Ph. D. Dissertation in Engineering

Three essays on accumulated technological knowledge of the firms

- Multifaceted nature, measure and strategy about accumulated technological knowledge -

기업의 축적된 기술 지식에 관한 세편의 소론
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- Multifaceted nature, measure and strategy about accumulated technological knowledge -

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이 논문을 공학박사학위 논문으로 제출함
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Abstract

Three essays on accumulated technological knowledge of the firms

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Firms that do not innovate cannot survive. This is because the innovation not only increases the firm's survival rate, but is also a necessary condition for adapting to a rapidly changing environment due to the emergence of new technologies. A firm's innovation is achieved through co-evolution between product innovation and technological innovation, which compose it. In particular, technological innovation precedes product innovation and forms the basis for product innovation. Firms can develop new innovative products based on accumulated technology and grow financially by selling these innovative products to the market. Therefore, it is essential to understand the characteristics of technology, which

is conceptually located at the very bottom layer, in order to understand the growth of a firm.

However, technological knowledge is not easily acquired and needs a long time for its accumulation. This is because technological knowledge can only be accumulated within a firm through a sufficient accumulation period to experience trials and error. Therefore, various concepts have been created to understand the nature of technological accumulation, which requires considerable resources. These concepts can be largely divided into methods of accumulation to explain how to accumulate technology, strategies of accumulation to carry out the methods of technology accumulation, and aspects of accumulation, which describe phenomena that appear as a result of technology accumulation strategies.

Yet, previous studies have room for improvement in the following three aspects. First, since the concept of technological accumulation is three-dimensional, it cannot be explained with just one concept. Next, the method of accumulation of technology varies over time as it follows dynamic changes. Lastly, since the complexity of technology development varies for each technology, the heterogeneity of technology will also affect the strategy of technology accumulation.

This study analyzed the discussions related to technological knowledge accumulation in firms from various aspects. In addition, a time-series analysis over time was confirmed to understand dynamic changes. To this end, an empirical analysis was conducted using an unbalanced panel data set that linked patents and financial information of the firm. Finally, this study revealed that the existing discussions on technological knowledge accumulation should be understood in a more elaborate manner.

Specifically, in Chapter 3, the dynamic process of accumulating technological knowledge within a firm was examined from a multifaceted perspective. First, as the firm's tenure increased, the entire technological knowledge (including both the core and the periphery) of the firm gradually migrated. Next, as the firm's tenure increased, the boundary of the firm's technological knowledge expanded. Finally, the firm's technological knowledge was accumulated following a pattern of punctuated equilibrium. Integrating all three perspectives, it is found that the accumulation of technological knowledge within firms follows the process of 'gradual migration with punctuated equilibrial expansion'.

In Chapter 4, a new method of measuring technological capability through the aspect of accumulated technological knowledge was presented. A firm's technology capability was measured indirectly through the breadth, depth, and coherence of its technological portfolio. Through the devised technology capability measurement, it was found that firms in Korea's 'Manufacture of Electronic Components, Computer, Radio, Television and Communication Equipment and Apparatuses ' industries have developed in the direction of deepening the depth of core technology. An inverted U-shaped relationship was observed between a firm's technological capability and its long-term financial performance, and a U-shaped relationship was observed between a firm's technological capability and its innovation performance. In the dilemma between innovation performance and long-term financial performance, firms have to decide whether to invest in technology capabilities for the future.

In Chapter 5, it was clarified how the strategy of technology accumulation (in terms of technological diversification and technological complexity) should differ depending on the size and the level of technology stock of the firm. First, technological diversification is the optimal technology accumulation strategy for financial performance of the firms with high technology stocks and large sizes. Next, for a small firm with a high technology stock, the optimal technology accumulation strategy is to increase financial stability rather than additional technology accumulation. Finally, for firms with low technology stocks, regardless of size, they need to either increase the complexity of their technologies or make efforts to increase their technology stocks. Through these results, it was found that the effect of technological diversification on financial performance should be interpreted differently depending on the condition of the firm.

