation, and the R&D intensity equation can be expressed as:

The R&D engagement equation:

$$g_{it} = x^0_{it}\beta_0 + u^0_{it}$$

$$g_{it} = 1 \text{ if } g^*_{it} > 0 \text{, else } g_{it} = 0 \qquad \text{Eq. (12)}$$

The R&D intensity equation:

$$k_i \mid g_{it} > 0 = x^1_{it}\beta_1 + u^1_{it}$$

$$k_{it} = k_{it} \text{ if } k^*_{it} > 0 \text{, else } k_{it} = 0 \qquad \text{Eq. (13)}$$

The second sub-model is the innovation output equation:

$$p_{it} = \gamma_1 k^*_{it} + x^2_{it}\beta_2 + u^2_{it} \qquad \text{Eq. (14)}$$

p_{it} is the innovation output proxied by (a) the annual sum of patent applications, (b) the share of new products in sales

k^*_{it} is the latent R&D intensity variable predicted from the generalized Tobit model in the first sub-model. x^2_{it} is a vector of the determinants of the innovation output. Vector β_2 corresponds to unknown parameters, and u^2_{it} is an error term.

This dissertation estimates the innovation output equation using the annual sum of patent applications as a dependent variable and a negative binomial generalized linear model. To examine the effect of the knowledge pool and network on innovation output, studies should use information from the patent application data; it would mean that firms without patent applications are omitted from the estimation. It can create sample selection biases in the R&D equation (Hall, Helmers, Rogers, & Sena, 2013); therefore, it is reasonable to adopt the generalized Tobit model like R&D Eqs (13) and (14). Nevertheless, because independent variables in the innovation output equation count the variables and the distribution is far from the normal distribution, it is not relevant to use OLS in the intensity part. The result of fitting that uses a negative binomial generalized linear model is better than the Tobit model in terms of the goodness of fit on the regression model.

The model takes the predicted value using the estimation result from the previous

stage equation (Griffith et al., 2006); for example, the innovation equation used the predicted R&D intensity from the estimated generalized Tobit equation. It takes care of the endogeneity of the R&D intensity variable in the innovation equation.

The third sub-model is the performance equation

$$q_{it} = \gamma_p p^*_{it} + x^3_{it}\beta_3 + u^3_{it} \qquad \text{Eq. (15)}$$

q_{it} is the firm's performance. For this measure, this dissertation uses (a) a firm's labor productivity, as defined by the log value added per worker, and (b) the share of a firm's turnover that is due to innovation.

p^*_{it} is the latent innovation output variable predicted from Eq (14). x^3_{it} is a vector of the determinants of labor productivity.

4.3 Analysis Result

4.3.1 Descriptive analysis

In total, 7,058 samples firms from merged databases were collected, and the study used 3,456 sample firms at the stage of R&D engagement analysis. The sizes of the sample used for the innovation output and productivity analysis were smaller than that used for the R&D engagement analysis, because the sample was limited to firms engaged in R&D expenditure, patent application, and product and process innovation.

As shown in Table 12, the percentage of the sample of firms that expended R&D costs in their financial statement during the relevant three-year period is 12.6% (R&D.yn),

while 24.3% of firms had product innovations that were new to the market. The sample mean of labor productivity was 71.491, and its skewness was 6.286. This means that almost all firms had a low level of related labor productivity. The R&D intensity, the sum of applications for one year (app_year_sum), the sum of IPC codes (ipc tech scope), the network density, and the number of employees in the R&D part (R&D emp) also show distributions similar to productivity. Contrary to this, the diversity in the technology pool and network clustering was skewed to the left (negative skew). These facts relating the characteristics of the technology pool and network can be confirmed in Figure 7.

This dissertation checked the difference between the characteristics of firms' technology pools and networks by the technology intensity of industry through Figures 8 and 9; the histogram in Figures 8 and 9 show higher diversity in technology pools, but lower density and diversity in the network. This means that firms in high technological-intensity industries have higher diversity in the technology pool than firms in technological-intensity industries in the Korea manufacturing industry. However, the frequency of inventions to which firms apply their various technology capabilities together is lower.

In low technological-intensity firms, the mean (Figure 8) of technology's scope (ipc.tech.scope) is higher than the median (Figure 9). This means that there is large gap within low technological-intensity firms in the scope of their technology, and most have a lower technology scope. Because the sum of applications for one year (app_year_sum), which is a dependent variable of the innovation equation, has the characteristics of

counting variables and a positive skew, this study uses a negative binomial generalized linear model to estimate the innovation equation.

Table 9. Descriptive statistics of the firm sample

Variable	Mean	S.D.	Median	Skew	Kurtosis	Obs
R&D.yn	0.126	0.332	0.000	2.247	3.050	3456
R&D intensity	1204.895	5693.374	0.000	10.139	162.979	3456
app_year_sum	10.555	159.247	0.000	32.714	1235.060	2957
nprd	40.052	32.316	30.000	0.618	-0.936	1148
productivity	71.491	83.580	50.490	6.286	65.672	3176
cum tech exp	1388.921	12905.455	79.000	18.319	367.554	505
ipc tech scope	163.715	533.094	36.000	9.385	120.270	505
diversity in tech pool	0.752	0.125	0.758	-0.636	0.829	505
network density	0.184	0.200	0.124	2.405	6.501	505
network diversity	1.676	0.711	1.510	0.919	0.429	498
network clustering	0.681	0.235	0.702	-0.509	-0.122	496
nprd.mk	0.252	0.434	0.000	1.145	-0.689	3455
nprd.firm	0.156	0.363	0.000	1.898	1.604	3455
nprc.mk	0.197	0.397	0.000	1.527	0.331	3455
nprc.firm	0.093	0.290	0.000	2.803	5.861	3455
R&D emp	27.294	243.496	2.000	38.479	1755.870	2719
emp	261.500	1311.522	45.000	14.593	255.795	3456
idustry HHI	0.076	0.065	0.057	3.145	25.958	3456
firm age	16.065	11.740	12.500	1.475	2.241	3456
Exp.yn	1.413	0.493	1.000	0.351	-1.877	3456

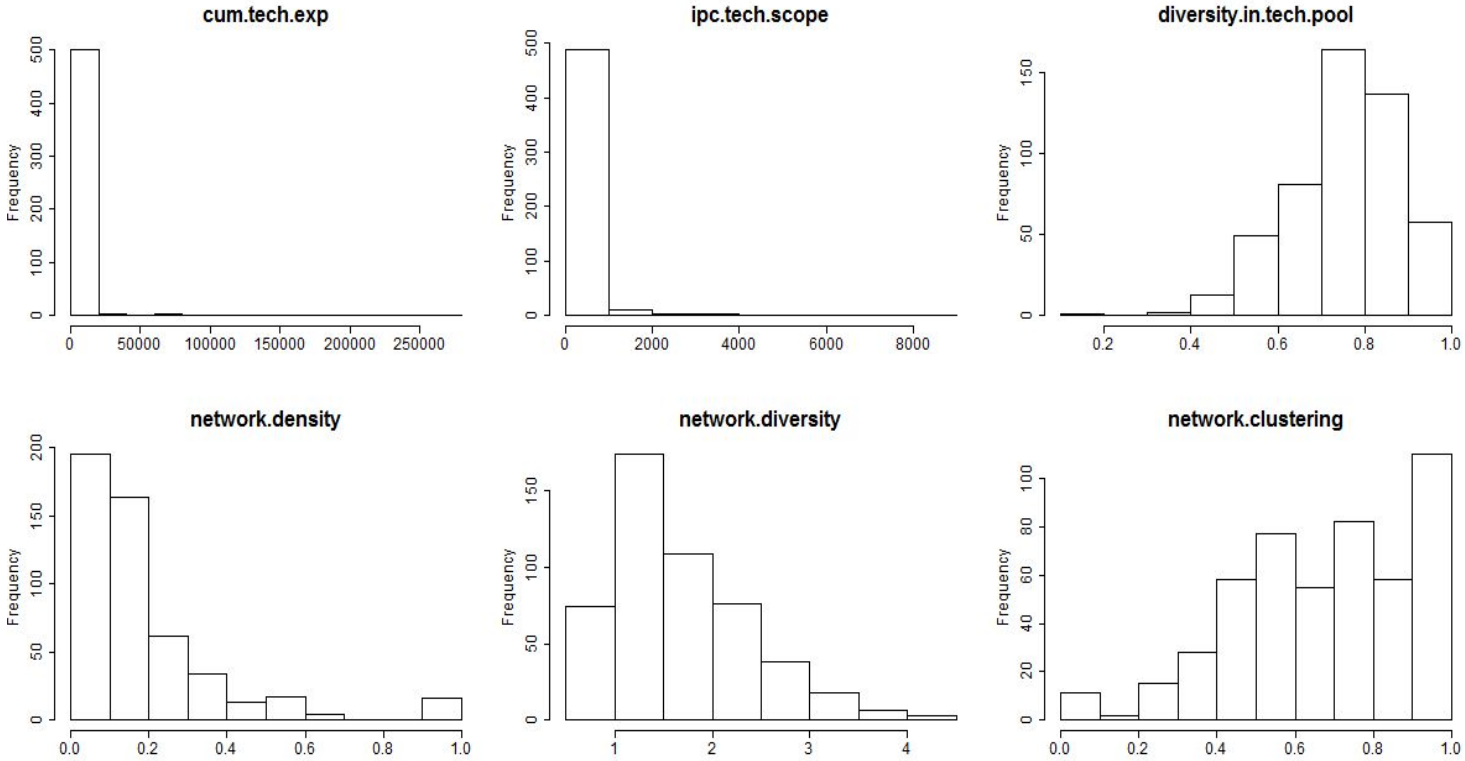


Figure 7. Distribution of firm according to characteristics of technology structure

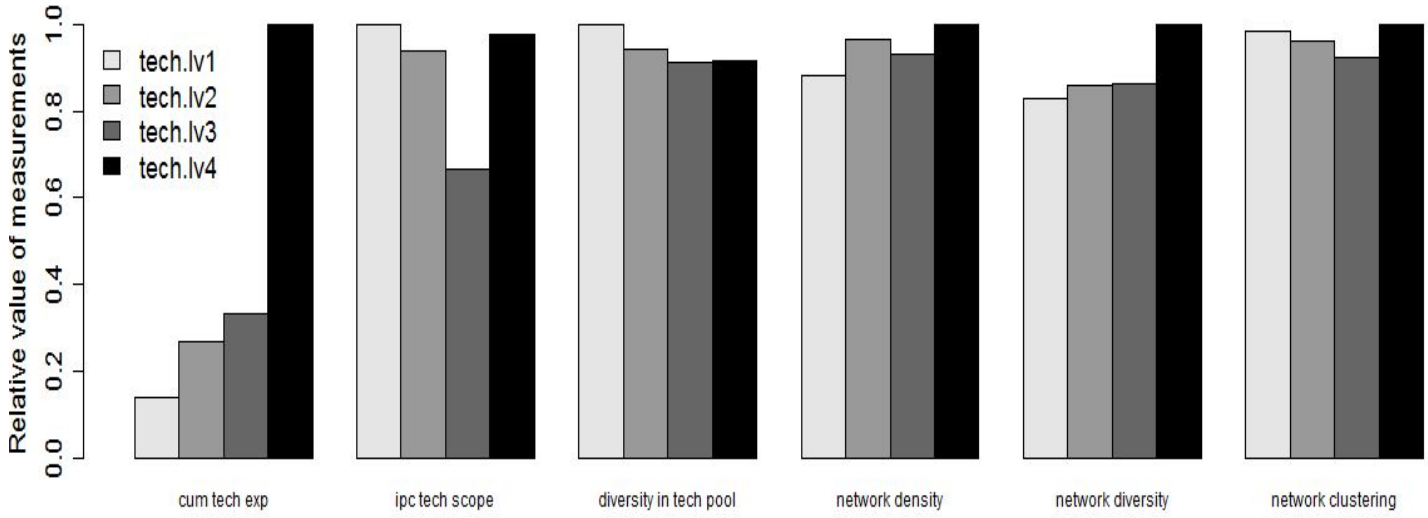


Figure 8. Characteristics of firm's technology structure by technology level (mean)

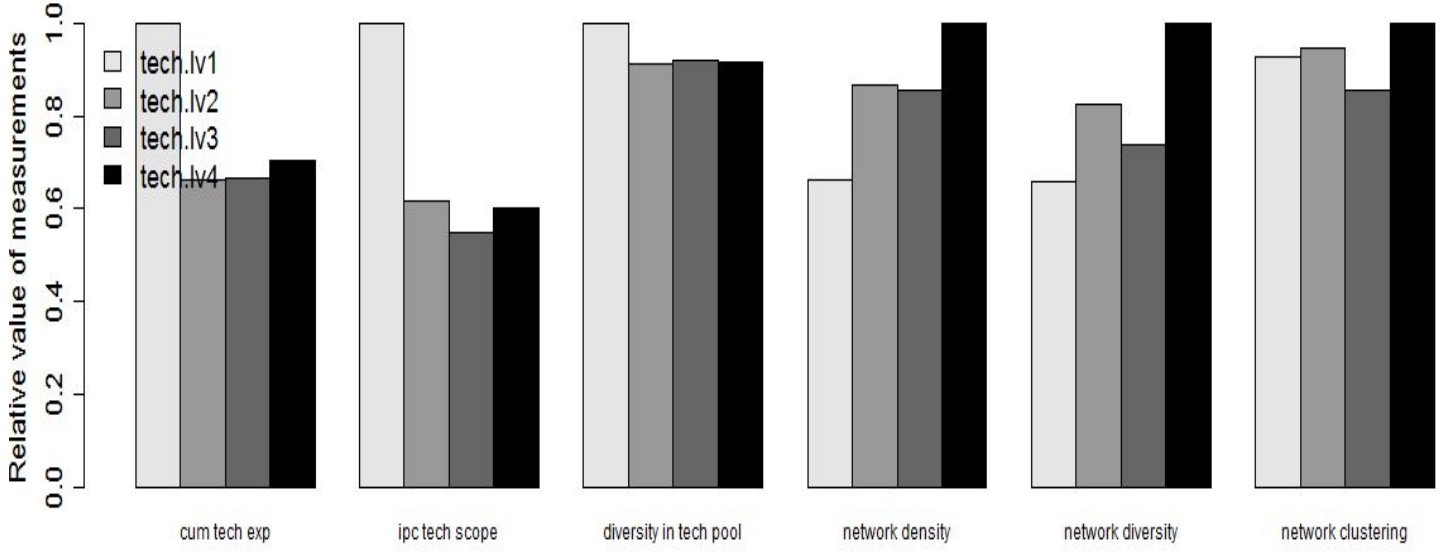


Figure 9. Characteristics of firm's technology structure by technology level (median)

4.3.2 The effect on Research and development activity

Table 13 summarizes the results of estimation from R&D engagement and the intensity equation using Generalized Tobit. As shown in Table 13, ρ is not significant. This means that the error terms u_{it}^{0} in Eq (12) and u_{it}^{1} in Eq (13) are not correlated, so the generalized Tobit model is not required to correct sample bias. As shown in Table 13, the results estimated from the Tobit part of the generalized Tobit model and OLS are identical.