Summarizing the results of the study, it is essential to take a more sophisticated approach that considers the multifacetedness, dynamics, and heterogeneity of technological knowledge for understanding and interpreting the technological knowledge accumulation within a firm. Existing studies related to the technological knowledge and its accumulation show i) unconverged results and ii) limitations in understanding and explaining our reality, which are caused by attempts to simplify and understand technological knowledge as much as possible, like drawing 'croquis'. This was an unavoidable choice despite the loss of information because it was prioritized to capture the characteristics of movement or form of technological knowledge. When we accept the three-dimensional, dynamic-changing, heterogeneous technological knowledge and firms as they are, we will be able to fully understand and explain technological innovation and the growth of firms.

Keywords: Technological knowledge accumulation, Technology accumulation pattern, Technology accumulation measurement, Technology accumulation strategy, Patent disambiguation, Empirical analysis

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Chapter 1. Introduction

1.1 Research motivation and purpose

The impact of a firm on national growth is absolute. In response, to find an answer to the question, 'Which firms are growing?', two approaches have been suggested. One, centered on Schmalensee (1985) and Porter (1980a, 1997), is an effort to understand the environment surrounding the firm. The other is the effort to look inside the firm, as opposed to looking outside. The two different approaches have been complementary in helping to understand firm growth.

In particular, various efforts have been made to look inside the firm. Among them, the Resource based view recognizes that resources within a firm determine its comparative advantage (Coase, 1995; Penrose, 2009; Nelson and Winter, 1982; Teece, 1982; Rumelt, 1984; Wernerfelt, 1984; Barney, 1986, 1991; Dierickx and Cool, 1989; Amit et al., 1993) and has focused on finding different resources that have an impact on firm growth. As a result, various types of tangible and intangible resources that affect a firm's growth have been investigated so far. Entrepreneurship (Alvarez et al., 2001), governance (Lockett and Thompson, 2001), human capital (Wright et al., 2001) and innovation (Schumpeter, 1934; Scherer, 1965a) are the typical resources.

Schumpeter (1934) suggested that, among others, innovation is at the center of economic growth and promotes the overall growth of the economy. According to

Schumpeter (1934), firms have an incentive to innovate for market entry and their growth. This is because the market is not a static equilibrium state, but a place where products and processes developed through innovation interact dynamically through heterogeneous firms. According to the Schumpeterian interpretation, a firm's growth is an evolutionary process that introduces new innovations to the market (Audretsch et al., 2014).

Therefore, firms that do not innovate cannot grow. A firm's failure to grow means a situation in which the firm is unable to grow, or at least cannot sustain further growth financially. In other words, it means that the firm cannot survive. Firms acquire a differentiated comparative advantage from other competitors only through innovation, which is an act of changing the organization by responding to changes in the external environment or preemptively responding to the influence of the external environment (Porter, 1980b; Damanpour, 1996). Since differentiated comparative advantage is directly linked to growth (Teece et al., 1997), firms that cannot secure comparative advantage through innovation will cease their growth soon. Even though firms exist for a variety of reasons, firms with negative growth rates eventually decide to stop operating and exit the market (Tirole, 1988), because they ultimately pursue profit (Mankiw, 2014).

The results of various empirical analyses, starting with Mansfield (1962), support the fact that innovation and dynamics (including entry, growth and exit) of firms are closely related. Audretsch (2014) observed that innovation generally has a positive effect on a firm's revenue and productivity growth. Coad and Rao (2008) also confirmed that innovation in high-growth firms has a positive effect on their growth. Coad (2009) revealed that there is a positive correlation between Research and Development (hereafter, R&D), innovation, and a firm's growth. According to Cefis et al. (2006), the more a firm innovates, the higher the probability of survival (Cefis et al. (2006) call this the 'innovation premium'). Audretsch (1995) showed that the probability of new entrants surviving more than 10 years is much lower in industries with active innovation activity than in industries with inactive innovation activity. If the firm develops new products, their growth rates and survival rates are increased (Audretsch, 1995).

Among the many theories and practices that have revealed 'the relationship between innovation and growth of the firm', we naturally ask the following questions. 'How does a firm's innovation that is so important to the firm occur?', 'What is the source of innovation that affects a firm's growth?'