The Probit part of Table 13 represents the effect of firm size, industry concentration, firm age, whether a firm exports, and whether it is engaged in R&D. Firm size is measured as the number of employees, and whether the firm exports has a positive relationship with the probability of it engaging in R&D. This is consistent with the previous literature (Crepon et al., 1998; Cohen at al., 1996; Crespi & Zuniga, 2012)

Table 14 summarizes the results of estimation from the R&D intensity equation using OLS and FGLS instead of the generalized Tobit model. The coefficient of technology use experience, the diversity in the technology pool, and network diversity are positive and significant. However, neither network diversity nor clustering is significant. This means all the density and diversity of technology capabilities have a positive relation with R&D intensity. Making a firm's technology capabilities broader and deeper requires greater R&D expenditure.

Table 10. R&D engagement/intensity equation (Generalized Tobit)

R&D engagement	Probit part(Obs.: 3722)
tech.lv2 (dummy)	0.508 (0.128)***
tech.lv3 (dummy)	1.169 (0.116)***
tech.lv4 (dummy)	1.330 (0.136)***
number of employees	0.626 (0.033)***
idustry HHI	-0.676 (0.541)
firm age	0.016 (0.055)
exp.yn (yes)	0.443 (0.085)***
constant	-5.174 (0.212)***
R&D intensity:	Tobit part(Obs.: 437)
log cum tech exp	0.346 (0.097)***
diversity in tech pool	1.615 (0.792)**
network density	0.959 (0.543)*
network diversity	-0.114 (0.163)
network clustering coef	0.088 (0.420)
tech.lv2 (dummy)	-0.238 (0.344)
tech.lv3 (dummy)	0.670 (0.356)*
tech.lv4 (dummy)	0.877 (0.384)**
number of employees	-0.135 (0.137)
idustry HHI	-1.431 (0.968)
firm age	-0.328 (0.112)***
4 Period_dummies	YES
constant	5.762 (1.329)***
σ	1.578 (0.057)***
ρ	0.126 (0.157)
-2LogL	1532.398

Significance levels: **** p<0.01; **p<0.05;*p<0.1

Table 11. R&D intensity equation (OLS, FGLS)

	OLS	OLS	FGLS
cum tech exp	0.360 (0.097)***	0.415 (0.097)***	0.359 (0.093)***
diversity in tech pool	1.650 (0.805)**	1.575 (0.821)*	1.226 (0.786)
network density	0.997 (0.551)*	0.536 (0.548)	0.800 (0.534)
network diversity	-0.127(0.165)	-0.306 (0.162)*	-0.155 (0.161)
network clustering	0.084 (0.428)	0.010 (0.436)	0.275 (0.416)
tech.lv2 (dummy)	-0.310 (0.338)	-0.458 (0.343)	-0.307 (0.344)
tech.lv3 (dummy)	0.511 (0.300)*	0.448 (0.306)	0.396 (0.295)
tech.lv4 (dummy)	0.699 (0.318)**	0.647 (0.325)**	0.580 (0.313)*
number of emp	-0.221 (0.087)**	-0.316 (0.083)***	-0.259 (0.082)***
idustry HHI	-1.347 (0.978)	-1.118 (0.982)	-1.483 (1.087)
firm age	-0.333 (0.113)***	-0.251 (0.113)**	-0.314 (0.108)***
4 Period_dummies	YES	No	YES
Constant	6.527 (0.933)***	7.972 (0.880)***	7.192(0.915)***
R-sq:	0.171	0.131	0.140
Adj R-sq:	0.144	0.108	0.112
Breusch-Pagan	23.0071*	10.1895	437

Significance levels: **** p<0.01; **p<0.05;*p<0.1

Note: Observation: 346

4.3.3 The effect on the innovative output

Table 15 and Table 16 summarize the results for the innovation output equation, to determine the relationship between the characteristics of the technology pool and network, and the innovation output. Table 15 presents the results from the model using the sum of patents as a dependent variable, Table 16 is the result of the model using the share of new products in sales.

As mentioned earlier by (Crepon et al., 1998), innovative output is not always patented or entirely patentable; thus, this paper also adopted the share of new products in sales instead of the number of patents. The results of the two submodels are similar to Table 15 and Table 16, even though the size of the effect and the statistical significance of the coefficients are different.

The density of the technology pool and network has a positive relationship with the innovation output. The positive effect of the network density on the innovation output, which is measured by the sum of patents and the share of new products in sales, is also robust for different models and methods. The effect of the technology usage experience is defined as the number of IPCs in all patent pools, which is also positive and robust for models that use the share of new products as an independent variable.

Unlike density, the diversity of the technology pool and network has a negative relation with the innovation output. The coefficient of the network diversity in a model using the sum of patents is significant and robust, as shown in Table 16. In addition, diversity in the technology pool shows a trend of a negative effect on the sum of patents,

but this is neither significant nor robust.

The effect of diversity of the technology pool and the network on the share of new products in sales shows a negatively trending relationship with the innovation output, but not to a significant degree.

Table 12. Innovation Output estimation results at the firm level (patent)

Variable	N.B GLM	N.B GLM	OLS	FGLS
observation	*n=355*	*n=355*	*n=355*	*n=355*
cum tech exp	0.861 (0.107)***	0.779 (0.099)***	70.080 (11.26)***	18.159 (3.78)***
diversity in tech pool	0.721 (0.646)	-1.180 (0.632)*	-104.764 (67.72)	-11.193 (19.53)
network density	0.970 (0.448)**	0.916 (0.436)**	125.108 (46.59)***	24.439 (13.96)*
network diversity	-0.775 (0.117)***	-0.693 (0.118)***	-71.300 (12.33)***	-17.081 (4.04)***
network clustering	0.038 (0.289)	0.116 (0.298)	52.392 (29.97)*	7.428 (8.55)
nprd.mk	0.122 (0.152)	0.060 (0.145)	3.530 (15.72)	2.664 (4.29)
nprd.firm	-0.001 (0.115)	-0.019 (0.119)	0.783 (12.06)	-1.766 (3.44)
nprc.mk	-0.071 (0.130)	-0.039 (0.133)	-9.389 (13.43)	-2.365 (3.70)
nprc.firm	0.046 (0.162)	0.124 (0.167)	5.392 (17.21)	1.671 (4.98)
tech.lv2 (dummy)	-0.120 (0.231)	-0.078 (0.235)	16.764 (24.30)	-6.050 (6.99)
tech.lv3 (dummy)	0.185 (0.226)	0.121 (0.227)	20.987 (23.76)	-0.696 (6.71)
tech.lv4 (dummy)	0.245 (0.253)	0.053 (0.251)	23.415 (26.59)	-0.172 (7.51)
predicted R&D intensity	-0.497 (0.208)**	-0.305 (0.186)	-13.591 (21.82)	-7.184 (6.15)
number of employees	-0.062 (0.094)	0.056 (0.087)	-1.178 (9.75)	-1.752 (2.75)
number of R&D emp	0.195 (0.052)***	0.184 (0.053)***	-1.474 (5.28)	2.962 (1.56)*
idustry HHI	-0.138 (0.610)	-0.240 (0.630)	35.750 (65.04)	6.872 (19.04)
firm age	-0.376 (0.096)***	-0.383 (0.093)***	-9.114 (10.10)	-5.488 (2.94)*
4 period_dummies	Yes	No	Yes	Yes
(Intercept)	4.642 (1.694)***	3.318 (1.529)**	-37.009 (177.70)	34.262 (50.89)
	AIC: 2658.8	AIC: 2658.8	R-sq: 0.418	R-sq: 0.199
	-2LogL: 2616.836	-2LogL:-2642.996	Adj R-sq: 0.385	Adj R-sq: 0.154
			Breusch-Pagan: 4.695***	

Significance levels: **** p<0.01; **p<0.05;*p<0.1

Table 13. Innovation Output estimation results at the firm level (new product)

Variable	N.B GLM	N.B GLM	OLS	Ordered Probit[a]
cum tech exp	0.115 (0.091)	0.191 (0.082)**	3.632 (3.01)	0.187 (0.118)
diversity in tech pool	-0.310 (0.584)	-0.026 (0.569)	-13.279 (19.30)	-0.293 (0.742)
network density	0.528 (0.357)	0.810 (0.338)**	16.229 (11.82)	0.936 (0.451)**
network diversity	-0.137 (0.108)	-0.160 (0.107)	-5.149 (3.57)	-0.257 (0.140)*
network clustering coef	-0.077 (0.256)	-0.064 (0.258)	-0.015 (8.46)	-0.069 (0.326)
tech.lv2 (dummy)	-0.457 (0.215)**	-0.505 (0.213)**	-14.719 (7.11)**	-0.575 (0.286)**
tech.lv3 (dummy)	-0.008 (0.200)	0.071 (0.197)	0.176 (6.61)	0.183 (0.260)
tech.lv4 (dummy)	0.073 (0.224)	0.178 (0.217)	2.303 (7.41)	0.286 (0.291)
predicted R&D intensity	-0.301 (0.159)*	-0.473 (0.129)***	-9.890 (5.25)*	-0.476 (0.204)**
number of employees	-0.118 (0.079)	-0.170 (0.072)**	-3.354 (2.61)	-0.154 (0.103)
number of R&D emp	0.062 (0.049)	0.071 (0.049)	1.949 (1.60)	0.091 (0.064)
idustry HHI	-0.048 (0.556)	-0.173 (0.557)	-1.544 (18.43)	-0.068 (0.703)
firm age	-0.189 (0.079)**	-0.251 (0.075)***	-7.300 (2.60)***	-0.326 (0.104)***
4 period_dummies	Yes	No	Yes	Yes
(Intercept)	7.019 (1.355)***	8.318 (1.160)***	152.743 (44.81)***	
	-2LogL: 3150.121	-2LogL: 3154.238	R-sq: 0.134	Residual Deviance: 1000.279
	AIC: 3184.1	AIC: 3184.1	Adj R-sq: 0.095	AIC: 1038.279
			Breusch-Pagan: 9.6172	

Significance levels: **** p<0.01; **p<0.05;*p<0.1

Note:[a]: dependent variable in Ordered Probit is transformed to Likert scale

Observation: 346)

4.3.4 The effect on firm's performance

Table 17 summarizes the results of the performance equation. At first, many of the coefficients for the index variables regarding the characteristics of the technology pool and the network are statistically insignificant, except for the network diversity.

In contrast to the effect on innovation output measured as the sum of patents, network diversity has had a positive correlation with labor productivity. However, network density has a negative correlation with labor productivity, measured as value-added per employee, despite its coefficient not being significant. This implies that what contributes to benefits in Korean manufacturing is not just the diversity of technology that a firm possesses and their experience of using that technology, but their experience and ability to produce new things with various technological capabilities.

In fact, to obtain the combining ability of technology capabilities, securing various technology capability pools in firms' innovative activities and the experiences of individual technology capability uses must be preceded. It can be inferred that the predicted number of patents is positively correlated with labor productivity. This is inferred from the positive coefficient of the predicted number of patents variable. In this model, the indirect effect of the technology usage experience through the interaction between the network diversity and the experience of technology usage cannot be known; however, it is found that this has a total positive effect on labor productivity.

In the performance equation, the experience of technology usage variable was omitted from the estimation. Instead, the predicted number of patents was used. The number of

patent applications has a high correlation with the experience of technology usage, because a firm's experience with technology is determined from their patent applications. In particular, the predicted number of patents could be a proxy variable of the technology use experience.

Further study that considers the relationships and causality between indices from the technology pool and network would provide better insights into innovation and performance studies, investigating the role of knowledge. This study also tries to use firms' employee growth as a measure of the firm's performance like (Hall, Helmers, Rogers, & Sena, 2013), but the relationship between the indices extracted from the technology structure is not significant. Furthermore, the quadric form of the indices extracted from the technology structure like (Gilsing et al., 2008) are not significant.

Table 14. Performance equation result at the firm level (productivity, Obs.: 351)

Variable	OLS	OLS	OLS
diversity in tech pool	0.255 (0.415)	0.692 (0.502)	0.511 (0.543)
network density	-0.449 (0.279)	-0.195 (0.281)	-0.283 (0.297)
network diversity	0.134 (0.068)**	0.148 (0.068)**	0.135 (0.070)*
network clustering	0.105 (0.211)	0.239 (0.217)	0.217 (0.220)
nprd.mk	0.053 (0.116)	0.004 (0.107)	0.034 (0.117)
nprd.firm	-0.109 (0.089)	-0.122 (0.089)	-0.119 (0.089)
nprc.mk	0.074 (0.099)	0.107 (0.097)	0.087 (0.100)
nprc.firm	0.069 (0.128)	0.049 (0.127)	0.070 (0.129)
tech.lv2 (dummy)	0.321 (0.167)*	0.259 (0.172)	0.283 (0.174)*
tech.lv3 (dummy)	0.280 (0.154)*	0.281 (0.167)*	0.257 (0.170)
tech.lv4 (dummy)	0.001 (0.163)	0.012 (0.183)	-0.015 (0.188)
Predicted number of patents(log)		0.167 (0.079)**	0.116 (0.097)
predicted R&D intensity		-0.034 (0.112)	0.013 (0.127)
number of emp	0.166 (0.050)***	0.104 (0.062)*	0.126 (0.068)*
number of R&D emp	-0.017 (0.040)	-0.060 (0.045)	-0.051 (0.046)
idustry HHI	0.283 (0.454)	0.198 (0.468)	0.259 (0.473)
firm age	0.066 (0.060)	0.104 (0.067)	0.107 (0.068)
4 period_dummies	Yes	No	Yes
constance	2.483 (0.493)***	2.370 (0.966)**	2.080 (1.059)*
R-sq :	0.1872	0.1914	0.1937
Adj R-sq	0.1432	0.1502	0.1475
Breusch-Pagan:	10.5694	12.2052	11.5668

Significance levels: **** p<0.01; **p<0.05;*p<0.1\

4.4 Discussion

Table 15. Summary of results at the firm level study

	R&D intensity	Sum of patents	Share of new product in sales	Labor productivity
log cum tech exp	+	+	+	
diversity in tech pool	+			
network density	+	+	+	
network diversity		-		+
network clustering				

*Note: blank cell means coefficient is not statistically significant

This study found similar effects for the technology usage experience and network density on innovation activity through the small correlation between two variables. Two variables have a positive effect on R&D intensity: The sum of patents and the share of new products in sales; however, they do not significantly affect labor productivity.