This study argues that firm's innovation is achieved through the co-evolution between technological innovation and product innovation.[1] The products produced by firms can also be seen as the result of intensive technological innovation of firms, but the two types of innovations are distinguished by the presence or absence of form. Technological innovation exists in intangible forms, such as human capital, codified manuals, in-firm routines, and patents. On the other hand, product innovation is a tangible result developed and produced based on technological innovation.

[1] Innovation activities include various methods such as new types of products or services, organizational structures, and development of new types of technologies. In the field of *Innovation and entrepreneurship*, firm's innovation is largely divided into product and service innovation (hereinafter referred to as product innovation) and technological innovation (Baregheh et al., 2009). Also, through the fact that various studies (Patel and Pavitt 1997; Miller 2006; Dosi et al. 2017) distinguish 'what a firm knows' from 'what a firm produces', we can infer and conclude that technology and products are different dimensional concepts.

In particular, technological innovation is the basis for product innovation. There are stages of activities such as a value chain between technology and product, and technology-related knowledge supports the components of the product used for product development (Helfat et al., 2000). In particular, through an empirical analysis Kang et al. (2020) found that past technology-related strategic choices affect current product-related strategic choices of firms in the Korean manufacturing industry, and not vice versa.

Technological innovation, which is located at the very bottom and the foundation, and product innovation, which is the embodiment of technological innovation, interact with each other. This interaction forms a feedback loop, and experiences co-evolution in which they develop together. Based on technological innovation, better product innovation will be born first. Trials and errors experienced in the process of product innovation are accumulated within the firm and used as nourishment for the next technological innovation. When this feedback loop is repeatedly passed through, the overall innovation of the firm occurs.

Therefore, the sentence 'firms that do not innovate cannot grow.' is like saying that the survival of a firm, that is, the fate of a firm, is determined on a conceptually layered structure composed of three different levels of technology-product-financial growth. This is because firms grow financially by building technology-related knowledge, developing innovative products based on the accumulated knowledge, and then selling these products to consumers in the market. As a result, it will be essential to have a prior understanding of technological knowledge, which is located at the very bottom level and has the most fundamental influence on determining the rise and fall of a firm.

However, technological knowledge within a firm does not appear suddenly, but is acquired and accumulated over a long period of planned and deliberate effort. Technology within a firm is accumulated through sufficient time of experiencing trials and error (Lee et al., 2015). Among them, design capability, which provides greater added value than implementation capability, is not something that can be easily obtained. This is because intangible resources such as technology follow a more complex method than the accumulation of physical assets, and cannot be increased simply by increases of investment (Knott et al., 2003). It is also because technological knowledge is created and accumulated in a different way from other resources as it cannot be accumulated through a lot of effort in a short period of time (Dierickx and Cool, 1989). Technology accumulation is challenging to such an extent that strategies for efficiently accumulating technological knowledge, like small betting and scale-up, are presented separately (Lee, 2017; Yeon et al., 2021).

The nature of the accumulation of technological knowledge also adds to the difficulty for firms to accumulate it. This is because technological knowledge requires a lot of cost in the process of accumulation, experience through trials and error for sufficient time (Mitchell and Hamilton, 1998; Lee, 2017). Also, there exists a risk and uncertainty of failure, and inefficiency, in that input versus output is not guaranteed (Mitchell and Hamilton, 1998; Lee, 2017). In particular, since a firm's resources are limited, it cannot devote infinite resources, so firms need to take a more prudent and strategic approach to accumulating technological knowledge.

Most important, while the process is tedious at the same time, various efforts have been made to understand the nature of technological knowledge accumulation. Various concepts such as total factor productivity and human capital (in traditional economics), creative destruction (in innovation economics), variety creation, fitness, market selection and routine (in evolutionary economics), cascades, interaction through network (in complex economics) have tried to explain the essence of technological knowledge accumulation. The reason why technology is defined differently in various fields is that it has an interdisciplinary character as it spans various disciplines, and as a result, interpretation differs depending on the aspect the researchers focus on. The multifaceted nature of technological knowledge makes it difficult for us to solely understand technology.

Nevertheless, interdisciplinary common phenomena have been discovered. The principle of relatedness (Hitt et al, 1997; Hidalgo et al., 2007), path dependence (David, 1985; Arthur, 1989, 1994), exploration and exploitation (March, 1991; Levinthal and March, 1993), ambidexterity and punctuated equilibrium (Tushman and Romanelli, 1985; Tushman and O'Reilly, 1996; Levinthal et al., 1998; Benner and Tushman, 2003) are commonly used in various disciplines. Through each concept, which can be likened to a single window, we have tried to understand the nature of technology, at least in part.