However, two diversity indices in the technology pool and network show different effects. Diversity in the technology pool (Diversity in the tech pool) only shows a positive relation with the R&D intensity. In contrast, the network diversity shows a negative relationship with the sum of patents and a positive relationship with labor productivity.

The effect of the clustering coefficient on R&D activity, innovation, and labor productivity is not statistically significant. Furthermore, the correlation of the clustering coefficient with the other indices is low, and the trend of the effect on R&D activity, innovation, and labor productivity differs from the other indices. This result gives the possibility of a clustering coefficient to analyze a firm's technology characteristics.

As Neuhäusler (2012) mentioned, firms are differentiated by several characteristics such as their sector and size, and have different amounts of R&D investment and innovation. In addition, it analyzed the differences of effects using an industry classification dummy for the degree of technology intensity.

This chapter checks the R&D activity, innovativeness, and productivity by groups of industry type, classified by technology intensity. In the case of the Korean manufacturing industry, more people participate, and investment is more concentrated in low-technology industry firms than in high-technology industry firms. Although no meaningful differences between groups in innovative result from patent's point of view could be found, firms in medium–high-technology industry were lower than high-technology industry firms were in innovative result of sale with new products. The other two groups, medium-low-technology industry and low-technology industry, did not show any meaningful difference

In innovative result, firms in medium–high-technology industry scored lower than in high-technology industry firms, but higher in labor productivity. In addition, medium–low-technology industry showed higher productivity than firms in high-technology industry. This result is opposite to that of Robin and Schubert (2013) in terms of innovative result.

4.5 Conclusion

This chapter investigated the effect of characteristics of technology pool and network on

R&D activity, innovation, and labor productivity of Korean manufacturing firms. This dissertation uses four databases to construct a more accurate sample. This empirical model averts selectivity bias in the R&D intensity equation by using the generalized Tobit model, as well as the predicted value for correcting endogeneity of R&D intensity variable in the innovation output equation and patent variable in the productivity equation.

Findings confirmed the different effects of characteristics of technology pool and network. Experience of technology capability usage shows a positive relation with R&D intensity, and sum of patents, share of sales of new products, while labor productivity showed a negative relation. Network diversity shows a negative relation with the sum of patents, but it shows a positive effect in labor productivity

In short, in terms of innovation activity and performance, diversity of technology had a positive impact, but only network diversity had a positive effect on intensity of value-added industrial competition pressures, as measured by HHI, effect on R&D engagement and intensity, while innovation output had a negative effect. In the future, it will be valuable to refine the model for finding determinants interacting with technological characteristics on firms' innovation systems. A further study examining firms' optimum configuration at technological pool and network would provide expanded insight in innovation activity and performance for studying the role of knowledge.

One limitation of this research is that it does not analyze the determinants involved in formation of characteristics of technology pool and network.

Chapter 5. Density and diversity of technology pool and network for national innovation

5.1 Introduction

The effect of diversity and density of technology pool and network on innovation activities and performance at the firm level was examined in Chapter 4. To expand the previous chapter, this chapter examines the relations between density and diversity of national technology pool and network and between density and diversity of national technology pool and network national innovation performance and the economic growth at country-level. As the effects of technological characteristics within companies of different sizes, industries, and ages in Korea were reviewed, this chapter identifies the effects of technological characteristics within countries of different competition structure, education environment, and infrastructure.

The economy grows in a system that evolves through the innovation of economic agents for gradually accumulating capital and credit (Schumpeter, 1928). One of the key points in the innovation is that it is a process of learning among agents promoted and regulated by institutions of the system, the so called a "system of innovation" (Edquist, 1997). Many previous innovation studies at the country level have been based on this perspective. Crepon and Duguet (1997), Lööf and Heshmati (2002), and Parisi, Schiantarelli, and Sembenelli (2006) examined the relation between R&D, innovation

output, and performance of firm within single countries like France, Sweden, and Italy. Castellacci and Zheng (2010), Hashi and Stojčić (2013), and Bogliacino and Pianta (2011) compared this relation across countries. These studies use a common variable for estimation, such as R&D expenditure, sum of patent count, share of new product in sales and labor productivity. Thereby, it is easy to compare results.

In this systematic approach to innovation, previous studies also investigated the structure of innovation systems at a variety of levels, including people (Wagner & Leydesdorff, 2005) and organizations (Balland & Vicente, 2013) to find sociological implications. For example, the structure of innovation systems is similar to that of complex networks that make societies small (Albert et al., 1999). Moreover, the network position correlates with the role of agents in a system of innovation, as long discussed in social science (Granovetter, 1973). Furthermore, Shin and Park (2010) suggested evolutionary optimization of technological knowledge network for the ICT industry of Korea based on the structure of knowledge influencing flow of capital and cost reduction. From this research, it can be inferred that the structure of overall technology connectivity affects the growth of technology, which belongs to its organization.

However, previous studies lack understanding of the structure of knowledge while concentrating on societies embodying the knowledge, though both of them are involved in the infrastructure for innovation and economic growth (Tassey, 1991). A number of researchers have formulated “organization” and “network” based not on the technology but on the related technology and studied the influence of innovation efficiency and the

outcome of the organization itself.

Industrial and technological structure at the country level are related with innovation and economic growth. Hidalgo and Hausmann (2009) showed that productive structure evolves by broadening product space, such as technology pool, as described in this dissertation. Dodaro (1991) also found a strong correlation between industrial structure, like the proportion of manufacturing, and economic growth. Malerba and Orsenigo (1997) showed that the technological environment, rate of innovation, and structure of innovative activities within sectors interact with each other. Thus, understanding the structure of technology pools and characteristics of each technology is more crucial than before. Moreover a technology network is not defined as discrete from organization network; rather, it is interconnected and offers a different view for analyzing an organization's activity.

If the producer of each technology is limited to a particular researcher or firm, this network of organization and technology perspective will not be different. For instance, if two technology set are studied in two different organizations, the connection between the two organizations cannot be found in technology network, and if each firm is developing different technology sets, the connection between two technology sets cannot be found in the organizations network.

In terms of perspective, this dissertation compares the structure of technology of each country through technology pool and technology network analysis instead of systematic analysis based on interaction among agents. Using characteristics of technology pool and

network, this dissertation identifies the influences on national innovation and economic growth, like examining the firm's innovation shape depending on the position of organization network, as in the previous chapter.

Surely, studying interaction of agents' perspectives can also provide good intuition, but if size and characteristic of members and purpose of subject for analysis are described in one node, it is difficult to construct and discuss the network as a whole. Patents contain homogeneous types of information, even where their applicants, inventors, and regions of application vary. Hence, it is convenient to compare the technological structures of different countries. By analyzing the effect of technology pool and network at different scales, this study can be applied for establishing innovation policy for similar and different structures of organizations such as firm, industry, region, and country.

5.2 Methodology

5.2.1 Data

Analysis in this chapter makes use of three kinds of databases: the CANA database, the Penn World Table (PWT) data, and Worldwide Patent Statistical Database from EPO. The CANA database, hosted by the Norwegian Institute of International Affairs, has a balanced cross-country panel dataset for the period 1980–2008. PWT, compiled by the Center for International Comparison at UPenn, provides a longer time span of country data covering 189 countries and territories for 1950–2009. Beside PWT's focus on providing a macro-economic index, such as GDP at chained PPPs and TFP at constant

national prices of country, the CANA database is providing indices in a broader dimension than PWT

The CANA database is classified into six dimension; 1) Innovation and Technological Capabilities, 2) Economic Competitiveness, 3) Education System and Human Capital. 4) Infrastructure, 5) Political-institutional factors, and 6) Social Capital. After analyzing the correlation among variables within these six dimensions, one or two variables are selected from each dimension to keep the panel analysis simple and highlight the effect of this paper's concern: technology pool and network of countries. Like the previous chapter analyzing the effect of technology pool and structure in firm, patent application data of EPO is used to measure characteristics of country technology.

This paper focuses on 31 countries listed in Table A5 sample countries over the period 1980–2008.

5.2.2 Measurement

To identify the characteristics of national-level technology pool and network, this dissertation applies the concept used to figure out the characteristic of firm's technology from the previous chapter. In other words, the dissertation produces it by accumulating national level of annual technology in the IPC code pool. Moreover, this dissertation constructs a co-occurrence network of which nodes are national-level patent IPC code in an annual cumulative unit.

After constructing the technology network and pool, six indices are measured as

follow:

1) Experience of technology usage, 2) scope of technology capability (richness of technology capability), and 3) diversity in technology pool, and three measurements concerning characteristics of technology network: 4) network density 5) network diversity and 6) clustering coefficient.

Similar to the firm-level case, the dissertation left out scope of technology capability among national level index, because it showed a high correlation between scope of technology capability and different indexes. In addition, a scaled entropy index of technology network is used (instead of none-scaled) for a similar reason to that used for the scope of technology capability.

In the final analysis, patent pool and network index change of 33 countries excluding two countries are shown in Figure A. 8-A. 15. In these figures, results show four specific patterns. The discussion about relations between indices from technology pool and network is an important research target, but it will be left to a future study

Table 16. Definition of variables for the country-level study

Variable	Measurements	Description	
count.appln	The number of patent application	Cumulative sum of patent applied at county patent office	(Wartburg et al., 2005).
count.ipc	Experience of technology base use	Total number of IPC in patent application	Sternitzke et al.(2008)
entropy.all.ipc	Diversity of technology base	Use entropy index of IPC	Chen and chang(2010)
density	Graph density(weithed network)	The ratio of the number of edges and the number of possible edges	Kim and Park(2009)
diversity.mean	Diversity of vertices(scaled)	Mean of diversity for all vertices which is scaled by the degree of vertex	Nathan Eagle et al(2010
clustring	Clustering coefficient	The probability that the adjacent vertices of a vertex are connected	Choi and Hwang(2013)

5.2.3 Empirical model

5.2.3.1 Variable and model for empirical analysis

The model in this chapter follows the model used in the previous chapter. However, instead of analyzing at the firm level, this chapter focuses and conducts analysis on national level. The difference from the previous chapter is the control variable, some dependent variables, data boundaries for measuring characteristics of technology pool and network, and the empirical methods deployed.

In order to examine the effect of characteristics of technology on countries' innovation and economic growth, R&D expenditures as a GDP percentage, annual sum of patent application, and GDP at current PPP are used as dependent variables. An empirical model is conducted to test the relation among variables, shown in Figure 10.

Unlike the firm management in the market, innovation and economic growth of the countries are involved not only in the innovation activities by various agents, but also in various factors such as education system, human capital, infrastructure, political freedom, liberty of press, and cultural characteristics. Under the condition of controlling various kinds of factors, the marginal effect of characteristics of technology pool and network must be compared. For this purpose, this chapter adopted control variables from various areas, like the study of Fulvio Castellacci, and Natera (2013), considering not only technological capabilities and economic competitiveness, but also education system and human capital, infrastructure, political-institutional factors, and social capital in innovation study. In this study, estimation only uses one or two variables in each category. In other words, variables with high correlations to those already included are omitted. Table 20 shows the variables and definitions

It is important to acknowledge the limitation in comparing the effect of technology structure of firm and country by having different scales and properties. However, by controlling various kinds of factors, such as setting up innovation measurement, and technology structure, such as using patent application identically, it is possible to compare the effect of technology structure on innovation and performance on different scales. Thus, it will help establish innovation policy that covers different size organizations, such as firm, industry, region, and country.