However, even if we utilize various concepts devised so far, there is still a limit to understanding the nature of technological knowledge. This is because firms are living organisms that accumulate technological knowledge, which is an intangible resource (as well as living organisms), and grow through the process of adapting and evolving to the ever-changing environment. When both the subject and the object evolve, the way of interpreting them inevitably becomes more complex and diverse. As a result, a more advanced and sophisticated approach is required as all various dimensions change simultaneously and dynamically over time.

In order to fully understand the nature of technological knowledge, which forms the basis of technological innovation of the firm, a new perspective is needed to understand technological knowledge accumulation. Therefore, this study proposes a new way of interpretation considering multifacetedness, dynamics, and heterogeneity of technologies in addition to the existing perspectives. Multifacetedness refers to the simultaneous observation of various concepts and dimensions; dynamics indicate that technology changes over time; and heterogeneity between technologies implies that all types and levels of technologies should be regarded differently.

As mentioned earlier, existing studies analyze only one phenomenon in a static way to understand the accumulation of technological knowledge, or describe the characteristics captured at a single dimension in the specific time. In addition, for the convenience of research, it has been assumed that the level of all technologies is the same without distinction. However, rather than being explained through only one concept, it is judged that the accumulation of technological knowledge within a firm will be a three-dimensional process in which the characteristics of various concepts are observed at the same time. Moreover, it is clear that the effect of different technologies on the accumulation of technological knowledge within a firm will vary according to its heterogeneous level. Empirical analyses have revealed various patterns of knowledge accumulation occurring simultaneously, and these patterns shift over time (Coad and Guenther, 2013). Moreover, it's found that firms' strategies for accumulating technological knowledge should adjust based on the heterogeneity between technologies (Kim et al., 2022).

Therefore, this study, in relation to the nature of technological knowledge accumulation, will answer to the questions:

1. What various characteristics are simultaneously observed in the process of technological knowledge accumulation within a firm
2. How can the capabilities of accumulated technological knowledge be measured by the aspects of a firm's technological portfolio?
3. How does a firm's technological knowledge accumulation strategy change when heterogeneity between technologies is considered?

In the meantime, attempts to look at the process of accumulating technological knowledge from various perspectives and efforts to analyze patterns simultaneously, which are changes over time, have been lacking. In addition, there is a lack of agreed-upon indices that measure the generalized technological capabilities through a firm's technological portfolio. Also, there are not many studies observing dynamic changes in technological capabilities according to a firm's tenure. Lastly, efforts to additionally consider heterogeneity between technologies beyond heterogeneity of firm were insufficient. As a result, it is difficult to understand the difference in technological knowledge accumulation strategies according to the different level of technologies.

The need is evident to discuss the accumulation of technological knowledge within firms in sophisticated way to fully understand the drivers of firm's growth. In this study, through an empirical analysis of US and Korean manufacturing firms, i) the process of accumulation of technological knowledge within the firm from various and dynamic perspectives, ii) the measurement of accumulated technological knowledge capability, and furthermore, iii) the heterogeneous technology accumulation strategy for the firm according to heterogeneity between technologies will be identified. A new three-dimensional and dynamic perspective, additional consideration of heterogeneity between technologies beyond the heterogeneity of firms, is expected to help a more sophisticated and systematic understanding of technological knowledge accumulation of firms.

1.2 Outline of the study

This study is largely composed of 6 chapters. The outline of the study is shown in Figure 1-1. Chapter 2 examines the theoretical background of firm's technological knowledge accumulation and various efforts to understand the nature of technological knowledge. First, the theories on the accumulation of technological knowledge devised in various academic fields have been organized by the main perspectives that each field focuses on. Next, after comprehensively reviewing previous studies to understand the nature of technological knowledge, they were divided into methods, processes, and aspects. Then, in order to supplement the limitations of previous studies related to the accumulation of technological knowledge, the reason why multifacetedness, dynamics, and heterogeneity between technologies should be additionally discussed is described.

In this study, the following three essays consider multifacetedness, dynamics, and heterogeneity among technologies. First, the dynamic aspects of the multifaceted characteristics of the technological knowledge accumulating process within the firm were examined. Second, after measuring the accumulated technology capability within the firm through its technological portfolio, the dynamic change of the technology capability and its effect on financial growth were investigated. Third, the differences in technological knowledge accumulation strategies according to heterogeneity among technologies were reviewed, and furthermore, its effect on firm's growth was empirically analyzed. To this end, a patent dataset of firms belonging to the US manufacturing sector and a unique patent dataset of firms belonging to the Korean manufacturing sector were constructed and used. Using various econometric methods, this study aims to identify the reasons why a multifaceted approach, dynamic analysis for technological knowledge accumulation, and consideration of heterogeneity among technologies are important.

In Chapter 3, various characteristics related to the accumulation of technological knowledge within the firm were simultaneously looked at, and changes in each characteristic according to the firm's tenure were observed. So far, various previous studies have devised various concepts to understand and explain the characteristics of technological knowledge accumulation in firms. However, existing concepts mainly describe the technological knowledge, which is intangible resource, in one dimension or a static state at a point in time. Therefore, in this study, various characteristics of the technological knowledge accumulation process have been presented so far, i) the principle of relatedness, ii) expansion of the boundary, and iii) punctuated equilibrium, are simultaneously investigated, and integrated into a new concept, 'gradual migration with punctuated equilibrial expansion'. This approach seeks to Understand the process of accumulating technological knowledge in a firm three-dimension, and track the dynamic changes by observing each firm's tenure.

In Chapter 4, after developing an index to measure the accumulated technological capability within a firm, the dynamic change of this index over time was analyzed. Then, the influence of the devised index on the prediction of financial performance and innovation performance was analyzed. In this study, it is believed that the technological capabilities accumulated within a firm can be measured through the aspect of the technological portfolio. The aspect includes breadth, depth, and coherence of technological portfolio as elements. In order to improve the realistic problems of various indexes used previously, the elements of each dimension were calculated as a single index through different weights taking into account their relative impacts.

In Chapter 5, it is clarified that the firm's technological knowledge accumulation strategy to increase financial performance should be different based on the size and the technological knowledge stock of the firm. So far, many studies have shown a positive causal relationship that the more a firm diversifies its technology, the more it grows financially. However, in reality, contrary to theory, small-scale firms that do not have a high stock of technology continue to operate and even grow. Therefore, even if the stock of technology is low, it does not mean that the financial growth rate is low. So we need to additionally consider the complexity of each technology. In this study, after classifying firms according to their size and stock of technological knowledge, we propose different strategies for accumulating technological knowledge for each group in terms of increasing technological complexity and technological diversification.

The last chapter 6 is the conclusion of this study. The results of the empirical analysis are summarized. The process of accumulating technological knowledge from our new perspective, the new index measuring accumulated technological knowledge capacity, and the distinguished strategies for accumulating technological knowledge were presented. From this, both managerial and policy implications were derived. Finally, the limitations of the study are mentioned and directions for future research are suggested.