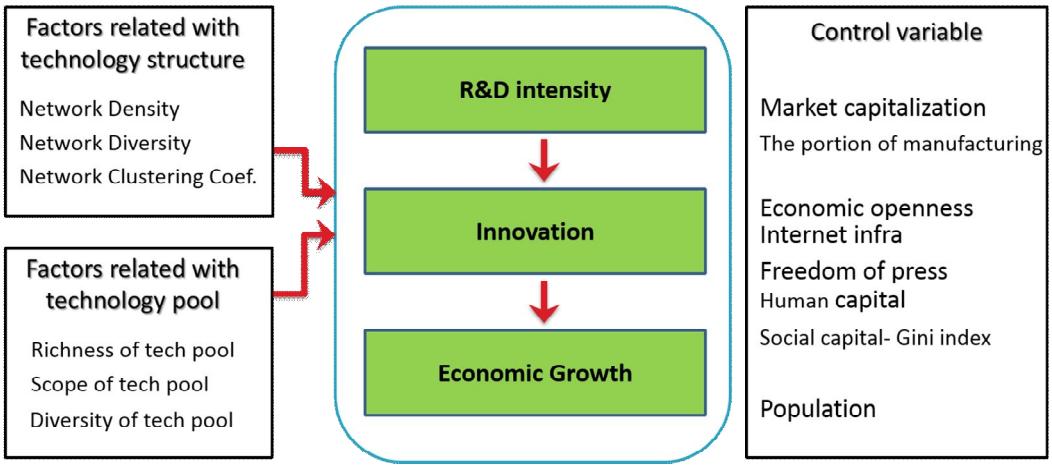


Figure 10. Empirical model in national level

Table 17. Variables for the empirical model at the national level

Variable	Name	Definition	Source
count.appln	The number of patent application	The number of patent application	measurement using EPO data
gdp.ppp	GDP at current PPPs	Output-side real GDP at current PPPs (in mil. 2005US$)	The Penn World Table 8.0
gdp.ppp.cpa	PPP per capita	PPP Converted GDP Per Capita at constant 2005 national prices (2005US$)	The Penn World Table 8.0
count.ipc	Experience of technology base use	Total number of IPC in patent application	measurement using EPO data
entropy.all.ipc	Diversity of tehcnology base	Use entropy index of IPC	measurement using EPO data
density.binary	Graph density(binary network)	The ratio of the number of edges and the number of possible edges(binary network)	measurement using EPO data
diversity.mean	Diversity of vertices(scaled)	Mean of diversity for all vertices which is scaled by the degree of vertex(imdex*`100)	measurement using EPO data
clustring	Clustering coefficient	The probability that the adjacent vertices of a vertex are connected	measurement using EPO data
mkt.captia.pct	Market capitalization of listed companies (% of GDP)	Market capitalization (also known as market value) is the share price times the number of shares outstanding. Listed domestic companies are the domestically incorporated companies listed on the country's stock exchanges at the end of the year. Listed companies does not include investment companies, mutual funds, or other collective investment vehicles.	Standard & Poor's, Global Stock Markets Factbook and supplemental S&P data.
manf.vad.pct	Manufacturing, value added (% of GDP)	Manufacturing refers to industries belonging to ISIC divisions 15-37. Value added is the net output of a sector after adding up all outputs and subtracting intermediate inputs	World Bank and OECD
open.trad	Economic Competitiveness	Openness Indicator. (Import + Export)/GDP. PPP, 2000 USD	CANA(UNCTAD)
rnd.exp.per.gdp	Innovation and Technological Capabilities	R&D expenditures as a percentage of GDP.	UNESCO, OECD, RICYT
int.usr	Internet users	Infrastructure-Internet users per 10 people. People with access to the worldwide web network divided by the total amount of population.	CANA(World Bank)
free.pres	Freedom of Press	Political-institutional factors: This index assesses the degree of print, broadcast, and internet freedom in every country in the world, analyzing the events of each calendar year. Index from -1 (no freedom) to 0 (high freedom)	CANA(Freedom House)
teacher.rto	Education System and Human Capital	Primary pupil-teacher ratio (inverse). Ratio (number of pupils enrolled in primary school) / (number of primary school teachers) multiplied by (-1/100)	CANA(UNESCO)
gini.idx	Gini Index	Social Capital-Gini Index	CANA(United Nations)
pop	population	Population (in thousands)	The Penn World Table 8.0

5.2.3.2 Empirical Methods

Concerns in estimating the effect of variables mentioned in previous subsection include 1) the endogeneity problem due to causality between dependent and explanatory variables. Innovation and economic growth of the country affect the amount and combination of input. As Marschak (1994) mentioned, it causes the correlation between error terms and inputs. 2) Time invariant unobserved heterogeneity of countries can be correlated with the explanatory variables, such as patent system and geography; 3) the presence of the lagged dependent variable on the explanatory variable set causes an autocorrelation problem.

In this case, coefficients of estimation using a least squares regression of innovation performance and economic growth will be inconsistent. To correct this problem, two econometric methodologies are applied handing the issue of endogeneity: the fixed effect model[2] and instrumental variable estimation (GMM).

5.2.3.2.1 Fixed effect model

Consider the following basic model using panel data

$$y_{it} = \alpha + \beta x_{it} + \gamma z_i + \omega_{it} + \varepsilon_{it}, \qquad \text{Eq. (16)}$$

where x is a vector of determinants of innovation output and economic growth and a control variable such as population of country. In addition, z is vector of country

[2] All Hausman tests in 3 model revel that the p-value is close to zero, so Random effect model is excluded

heterogeneity such as size and region of country. ω_{it} is a transmitted effort, which a decision maker can identify before make policy and strategy and is changed to country *i* in period *t*. ε_{it} represents the unobservable shocks to innovation output and economic growth of country *i* at period *t*, such as unexpected and unobservable changes in technology flow among countries and measurement error in the innovation output.

Since different nations have different policies to protect and promote intellectual property, and law and policy do not change rapidly, time-invariant unobserved heterogeneity at country level is presented. In this case, if OLS and random effect estimator are applied in Eq. 16, contemporaneous correlation between explanatory variable and the error terms causes inconsistency bias.

When there are no unique attributes of countries within variables, and no time invariant effects, OLS using pooled panels could be one option. Nevertheless, the fixed effect model as known as Least Squares Dummy Variable Model (LSDVM) is better in this case

In the fixed effect model, the basic model in Eq. (16) can be rewritten as

$$y_{it} = \alpha + \beta x_{it} + \gamma z_i + \omega_i + \varepsilon_{it}, \qquad \text{Eq. (17)}$$

where ω_i is unobserved group heterogeneity. This paper focus on the effect of the dynamic properties of technology pool and network. The fixed effect model can control for the effects of unobserved individual attributes; thus, this paper considers this model, even

though the fixed effect model has disadvantages such as wiping out all time invariant variables.

5.2.3.2.2 Instrumental Variable Estimation (GMM)

The other estimation method that deals with the endogeneity problem is instrument variable estimation (GMM). This dissertation uses the difference GMM of Arellano & Bond (1991) and the system GMM of Blundell & Bond (2000) to deal with the autocorrelation problem in addition to the problems of endogeneity from causality and fixed effect.

Arellano & Bond (1991) proposed a model that included lagged dependent variables in the explanatory variable set to correct inconsistency. The difference GMM uses first-differences to transform equation Eq. (16) into

$$\Delta y_{it} = \gamma \Delta y_{i,t-1} + \beta \Delta x_{it} + \Delta \varepsilon_{it} \qquad \text{Eq. (18)}$$

Because the first-differenced lagged dependent variable ($\Delta y_{i,t-1}$) is instrumented with its past levels ($y_{i,t-2}, y_{i,t-3}, \cdots$), the autocorrelation problem (AR(1)) is corrected.

Arellano & Bover (1995) and Blundell & Bond (2000) revealed a potential weakness in the difference GMM; when the variables showed the property of a random walk, the lagged levels could become poor instruments for first differenced variables. They

considered a set of additional restrictions on the condition of Eq. (18) to fix this problem.

$$E\left[\Delta y_{it-1}(\omega_i + \varepsilon_{it})\right] = 0 \qquad \text{Eq. (19)}$$

5.3 Analysis Result

5.3.1 Descriptive statistics at national level

This dissertation uses strongly balanced panel data from 31 countries during the period 1980–2008. As shown in Table 21, which contains descriptive statistics for 31 sample countries, there are a few missing variables in the Market capitalization of the listed companies and in the manufacturing and value added.

The skewness of the network density is high compared with the other index of technology and that of network density in the firm level study, and the clustering coefficient shows high skewness. In addition, the clustering coefficient has a positive contrast to that of the firm level study. The other index of technology is not skewed. Specially, the experience of technology base usage (sum of IPC) is -1.051, while it is 18.319 in the firm level study. This is why the size of the patent application pool is similar and its absolute size is large in the country-level study

Table 18. Descriptive statistics for 31 sample countries

Variable	N	Mean	S.D.	Median	Skew	Kurtosis
ln.gdp.ppp.out	879	12.369	1.027	12.192	0.371	-0.727
ln.gdp.ppp.cpa	879	9.558	0.825	9.800	-1.008	0.631
ln.count.ipc.	899	11.949	1.633	12.138	-1.051	2.574
entropy.all.ipc	899	0.768	0.075	0.767	0.209	-0.682
density.binary	899	0.296	1.699	0.141	19.073	417.089
diversity.mean	899	0.982	0.009	0.983	-0.832	0.479
clustring	899	0.279	0.104	0.252	4.040	19.748
mkt.captial	612	53.485	52.343	36.997	1.954	4.593
manf.vad	621	0.196	4.816	19.034	0.524	0.376
open.trade	899	0.578	0.313	0.514	1.298	1.955
rnd.exp.per.gdp	870	1.256	0.872	1.035	1.260	1.810
int.usr	899	0.133	0.224	0.005	1.724	1.784
free.pres.brd	899	-0.288	0.200	-0.230	-1.038	0.242
teacher.rto	899	-0.193	0.082	-0.169	-1.232	1.155
gini.idx	812	0.337	0.096	0.322	1.169	0.899
pop	889	57622.453	168541.847	10937.612	5.164	26.391

5.3.2 The effect on the R&D expenditure

Table 22 reports the results from the R&D intensity estimation at the country level from the dynamic panel of 28 countries. The null hypothesis of no first-order autocorrelation in the differenced residual is rejected, whereas the null hypothesis of no second-order autocorrelation is not rejected for differenced GMM and system GMM. Therefore, the two models do not have the problem of the exogeneity of instrument variables. For comparison among empirical models, in the original OLS regression, the lagged dependent variable is positively correlated with the error, biasing its coefficient upwards.

However, the coefficient from fixed effects model is biased downwards. There, consistent estimates should lie between the OLS and fixed-effect (Arellano and Bond, 1991).

As shown in Table 22, the coefficient of the lagged dependent variable of the differenced GMM is out of bounds, but that of the system GMM lies between 0.998 and 0.893. Therefore, the differenced GMM cannot be a candidate for a consistent estimator, but the system GMM can be a consistent estimate. In addition, the coefficient estimation for the system GMM is more precise than that of the differenced GMM as shown in SE, but it is similar to that of the fixed effect model. Therefore, this paper interprets the relation between the characteristics of the technology pool and the network using the results from the fixed effect and the system GMM estimation.

The coefficient of the technology usage experience, diversity in the tech pool, and network clustering are positive and significant. However, network density and diversity are not significant, and the elasticity of diversity is higher than that of density, this means that to enhance a countries' diversity of technology capabilities or advance a frontier of technology, requires greater R&D expenditure.

Table 19. R&D intensity estimation results in country level

Variable	OLS	FE	Diff_GMM	sys_GMM
Observation	537	537	509	537
L1.rnd.exp.per.gdp	0.998(0.009)***	0.893(0.019)***	0.664(0.046)***	0.894(0.019)***
ln.count.ipc	-0.025(0.038)	-0.041(0.093)	0.286(0.151)*	0.193(0.092)**
ln.entropy.all.ipc	-0.366(0.373)	-0.121(0.756)	3.392(1.249)***	1.871(0.791)**
ln.density.binary	-0.037(0.034)	-0.119(0.075)	0.111(0.123)	-0.054(0.068)
ln.diversity.mean	-2.099(2.420)	-13.630(7.594)*	-4.752(12.501)	0.135(7.270)
ln.clustring	0.040(0.044)	0.046(0.077)	0.149(0.183)	0.314(0.101)***
manf.vad	0.001(0.001)	0.003(0.002)	0.004(0.004)	0.003(0.003)
open.trade	-0.026(0.016)*	0.034(0.043)	0.059(0.067)	0.065(0.045)
int.usr	-0.013(0.023)	0.024(0.028)	0.105(0.046)**	0.006(0.031)
free.pres.brd	0.017(0.041)	-0.013(0.062)	0.097(0.155)	0.029(0.108)
teacher.rto	-0.116(0.088)	-0.432(0.257)*	-0.694(0.353)**	-0.495(0.252)**
gini.idx	-0.074(0.053)	-0.007(0.132)	-0.188(0.164)	-0.224(0.137)
ln.pop	-0.009(0.007)	0.018(0.093)	0.061(0.159)	-0.051(0.025)**
free.pres.brd	0.272(0.263)	-0.150(0.761)	-2.536(1.398)	-0.974(0.590)
AR(1)(prob > z)			0.0184	0.0184
AR(2)(prob > z)			0.1255	0.1255
R-sq:within		0.9977		
Between		0.9874		
Overall	0.9876	0.99		

5.3.3 The effect on the Innovative Output

Table 23 summarizes the results from the innovation output estimation at the country level to find the relationship between the characteristics of the technology pool and the network and innovation output. The annual sum of patent applications that are filed by each country for each year is used as the innovation output.

As mentioned by Yoon & Lee (2008), the IPR strategies of each sector is different. While most firms in the manufacturing sector have a high proportion of patenting as an IPR strategy, firms in service areas such as financial and business services tend to use trade secrets instead patents to protect their IPR. As different countries' industrial structures differ, countries' overall preferences for patents over IPR differ. In this situation, adopting patents to measure the innovation output can raise the biased result. To control this problem, this paper uses a fixed effect model and the percentage share of manufacturing, and value added from GDP as control variable.

Like the results of the previous subsection, the estimation result of system GMM is superior to differenced GMM. The null hypothesis of there being no first-order autocorrelation in the differenced residual is rejected, and the null hypothesis of no second-order autocorrelation is not rejected for differenced GMM and system GMM. However, only the coefficient of the lagged dependent variable in the system GMM lies between the OLS and the Fix effect estimation.

As shown in Table 23, the diversity of the technology pool and the network show a significant and positive effect on the innovation output and elasticity. The network

diversity is much higher in relation to the innovation output than that of the R&D expenditure. Moreover, the effect of the technology usage experience is also positively related. However, network density is not significant in system GMM, and is significant but small in fixed effect estimation.

This infers that various types of technological implementation and variety in the technology pool are more likely to be determinant than the density of links for the same invention. This side can also be inferred by the fact that the clustering coefficient effects innovation in the positive direction.