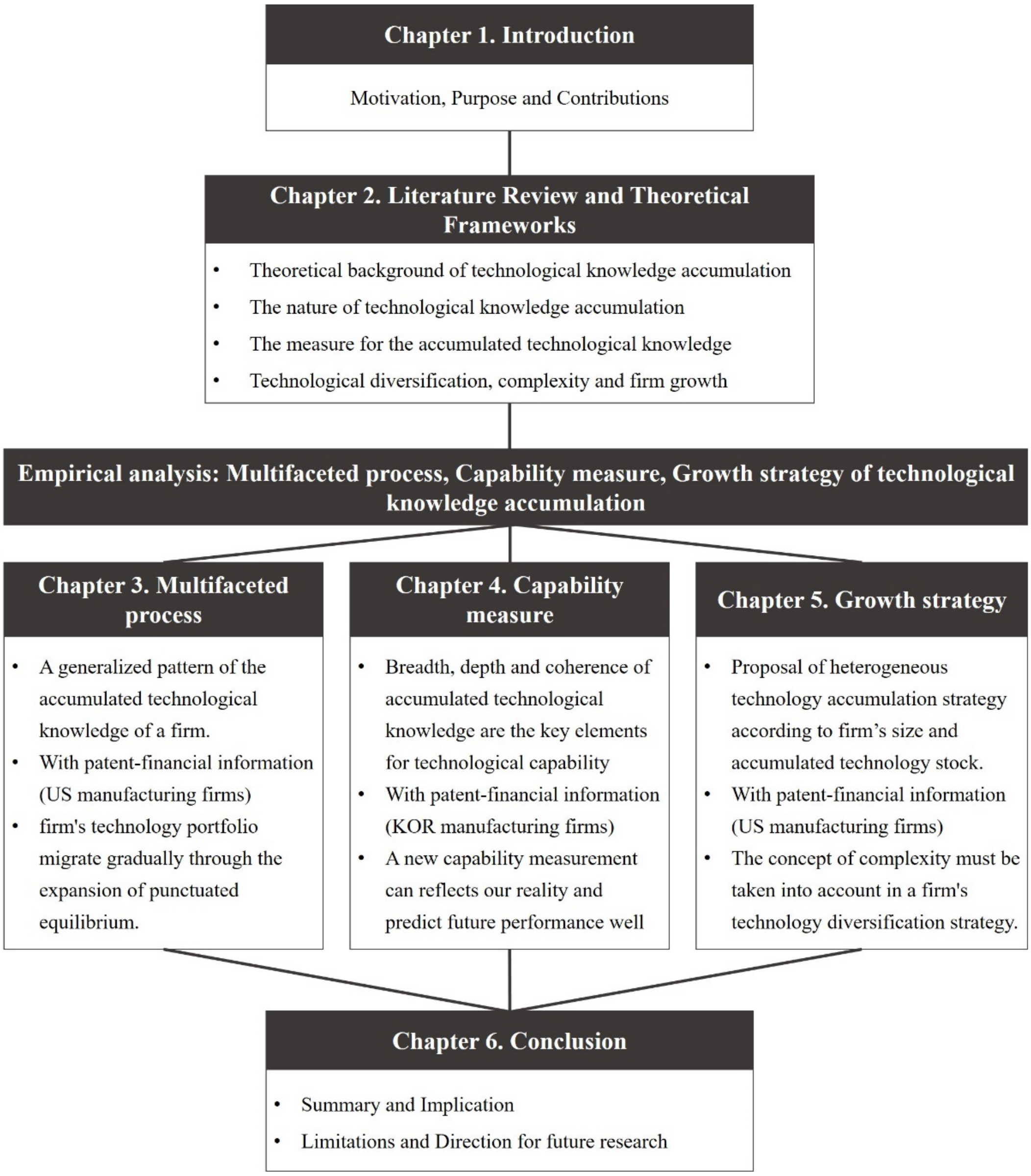

Figure 1-1. Research outline

1.3 Contribution of the study

This study goes a step further from the previous efforts to understand the accumulation of technological knowledge in firms, and organize concepts that have been mixed according to various contexts. Moreover, this study simultaneously illuminates the process of accumulating technological knowledge from various angles, and examine the aspects of technological portfolios. Through this study, heterogeneity among technologies was reflected in the measurement of technological capabilities or the establishment of strategies, and an attempt was made to understand dynamic changes over time. The results of this study are meaningful in seeking out and providing new perspectives on firm's technological knowledge accumulation strategies and policies.

First, in this study, various concepts and terms designed to understand and describe the accumulation of technological knowledge are classified according to our established criteria. To this end, this study i) extensively researched previous studies defining concepts and terms, ii) selected keywords that could characterize each concept, and iii) divided them with our new standards. In addition, i) studies analyzing definitions and characteristics of each concept and term, ii) studies devising measurement, and iii) studies conducting empirical analysis were classified and organized. As a result, studies on the accumulation of technological knowledge are presented with criteria for our new classification: method, process, and aspect of technological knowledge accumulation.

Second, after studying disambiguation efforts of various format of patent applicant name, a patent data set is constructed for empirical analysis. In this study, the DISCERN

(Duke Innovation & Scientific Enterprises Research Network) data set matching the patent applicant names of US firms and the unique data set matching the applicant names of large and small firms subject to external audit within Korean manufacturing firms were used. In particular, through a unique dataset treating large and small and medium-size firm (hereafter, SME) subject to external audit of Korean manufacturing firms, we go beyond the existing analysis of large firms. It is expected that we will be able to understand the overall technological knowledge accumulation activities of Korean firm more systematically.

Third, the process of technological knowledge accumulation can be understood more concretely by taking a multi-faceted approach from the previous cross-sectional effort to understand the characteristics of technological knowledge accumulation within a firm. Although the importance of technology and technological innovation as a source of firm's a growth is being emphasized, we still do not fully understand what technology is, and we are even more ignorant of the process by which technology is accumulated. Various concepts have been devised to explain the methods, processes, and aspects of the accumulation of technological knowledge, but they are all a single window to understanding only fragmentary aspects. Since technology is intangible, a more detailed three-dimensional approach is needed. This study suggests the general pattern of technological knowledge accumulation by looking at the process of technological knowledge accumulation by applying various concepts at the same time.

Fourth, the dynamic viewpoint of the firm's technological knowledge accumulation is illuminated. Existing studies suggest a unique concept related to technological knowledge accumulation and help with our clear understanding, but it is similar to the screenshot image of technological knowledge accumulation which can be seen as a static viewpoint. In this study, we tried to understand the dynamic pattern of technological knowledge accumulation more elaborately by analyzing the firm's technological knowledge accumulation process and the firm's technological capability by the firm's tenure.

Fifth, heterogeneity among technologies is additionally considered. Different types of technologies are all different because the background principles and difficulties for development are different, but existing studies have not considered the difference in level for each technology. As a result of ignoring the differences in level between technologies, the heterogeneous complexity of technologies and the heterogeneous proximity between technologies are not considered. This simple approach has limitations in explaining our reality. In order to compensate for these limitations, this study considered the distinctive complexity level of each heterogeneous technology and the proximity between technologies. Thus, it is necessary to consider the heterogeneity of technology as an axis to understand the process and strategy of accumulating heterogeneous technological knowledge of a firm.

Chapter 2. Literature Review and Theoretical Frameworks

2.1 Theoretical background of technological knowledge accumulation of the firm

In order to enhance the firm's financial growth, it is necessary to understand the firm's accumulation of technological knowledge in advance. The reason can be summarized in the following four points. First, technological knowledge is the source of a firm's technological innovation and product innovation, and as a result of innovation, a firm can secure a comparative advantage in the market. Second, as accumulated technological knowledge leads to products or process innovation, firms can earn additional profits through increased production without additional costs. Third, innovations generated through accumulated technological knowledge act as barriers to entry that help firms maintain a comparative advantage for a long time. Fourth, in an environment where technology and business are rapidly changing, if a firm has abundant accumulated technological knowledge, then the firm can better adapt to new trends and changes and have a higher probability by seizing new technological opportunities.

For the foregoing reasons, understanding the accumulation of technological knowledge in a firm will be a starting point in identifying the growth and survival of a firm. But understanding a firm's accumulation of technological knowledge is not as straightforward as it might seem. This is because the accumulation of technological knowledge in different disciplines, theories and perspectives has always been an important topic and has therefore been defined in different ways in different contexts.

In this section, we will first look at how the accumulation of technological knowledge is defined in various disciplines, theories, and perspectives based on previous studies related to technology accumulation in firms. In particular, the main concepts focused on in each discipline, theory, and perspective are summarized.

2.1.1 Traditional economics

Traditional economics uses the concept of production sets to express what a firm can do. Firms can also be referred to production functions because they play a role in converting production factors in the production set into outputs. Alternatively, the production function is also called a black box, because traditional economics is not interested in how the black box is structured and what happens in it. Thus, the production set represents the entirety of a firm's knowledge used in the process of converting inputs into outputs (Arrow and Hahn, 1971).

The growth of firms is determined by the amount of inputs into their production. The contribution to the growth of capital and labor, which are representative production factors, is determined by each marginal productivity. Which of these two factors of production contributes more to a firm's growth depends on the firm's factor endowment ratio, which is the relative endowment of capital and labor. For example, in labor-abundant firms, an increase of one unit of capital plays a larger role in firm growth. Looking at the importance of factors by comparing the relative impact of each factor's contribution to a firm's growth is called growth accounting (Hulten, 2010).