Table 20. Innovation Output estimation results at the country level

Variable\Model	OLS	FE	Diff_GMM	System _GMM
observation	446	446	418	446
L1. ln.count.appln.cpa	0.845(0.013)***	0.539(0.022)***	0.367(0.049)***	0.590(0.009)***
ln.count.ipc	0.224(0.026)***	0.485(0.042)***	0.546(0.068)***	0.523(0.018)***
ln.entropy.all.ipc	1.181(0.176)***	1.315(0.25)***	0.921(0.466)**	1.785(0.101)***
ln.density.binary	0.022(0.018)	-0.082(0.026)***	-0.28(0.058)***	< 1e-3 (0.008)
ln.diversity.mean	-0.198(1.277)	-0.903(2.267)	-14.228(5.909)**	5.633(0.817)***
ln.clustring	0.056(0.026)**	0.028(0.023)	0.125(0.005)**	0.026(0.014)*
mkt.captia~t	-0.014(0.004)***	0(0.003)	< 1e-3(0.003)	0.002(0.001)
manf.vadt	0.003(< 1e-3)***	0.001(0.001)**	0.001(0.001)	< 1e-3 (< 1e-3)
open.trade	-0.011(0.006)*	-0.001(0.009)	0.019(0.016)	0.012(0.005)**
rnd.exp.per.gdp	-0.001(0.004)	-0.008(0.005)	-0.004(0.011)	-0.003(0.003)
int.usr	-0.033(0.009)***	0.026(0.006)***	0.005(0.019)	0.016(0.003)***
free.pres.brd	-0.028(0.019)	-0.026(0.017)	0.055(0.033)	-0.051(0.009)***
teacher.rto	-0.009(0.035)	-0.119(0.058)**	-0.112(0.058)*	-0.020(0.027)
gini.idx	-0.104(0.024)***	-0.015(0.031)	-0.063(0.056)	-0.061(0.016)***
ln.pop	-0.164(0.012)***	-0.273(0.035)***	-0.289(0.073)***	-0.442(0.011)***
cons	-0.488(0.155)***	-2.582(0.279)***	-3.629(0.766)***	-0.986(0.099)***
AR(1)(prob > z)			0.0144	0.054
AR(2)(prob > z)			0.7605	0.3892
R-sq:within		0.9977		
between		0.9874		
overall	0.9997	0.99		

5.3.4 The effect on the Economic Growth

Table 24 summarizes the estimation of economic growth at the country level. The coefficient of the lagged dependent variable of differenced GMM is out of bounds, but that of the system GMM is bound between 0.998 and 0.961. Therefore, the system GMM can be a consistent estimate like the previous two estimation results. As shown for the estimated coefficients in the system GMM estimator, the network density and network-clustering coefficient show a statistically significant relationship. In contrast to the effect on the innovation output measured as the sum of patents, the network diversity has a positive correlation with economic growth. Contrary to this, the network density had a positive correlation with the innovation output measured as the sum of patents and the share of new products on sale; the coefficients of network diversity are not significant in the economic growth equation.

From this result, it can be interpreted that creating economic value in Korean industry does not mean the variety and amount of technology possession, but stands for experience of using specific technology. In other words, invention by technology concentration brings better economic performance than that by technology diversification.

This model cannot know the indirect effect of experiencing technology usage through the interaction between network diversity and the experience of technology usage, but it can find the total positive effect of this on economic performance; this positive effect can be checked synthetically.

Table 21. Economic Growth results equation at the country level

Variable\Model	OLS	FE	Diff_GMM	System_GMM
observation	746	746	719	746
L1.ln.gdp.ppp.cpa	0.998(0.013)***	0.961(0.022)***	0.842(0.049)***	0.995(0.009)***
ln.count.ipc	0.029(0.011)***	0.030(0.020)	0.096(0.027)***	-0.001(0.018)
entropy.all.ipc	0.131(0.107)	0.041(0.177)	0.549(0.236)**	-0.211(0.167)
density.binary	0.029(0.011)***	0.042(0.017)**	0.143(0.024)***	0.069(0.016)***
ln.diversiy.mean	2.758(0.779)***	4.019(1.656)**	8.686(2.329)***	2.424(1.531)
ln.clustring	-0.017(0.011)	-0.044(0.015)***	-0.189(0.031)***	-0.179(0.022)***
Open.trade	0.025(0.004)***	0.068(0.01)***	0.069(0.013)***	0.114(0.01)***
rnd.exp.per.gdp	0.001(0.003)	-0.001(0.005)	0.013(0.011)	-0.017(0.008)**
int.usr	-0.007(0.007)	-0.005(0.008)	0.091(0.014)***	-0.018(0.008)**
free.pres.brd	0.023(0.009)**	-0.013(0.017)	-0.117(0.028)***	0.036(0.017)**
teacher.rto	-0.023(0.026)	0.139(0.067)**	0.085(0.088)	0.027(0.068)
gini.idx	-0.059(0.015)***	0.051(0.035)	0.021(0.039)	-0.053(0.031)*
ln.pop	0.007(0.003)**	0.004(0.022)	-0.086(0.032)***	0.03(0.007)***
cons	-0.256(0.155)**	0.070(0.279)	1.476(0.766)***	-0.332(0.099)*
AR(1)(prob > z)			0.0817	0.0713
AR(2)(prob > z)			0.7444	0.6049
R-sq:within		0.9758		
between		0.9989		
overall	0.9986	0.9977		

5.4 Discussion

Table 22. Summary of results for the country level study

	R&D intensity	Sum of patents	GDP per capita
log cum tech exp	+	+	
diversity in tech pool	+	+	
network density			+
network diversity		+	
network clustering	+	+	-

Note: blank cell means coefficient is not statistically significant

The elasticity of technology indices from technology pool and network with respect to the economic performance is estimated in this chapter. Before measuring the characteristics of technology, a country's technology capability network was constructed using IPC co-occurrence on the same invention. All raw patent data is from 1980–2007. As in chapter 3, it is also valuable to analyze the properties of the technology pool and network of a certain country, but this dissertation is focused on comparing different countries that have different technology pools and networks. Different indices that represent the characteristics of the entire structure are examined instead of the position of certain nodes such as emerging technology and firms in certain industries among their network.

To estimate the relationship between these technology indices and innovation and economic performance, OLS, Fixed effect models, differenced GMM, and system GMM estimation are applied. As for the results from Arellano-Bond test for zero autocorrelation in first-differenced errors and the criteria of model consistency considering the location of the coefficient of lagged dependent variables between results from the fixed effect and

OLS model, the result of the system GMM are adopted.

5.5 Conclusion

In this chapter, the effect of the characteristics of the technology pool and network on the share of R&D expenditure to GDP, innovation output and GDP per capita of 28 countries are investigated. Three main databases are used to reflect the effect of factors in various dimensions; the social properties from the CANA database, the macro-economic index from The Penn World Table (PWT) data, and the raw patent data from the Worldwide Patent Statistical Database from EPO. This empirical study takes care of the endogeneity problem using the system GMM. The result confirms the different effects of the characteristics of the technology pool and network at the national level. The empirical results can be summarized as: 1) The degree of network clustering has a significant positive effect on innovation activity and a negative effect on economic growth. 2) The diversity and usage experience for the technology pool have a positive relationship with innovation activity. 3) The network density only has a positive relationship with the economic performance, as measured by the PPP Converted GDP Per Capita.

In short, all indices from the technology pool and network, except the clustering coefficient, have a positive relationship with innovation and the economic performance, except insignificant relationships. The clustering coefficient affects R&D expenditure and innovation output positively, and economic performance negatively. Only the network diversity and the clustering coefficient are relative to economic performance, and their

effect is positive.

This finding expects to help develop understanding of the relationship between the structure of technology and innovation performance in a systematic perspective focused on technology characteristics. The proposed framework is expected to link studies in a systematic perspective, focused on the interaction between agents such as firms, universities, and governments to study focused on the interactions among technologies created by agents. By considering the accumulated technology in addition to the active agents as resources, policymakers will improve national level technology policies.

This research has limitations in its consideration of the coevolution property between technology structure and economic performance over time. To solve this problem, applying a Vector Auto Regression (VAR) model as in (Fulvio et al., 2013) can be considered, which examines the coevolution between innovative capacity and absorptive capacity.

Moreover, for investigating the relationship by regional cluster, phase of technology and economic development will be valuable. Through such investigation, a customized innovation policy for a country that has various different environments can be developed.

Chapter 6. Conclusion

6.1 Summary of results

This dissertation examined how to characterize the effects of technology pools and networks on innovation and performance, and the role of ICT when technology networks grow. In Chapter 3, the changes of the Korean technology network are divided into two periods, from the perspective of understanding the mechanism that generates a technology network. This dissertation checked whether there exists a difference in a specific sector's role in the process of generating a network. For this work, this dissertation analyzed and compared technology related to ICT industry, Korea's representative industry, and other technologies.

The results showed that ICT has high-degree centrality and clustering coefficients, but low E-I index. This means that Korea's ICT has been more active in promoting convergence with neighboring technologies, and ICT has contributed to the technology coevolution of Korea, centralizing related convergence rather than convergence with unrelated technology.

In Chapters 4 and 5, an empirical study on firms and nations are made using network theory and the econometric method. The technology network contained technology classification codes as nodes that have similar characteristics, as discussed in Chapter 3.

This dissertation used R&D investment per person for the firm's case, and the R&D investment ratio to GDP in the national case. For innovation outcomes, the patent rate for

both firms and nations were used. Finally, this dissertation used labor productivity for firms and PPP on GDP for nations in economic achievements.

All indices from the technology pool and networks except the clustering coefficient have a positive relationship with innovation and economic performance, except for insignificant relations.

The results showed that diversity for the technology capability pool and the technology usage experience have a positive relationship with innovation activity in both firm- and country-level studies, except for the effect on innovation output, measured as the sum of patent applications in firm-level studies. In contrast to the indices from the technology pool, indices from the technology network show a different effect for firms and countries. The network density of a firm has a positive relationship with the R&D intensity and innovation output. However, the network density of a country is not significant for them. The network diversity shows contrary results for innovation output. The network diversity of a firm has a negative relationship with the innovation output, but the network diversity of a country has the reverse, a positive relationship.

The effect of the network clustering coefficient for countries is statistically significant for overall innovation activity (R&D expenditure and innovation output) and economic growth. It shows a positive relationship with the innovation activity and a negative relationship with the economic growth. However, for firm-level studies, the coefficient does not have any significant relationship.

6.2 Discussion

In Chapters 4 and 5, this dissertation examined how different levels of knowledge structure affect innovation. This dissertation has examined the relationship between R&D, innovation output, and financial performance for different types of agent such as firms and countries. By using a homogeneous index such as the density and diversity of a technology network, this dissertation could compare the effectiveness of technology characteristics being studied for different agent levels, that of firms and countries.

For this issue, the relationship between the technology index and innovation seem similar, yet also show differences. In this study, the types of influence from the experience of technology use showed a similar shape for the innovative result for both firms and countries. However, for the network-clustering coefficient for national level R&D, innovation showed a positive value, whereas no meaningful results were shown for firm-level studies. This can be inferred to be because of the insufficient size of the technological pool, in other words, each Korean manufacturing firm had a small technology cluster, or was in the initial stages of technology development.

Moreover, network diversity meant that the variety of cohesion between each technology that formed a network showed a positive relationship to innovation at the national level, where it showed a negative effect at the firm level. This result can be interpreted by assuming that organizations' diversification strategies having different goals and being different sizes. Firms try to diversify to i) increase technology cross-

fertilization between different technologies by improving firms' absorptive capacity, therefore obtaining more innovations (Quintana-García & Benavides-Velasco, 2008), ii) manage the risks from the failure of R&D projects (Garcia-Vega, 2006) iii) prevent negative lock-in effects. (Suzuki & Kodama, 2004). However, it also has disadvantages related to the cost problem from lacking of economies of scale in knowledge production and transaction costs (Joshi and Jackson, 2003; Østergaard et al., 2011). In contrast to diversification, specialization has advantages in the learning process and cost cutting in managing resources by economies of scale.

Previous empirical studies have shown the positive relationship between the size and the diversification of firms. The resource-based theory argues that the pre-condition for diversification is the existence of extra resources. Normally, SMEs possess fewer excess fungible resources than big companies or countries. Therefore, SMEs specialize in one or two potential hot items without dispersing their resources.

As shown in the descriptive analysis of the two empirical studies in Chapters 4 and 5, a firm's average cumulative sum IPC code is 1389, and they have only 164 types of technology capability. This value is highly skewed because of the existence of hub firms. However, a country's average cumulative sum IPC code is about 154,000. Most countries have at least ten thousand types of technology capability. In accordance with these factors, Diversified small firms can show a negative relationship with innovation output in Korea.

By using homogeneous measurements such as the technology pool and technology index targeting the different characteristics of organizations like firms and countries, this

dissertation found the influences of innovation and outcomes, and different relationships as a result. In this sense, although entrepreneurs and politicians set up identical goals, the aiming value of the mid index to achieve its goals has to differ. As shown from this study, it implies that aiming at the overall technology accumulation rate can be different, even though entrepreneurs and politicians' goals are the achievement of national knowledge property, in other words, making the technology pool richer.

Moreover, if someone were about to make a strategy or policy for a firm's or nation's network density enhancement, the study of Chapter 3, which explains the individual technology relationship in the overall technology network would be useful.

If your goal is technology innovation similar to Korea's environment, you may consider the promotion of ICT-related technologies as a means of policy that have a high degree of centrality for the technology sector itself and well-clustering neighbor technologies. The findings in this dissertation highlight the importance of taking a systemic approach that considers various factors for enhancing the innovation output and financial performance of a country that consists of different types of components such as firms and technology clusters.

6.3 Contribution and limitations

The contribution of this study is examining the relationship between the structure of technology and innovation from a systematic perspective focused on technology

characteristics, instead of the interactions between agents such as firms, universities, and governments. Agents create knowledge and technology; they are one of the most important resources for creation, and technology development is one of the objectives made by the agent. However, as the amount of accumulated technology and the complexity of technology and products increases, technology itself affects agents' decisions and behavior. Moreover, it influences innovation and performance.

This dissertation proposed a measurement set for innovation study, dealing with different kinds of agent such as firms and countries. A country's industry is composed of many firms, but it is difficult to analyze the innovation procedures of two groups on the same lines. However, by using identical patent network and indices to represent these characteristics, government policymakers and the firm mangers can use the same words when discussing subjects that can affect each other. Lastly, this dissertation contributes to examining the properties of the technology groups involved technology convergence using technology capability networks defined by IPC co-occurrence. Kim, Lee, Jung, Hong, Hwang & Jung (2014) proposed the Pear Theory, which is a general evolution theory that describes the change and adoption of technology, structure, rules, and philosophy in society such as firms, industries, and countries. It uses four states to describe the theory: Perpendicular, equilibrate, alignment, and relative latch. This theory is useful to understand these overall findings and to take implications from this dissertation. Perpendicular is emergence of new ideas and things such as new technology capabilities. Equilibrate is the mid process of agreement for alignment and adoption. An

important factor in the equilibrate state is agreement regarding diversity and the sharing of identity. To develop knowledge and technology, we must understand diversity and similarities. After equilibration, the new technology is diffused into society and mixed with existing technology, as in technology convergence. Lastly, laws or rules related with new technology are enacted and are applied to society rapidly. These are all processed in Pearl theory pursuit change for better value in society, not just to describe change. Along with this theory, this dissertation makes an effort to find the determinants of and relationships between innovation and economic growth, one of the objectives of our society and our lives. It is a valuable challenge to generalize the framework of this dissertation like Pearl theory.

This dissertation has limitations, considering the dynamical technology interaction within the technology network and with other innovation indices. This dissertation examines the relationship between technology indices, R&D intensity, innovation outputs, and productivity. Even though the endogeneity problem is controlled using system GMM, this dissertation does not analyze the determinants of technology network formation and the relationship between network indices. However, if policymakers or managers know the causality and relationships among these indices, they can construct effective empirical models for determining the relationships among many factors.

Every country has a different industrial structure and innovation system. Research for determining the characteristics of the technology involved in convergence requires regarding other countries. In particular, we need a comparison study using technology

networks composed of different kinds of technology capability sets to determine the general characteristics of technology.

Moreover, it is valuable to investigate the relationship by regional cluster; such investigation will lead to customized innovation policies for countries that have a variety of different environments.

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Appendix

Table A1. Table of technology sector and field with code and delineation by IPC

Technology Sector, Field	IPC code
1. Electrical engineering	
1) Electrical machinery, apparatus, energy	F21#, H01B,C,F,G,H,J,K,M,R,T, H02#, H05B,C, F, H99Z
2) Audio-visual technology	G09F,G, G11B, H04N-003,-005,-009,-013,-015,-017, H04R,S, H05K
3) Telecommunications	G08C, H01P,Q, H04B,H,J,K,M, H04N- 001,-007,-011, H04Q
4) Digital communication	H04L
5) Basic communication processes	H03#
6) Computer technology	(G06# not G06Q), G11C, G10L
7) IT methods for management	G06Q
8) Semiconductors	H01L
2. Instruments	
9) Optics	G02#, G03B,C,D,F,G,H, H01S
10) Measurement	G01B,C,D,F,G,H,J,K,L,M,P,R,S,V, (G01N not G01N-033), G01WG04#, G12B, G99Z
11) Analysis of biological materials	G01N-033
12) Control	G05B,D,F, G07#, G08B,G, G09B,C,D
13) Medical technology	A61B,C,D,F,G,H,J,L,M,N, H05G
3. Chemistry	
14) Organic fine chemistry	(C07B,C,D,F,H,J, C40B) not A61K, A61K-008, A61Q
15) Biotechnology	(C07G,K, C12M,N,P,Q,R,S) not A61K
16) Pharmaceuticals	A61K not A61K-008
17) Macromolecular chemistry, polymers	C08B,C,F,G,H,K,L
18) Food chemistry	A01H, A21D, A23B,C,D,F,G,J,K,L, C12C,F,G,H,J, C13D,F,J,K
19) Basic materials chemistry	A01N,P, C05#, C06#, C09B,C,F,G,H,K,D,J, C10B,C,F,G,H,J,K,L,M,N, C11B,C,D, C99Z
20) Materials, metallurgy	C01#, C03C, C04#, C21#, C22#, B22#

21) Surface technology, coating	B05C, B05D, B32#, C23#, C25#, C30#
22) Micro-structure and nano-technology	B81#, B82#
23) Chemical engineering	B01B, B01D-000#, B01D-01##, B01D-02##, B01D-03##, B01D-041,-043,-057,-059, B01D-06##,-07##, B01F,J,L, B02C, B03#, B04#, B05B, B06B, B07#, B08#, D06B,C,L, F25J, F26#, C14C, H05H
24) Environmental technology	A62D, B01D-045, B01D-046,-047, B01D-049,-050,-051,-052,-053, B09#, B65F, C02#, F01N, F23G,J, G01T, E01F-008, A62C
4. Mechanical engineering	
25) Handling	B25J, B65B,C,D,G,H, B66#, B67#
26) Machine tools	B21#, B23#, B24#, B26B,D,F, B27#, B30#, B25B,C,D,F, G,H
27) Engines, pumps, turbines	F01B,C,D,K,L,M,P, F02#, F03#, F04#, F23R, G21#, F99Z
28) Textile and paper machines	A41H, A43D, A46D, C14B, D01#, D02#, D03#, D04B,C,G,H, D05#, D06G,H,J,M,P,Q, D99Z, B31#, D21#, B41#
29) Other special machines	A01B,C,D,F,G,J,1K,L,M, A21B,C, A22#, A23N,P, B02B, C12L, C13C,G,H, B28#, B29#, C03B, C08J, B99Z, F41#, F42#
30) Thermal processes and apparatu	F22#, F23B,C,D,H,K,L,M,N,Q, F24#, F25B,C, F27#, F28#
31) Mechanical elements	F15#, F16#, F17#, G05G
32) Transport	B60#, B61#, B62#, B63B,C,G,H,J, B64#
5. Other fields	
33) Furniture, games	A47#, A63#
34) Other consumer goods	A24#, A41B,C,D,F,G, A42#, A43B,C, A44#, A45#, A46B, A62B, B42#, B43#, D04D, D07#, G10B,C,D,F,G,H,K, B44#, B68#, D06F,N, F25D, A99Z
35) Civil engineering	E02#, E01B,C,D, E01F-001,-003,-005,-007,-009, E01F-01#, E01H, E03#, E04#, E05#, E06#, E21#, E99Z

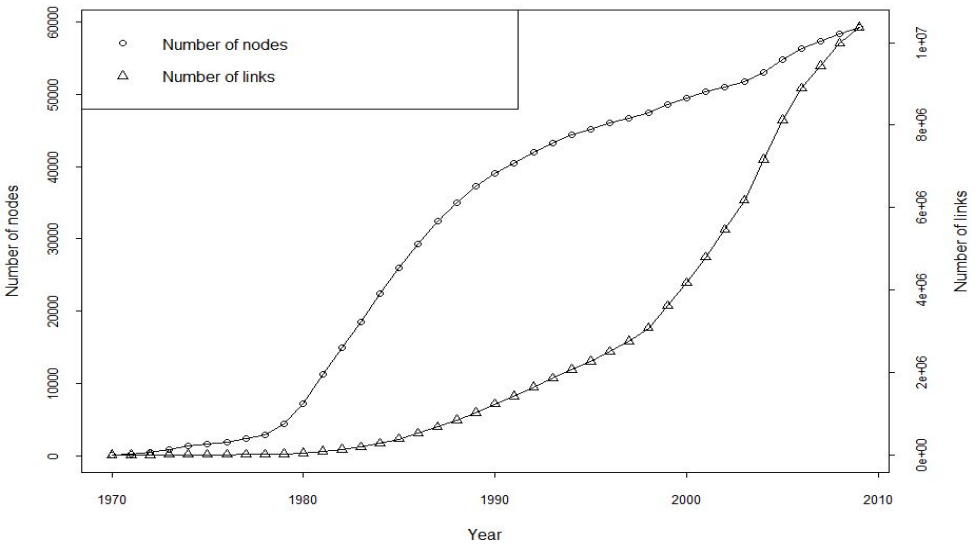

Figure A1. Growth of Technology Network in Korea

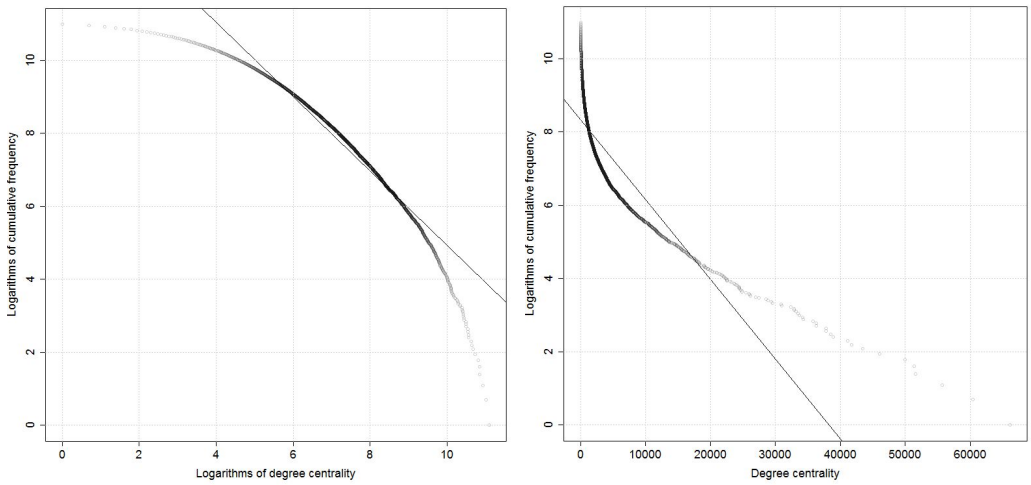

Figure A2. Cumulative Degree Distributions of Korean Distributions of Korean Technology Network in Log-Log Scales(Left) / Log-Linear Scales (Right) (1970~2009)

Table A2. Tests of power-law behavior in the cumulative network

	OLS			CSN		
Year	Gamma	p-value	R.squared	Gamma	KS.p	xmin
1970	1.699	0.007	0.666	1.388	0	1
1974	2.295	0.000	0.86	4.535	1	120
1979	2.481	0.000	0.899	2.14	0.001	10
1984	2.328	0.000	0.954	2.433	0.524	89
1989	2.261	0.000	0.944	2.527	0.556	326
1994	2.195	0.000	0.935	2.571	0.556	706
1999	2.124	0.000	0.932	2.406	0.155	867
2004	2.036	0.000	0.933	2.361	0.156	1889
2009	2.018	0.000	0.935	2.18	0.001	1181

Note: For H1: Degree distribution of five technology sectors

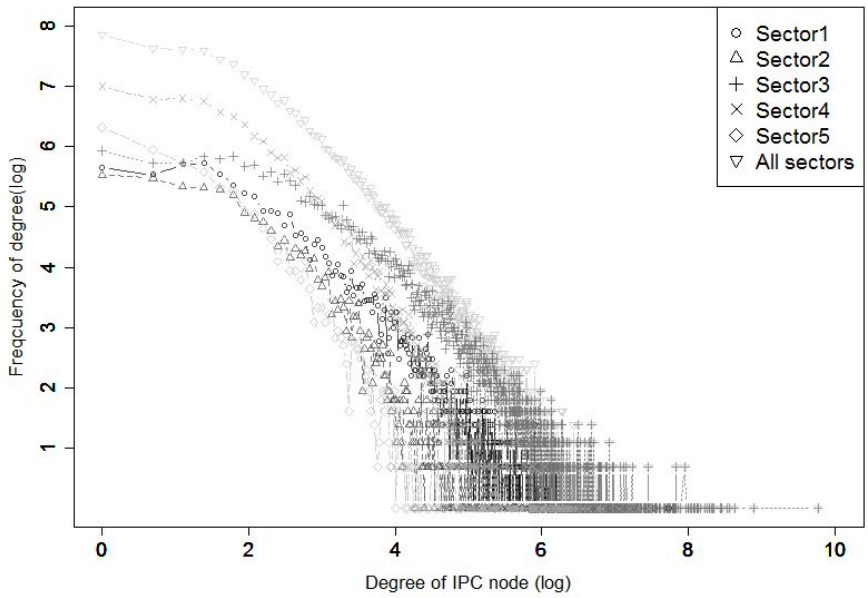

Figure A3. Degree Distributions of Korean Technology Network in Log-Log Scales by technology section (1970~1989)

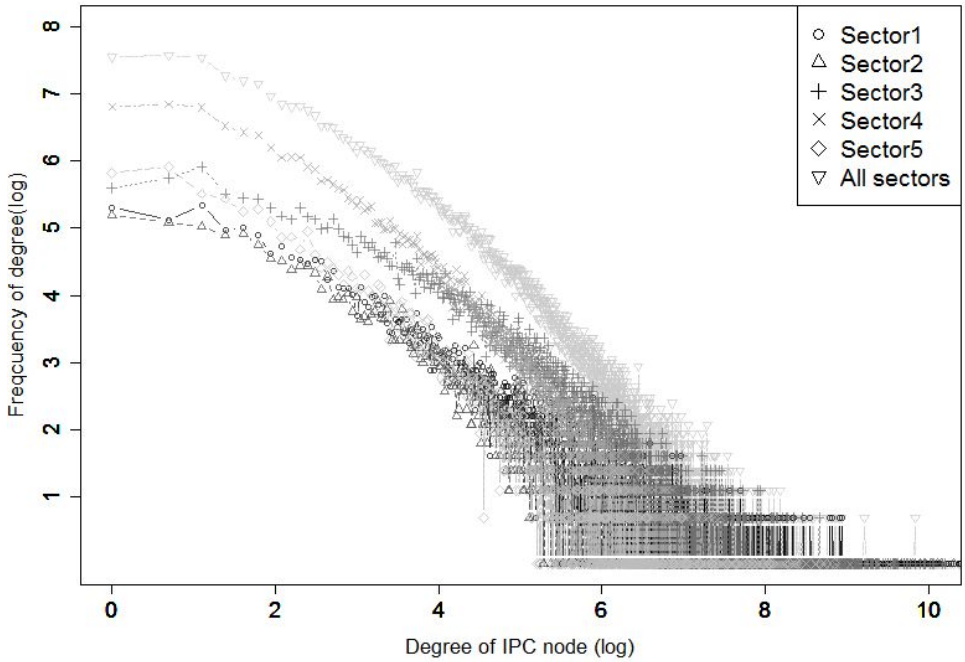

Figure A4. Degree Distributions of Korean Technology Network in Log-Log Scales by technology section (1990~2009)

Table A3. Tests of power-law behavior of each sector in the cumulative network

	1970-1989			1990-2009		
sector	gamma	KS.p	xmin	gamma	KS.p	xmin
1	3.162	0.997	327	2.125	0.028	2390
2	2.184	0.218	25	2.359	0.975	1114
3	2.382	0.216	267	2.321	0.072	1372
4	2.478	0.447	47	2.664	0.619	490
5	3.005	0.686	43	2.518	0.958	377

Note: For Hypothesis 3 Clustering coefficient distributions by five technology sectors

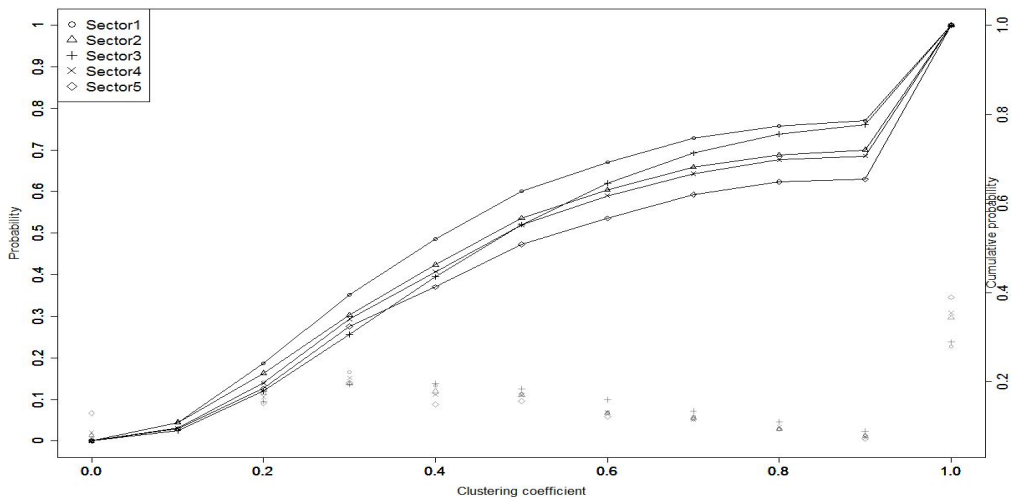

Figure A5. Clustering coefficient distributions of Korean Technology Network by technology section (1970~1989)

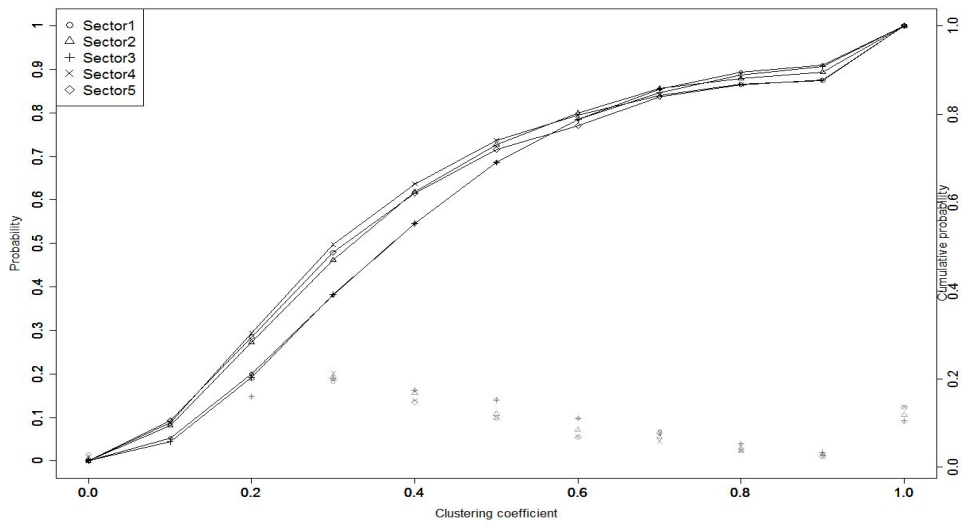

Figure A6. Clustering coefficient distributions of Korean Technology

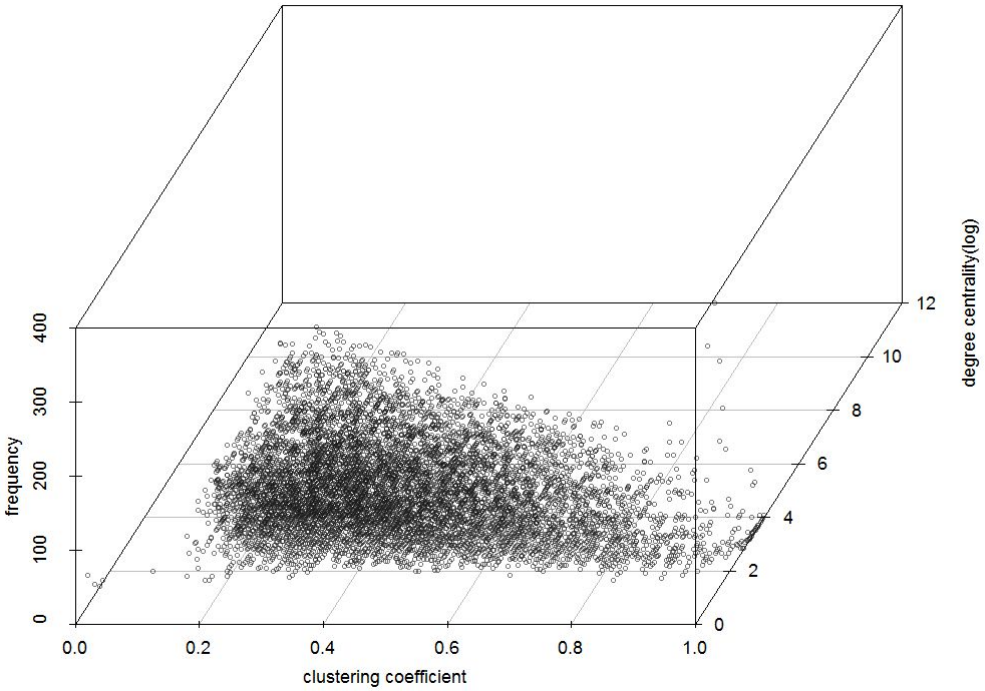

Figure A7. Distribution of clustering coefficient and degree (1970~2009)

Table A4. Correlation matrix in firm innovation study

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1)R&D intensity	1.000													
(2)app_year_sum	0.030	1.000												
(3)nprd	0.055	-0.004	1.000											
(4)productivity	0.047	0.061	-0.091	1.000										
(5)cum tech exp	-0.001	0.948	-0.010	0.022	1.000									
(6)ipc tech scope	-0.011	0.853	0.001	0.153	0.850	1.000								
(7)diversity in tech pool	-0.098	-0.202	-0.143	0.016	-0.175	-0.178	1.000							
(8)network density	0.031	-0.142	0.134	-0.168	-0.104	-0.237	-0.012	1.000						
(9)network diversity	0.014	0.158	0.057	0.098	0.168	0.215	-0.457	0.071	1.000					
(10)network clustering	-0.072	-0.215	-0.010	-0.037	-0.179	-0.263	0.371	0.396	0.103	1.000				
(11)R&D emp	0.046	0.910	0.008	0.041	0.908	0.821	-0.095	-0.146	0.132	-0.182	1.000			
(12)emp	-0.072	0.545	0.072	0.171	0.479	0.719	-0.013	-0.243	0.089	-0.191	0.611	1.000		
(13)idustry HHI	-0.001	0.064	0.073	0.093	0.059	0.085	0.057	0.056	0.081	0.049	0.105	0.219	1.000	
(14)firm age	-0.281	-0.022	-0.196	0.116	-0.023	0.050	0.106	-0.103	0.126	0.052	-0.045	0.124	-0.189	1.000

Table A5. Sample countries

no	Country name	Country	no	Country name	Country
1	Slovenia	SI	17	Netherlands	NL
2	New Zealand	NZ	18	Romania	RO
3	Ireland	IE	19	Morocco	MA
4	Norway	NO	20	Canada	CA
5	Slovakia	SK	21	Poland	PL
6	Finland	FI	22	Argentina	AR
7	Denmark	DK	23	Spain	ES
8	Bulgaria	BG	24	South Korea	KR
9	Israel	IL	25	South Africa	ZA
10	Switzerland	CH	26	Italy	IT
11	Austria	AT	27	United Kingdom	GB
12	Sweden	SE	28	Egypt	EG
13	Hungary	HU	29	Mexico	MX
14	Portugal	PT	30	Brazil	BR
15	Greece	GR	31	India	IN
16	Belgium	BE			

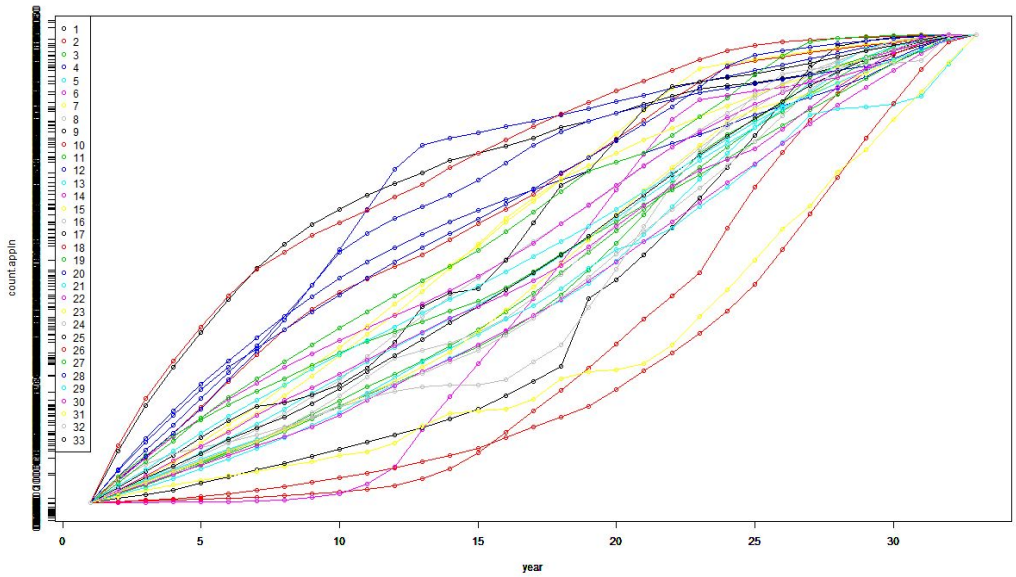

Figure A8. Pattern type1 (the number of patent application)

Note : The *x*-axis is year, The y-axis is the number of patent application of each country

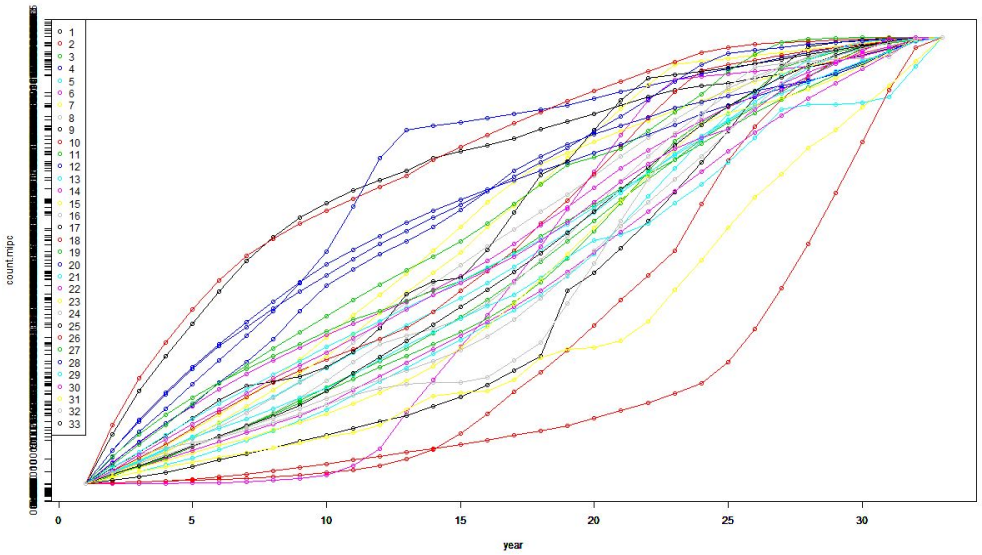

Figure A9. Pattern type1 (the number of IPC in pool)

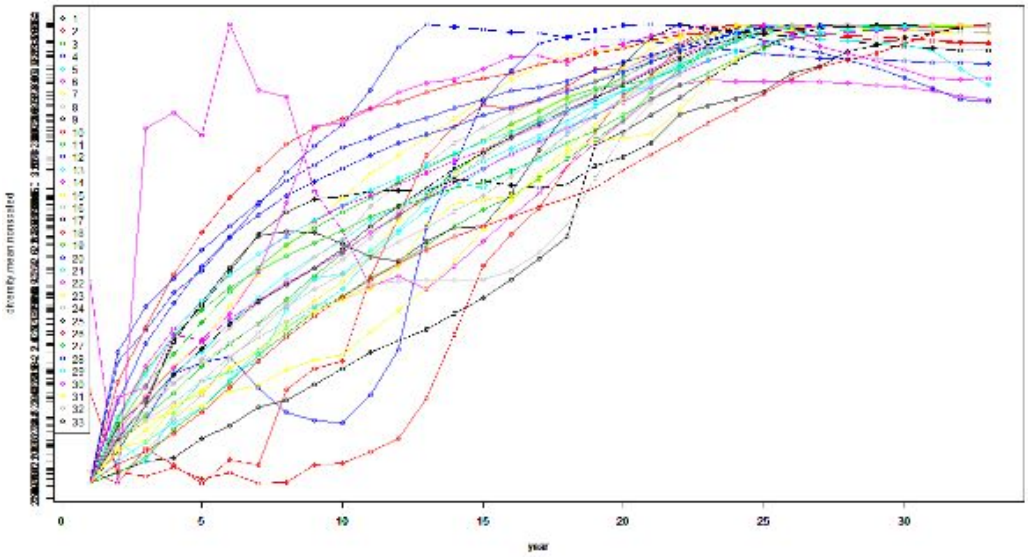

Figure A10. Pattern type2 (diversity.mean-nonscaled)

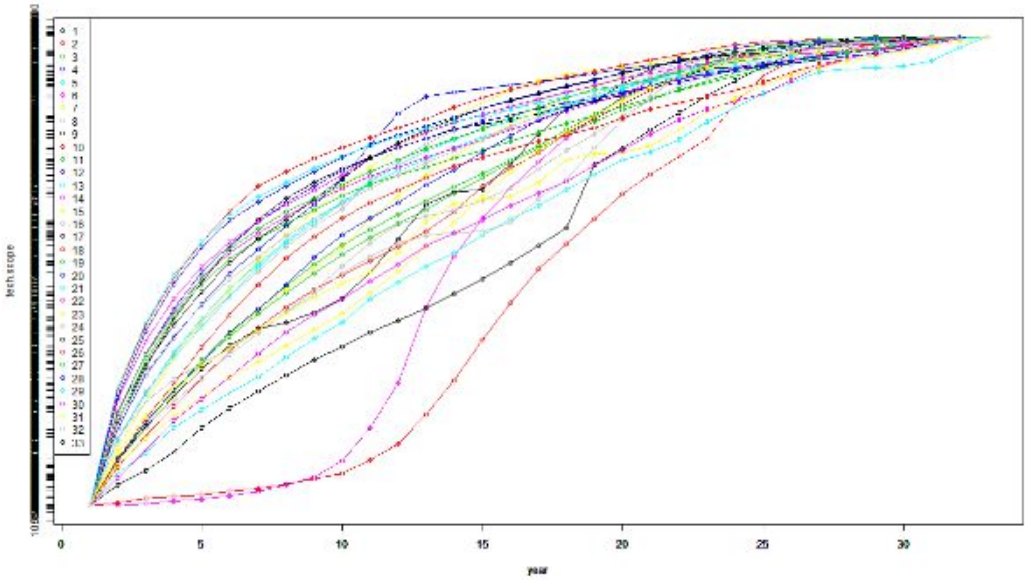

Figure A11. Pattern type2 (technology scope of IPC pool)

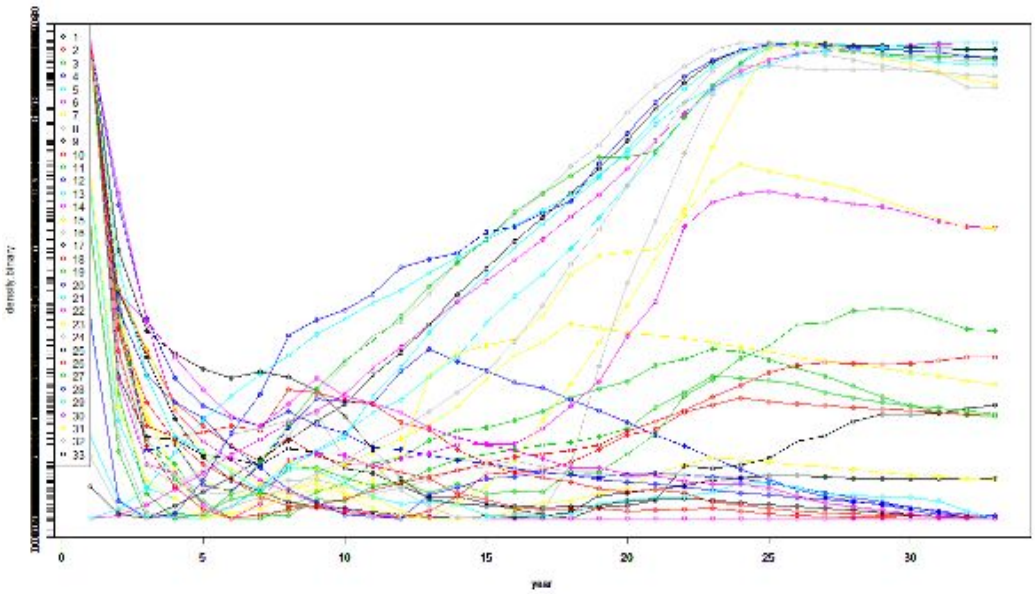

Figure A12. Pattern type3 (binary network density)

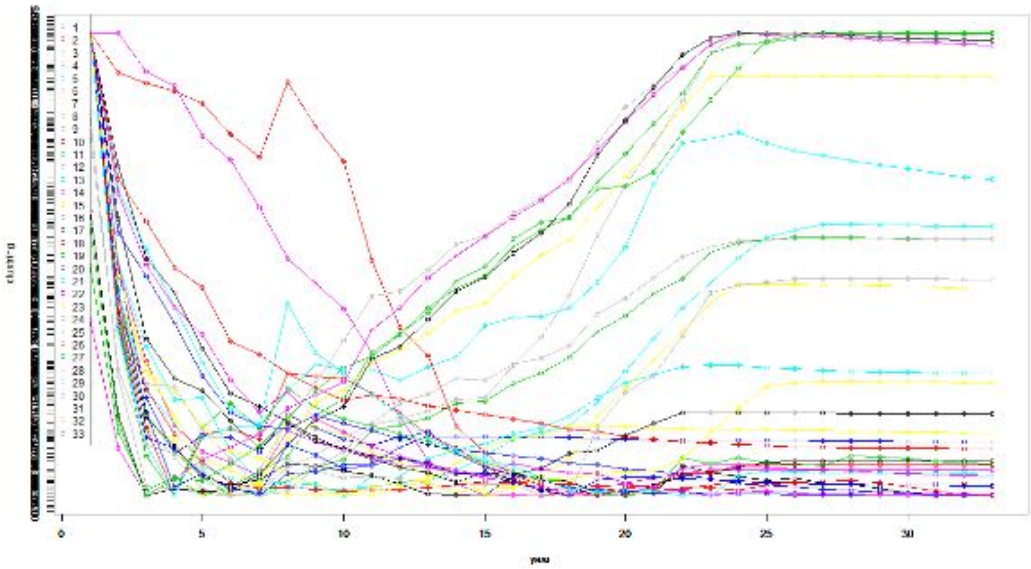

Figure A13. Pattern type3 (network clustering coefficient)

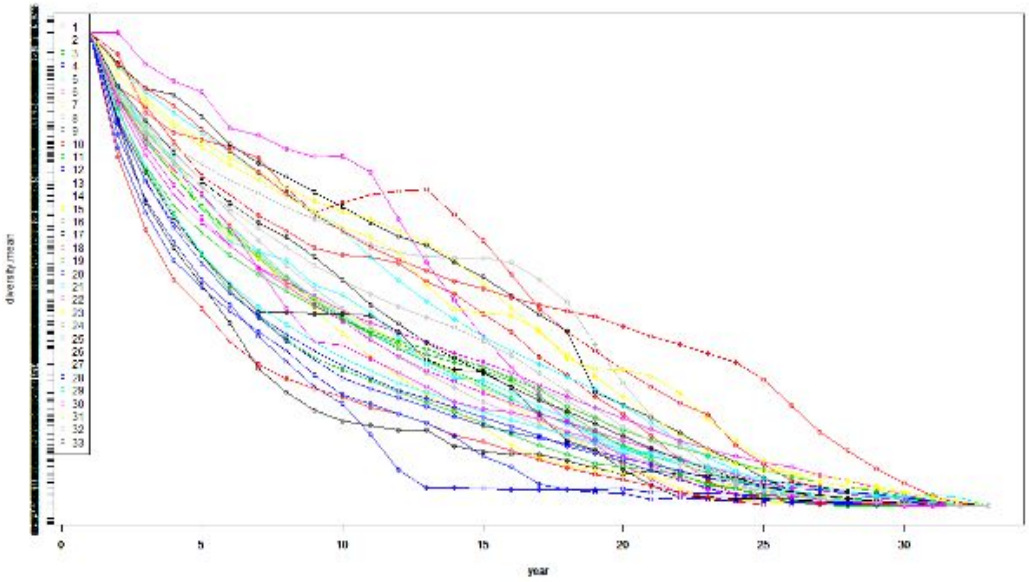

Figure A14. Pattern type4 (network diversity)

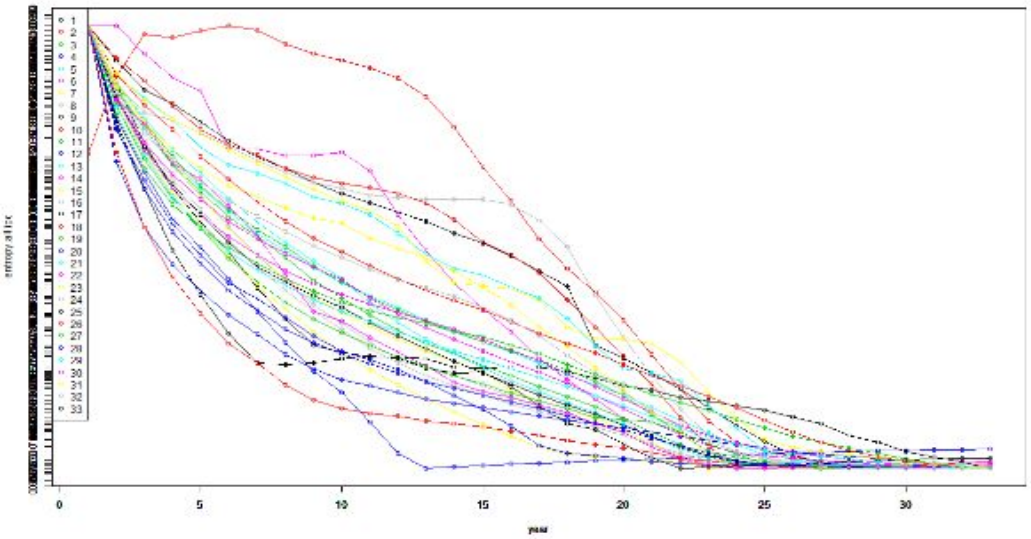

Figure A15. Pattern type4 (diversity of IPC pool)

Table A6. Correlation matrix in national innovation study

(1)ln.count.ipc	1															
(2)ln.gdp.ppp.out	0.421	1														
(3)ln.gdp.ppp.cpa	0.489	-0.119	1													
(4)ln.count.ipc	1	0.421	0.489	1												
(5)entropy.all.ipc	-0.795	0.03	-0.361	-0.795	1											
(6)density.binary	-0.286	-0.521	-0.318	-0.286	-0.257	1										
(7)div.mean	-0.942	-0.49	-0.428	-0.942	0.698	0.199	1									
(8)clustring	-0.314	-0.462	-0.414	-0.314	-0.165	0.766	0.351	1								
(9)mkt.captial.pct	0.24	0.157	0.239	0.24	-0.093	-0.218	-0.253	-0.276	1							
(10)manf.vad.pct	-0.123	-0.157	-0.101	-0.123	0.083	-0.007	0.125	-0.136	-0.101	1						
(11)open.trade	-0.065	-0.344	0.407	-0.065	-0.058	0.047	0.121	0.07	0.092	0.108	1					
(12)int.usr	0.438	0.048	0.525	0.438	-0.422	-0.026	-0.391	0.016	0.329	-0.232	0.367	1				
(13)free.pres.brd	0.352	-0.228	0.768	0.352	-0.235	-0.342	-0.25	-0.3	0.25	-0.161	0.282	0.393	1			
(14)teacher.rto	0.237	-0.346	0.748	0.237	-0.251	-0.07	-0.146	-0.03	-0.04	-0.156	0.353	0.366	0.632	1		
(16)gini.idx	0.013	0.304	-0.504	0.013	-0.057	0.132	-0.042	0.078	0.055	0.022	-0.426	-0.328	-0.52	-0.489	1	
(17)pop	-0.192	0.477	-0.592	-0.192	0.349	-0.22	0.177	0.023	-0.075	-0.15	-0.329	-0.213	-0.328	-0.633	0.08	1

Abstract (Korean)

혁신 연구들은 기업, 대학, 정부와 같은 혁신 주체들 사이의 상호작용을 중요시 하는 시스템 관점에서의 혁신에 관심을 보여 왔다. 최근에는 이 상호작용의 결과인 지식이 혁신 성과에 미치는 영향과 더불어 지식의 구조적 특징을 이해하기 위해 많은 연구들이 네트워크 분석법을 특허와 논문과 같이 지식이 성문화된 문서 분석에 적용하고 있다. 네트워크 분석법을 이용한 많은 비교연구들이 네트워크 상의 혁신 주체들 위치 혹은 주체의 조직적 구조의 영향에 대해 초점을 맞춰 왔다. 하지만 주체가 개발하고 보유한 기술과 인적자원을 우선적으로 고려하는 것이 기술 경영을 위한 전략과 정책 수립에 최우선적으로 중요하다. 이러한 이유로 많은 연구자들이 주체들이 보유한 기술과 제품의 다변화, 특성화, 깊이와 폭에 대한 연구를 진행하고 있다.

하지만 최근에 기술의 조합과 융합이 더욱 중요해 지고 있지만 이 과정상에서 기술의 다양성과 긴밀도의 영향과 상호작용은 충분이 조사되어 지지 못 하고 있다. 디지털 경제에 있어 기술 포트폴리오의 구성뿐 아니라 주체가 보유한 기존 기술 자원을 융합하는 능력 역시 중요하다. 따라서 본 논문은 혁신 주체가 보유한 기술 풀의 특성과 혁신에 있어 기술 융합의 경향을 반영하는 기술 네트워크의 구조적 특성에 대해 논의한다. 나아가 혁신 성과에 있어 기술 풀과 네트워크의 영향도 조사한다.

이를 위해 기술 섹터, 기업, 국가의 3가지 레벨에서 국제 특허 분류를 이용한 3종류의 기술 분류 네트워크를 구성한다. 다른 산업들로부터 발생하는

기술 융합의 성격을 분석하기 위해 한국의 출원 특허를 이용한다. 기업과 국가에 있어 기술 구조와 혁신 성과 사이의 관계를 조사하기 위해 특허, 혁신 설문 자료 그리고 경제 자료들이 결합되었다. 연구는 특허 네트워크와 풀의 구조적 긴밀도와 다양성의 영향에 초점을 두고 수행한다.

기술 융합의 특성에 대한 비교는 한국의 경제성장을 이끌어 온 정보통신기술을 바탕으로 하였다. 분석 결과, 한국의 정보통신기술은 비관련 기술 융합 보다 관련 기술의 융합을 중심으로 한국의 기술 공진화에 공헌해 왔음을 확인할 수 있었다. 기술 풀과 네트워크의 성격과 혁신 사이의 관계는 기업 단위의 혁신 산출에 대한 영향을 제외하고 기술 풀의 다양성과 긴밀도는 혁신 활동과 양의 관계를 보였다. 이와는 달리 기술 네트워크 지표는 기업과 국가에 다른 영향을 보였다. 기업의 네크워크 긴밀도는 연구개발 투자와 혁신 산출에 양의 관계를 가진 반면 국가의 기술 긴밀도는 그들과 유의한 영향을 보이지 않았다. 네트워크 다양성은 혁신 산출에 상반의 결과를 나타냈다. 즉 국가의 네트워크 다양성은 양의 관계를 보인 반면 기업은 음의 관계를 보였다. 이러한 발견과 기술 네트워크에 바탕을 된 접근은 기술 촉진과 각기 다른 조직에서의 성과를 촉진시키기 위한 전략과 정책 수립에 기여할 것이다.

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주요어 : 지식 네트워크, 국가 혁신 시스템, 특허 분석, 구조방정식모형, 비모수적 추정

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