The general form of the production function introduced by Solow (1957), a representative neoclassical economist, is as follows.[2]

$$Q = A(t)f(K, L) \cdots\cdots\cdots\cdots\cdots\cdots \text{Eq. (2.1)}$$

In Equation (2.1), Q is the output, K is the capital input, L is the labor input, and t is the time, which is reflected in $A(t)$, the technological change[3]. Solow (1957) suggested a method for obtaining the unobservable $A(t)$ based on observable information such as the amount of labor input and capital input in the firm. The key premise here is that labor and capital are mutually substitutable, both output and input markets have a perfectly competitive market structure, and technological change is not affected by any variables in the model. The formula that omits the process and shows only the result is as follows.

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[2] The Eq (2.1) is a case in which technological progress is viewed as neutral (or Hicks neutral). Neutral technological progress means that when a given output is increased by one unit, the ratio of labor to capital does not change even if technological progress is made.

[3] Solow (1957) expressed it as any change that could shift the country's production function, such as improvements in the education of the labor force.

$$\frac{\Delta A}{A} = \frac{\Delta Q}{Q} - [S_L \frac{\Delta L}{L} + S_K \frac{\Delta K}{K}] \cdots\cdots\cdots\cdots \text{Eq. (2.2)}$$

The left side, $\frac{\Delta A}{A}$ is the increase in technological change (rate of technological progress), and it is obtained by subtracting the contributions of labor and capital (the sum of labor input ratio multiplied by labor increment and capital input ratio multiplied by capital increment) to economic growth from the increase in output, which is the right-hand side. Therefore, the left side, $\frac{\Delta A}{A}$, is called Solow's residual. Because economic growth is affected by factors other than the input of production factors. Solow's residual is also called as Total Factor Productivity (TFP) or Multi-Factor Productivity (MFP) in other words.

The rate of technological progress contributing to economic growth is affected by; the level of technology, industrial structure, economic system, etc. in the macroscopic (i.e. national economy) level; entry and exit of firms due to market forces and competition; spillover effects from human capital, R&D, and information technology investments; Competence enhancement due to international competition at the micro (i.e. firm) level (Hulten, 2010; Bartelsman et al., 2000).

As in Solow's (1957) model, which assumed that technological change was an exogenously given variable, it could not explain the different economic growth rates due to heterogeneous government policies and institutions by country, the endogenous growth theory was then introduced, showing that the variables in the model could affect economic growth. Endogenous growth theories can be divided into four main streams: i) Lucas (1988) who argued that economic growth can be achieved by changes in human capital without technological change; ii) Arrow (1962a) and Lucas (1993) argued that both technology and human capital are accumulated in individual firms through experiential learning and affect the production of individual firms through externalities; iii) Romer (1990), who argued that the technology innovation and technology transfer affect economic growth, and vi) Putnam (1993), who emphasized institutional factors.

Among them, despite the characteristics of non-rivalry, which makes technology accessible to anyone, and non-excludability, which allows several people to use it at the same time, Romer's (1990) model, which revealed that technology accumulation affects long-term economic growth, highlights the importance of technology accumulation. Romer (1990) assumed that an economic agent pursues innovation through R&D investment for their own benefit, and protects the results of non-rivalry and non-excludable technological innovation through intellectual property rights. The technology production function, which is the core of Romer's model built under this assumption, is as follows.

$$\dot{A}_t = \delta L_{A_t} A_t \cdots\cdots \text{Eq. (2.3)}$$

The left side variable ($\dot{A}_t$) is the new technology level created in period *t*, and the right-hand side (L_{A_t}) is the amount of labor input ($L_{A_t} = L_t - L_{Y_t}$) for technological innovation in period *t*. A_t is the sum of technologies accumulated up to time *t*. In Romer's model, it is the creation of new technology ($\dot{A}_t$) that has a significant effect on the economic growth rate, and for this, it was argued that the number of labor force in the R&D sector (L_{A_t}) and the accumulated technology-related knowledge (A_t) should be increased.

2.1.2 Innovation economics

Schumpeter (1934) paid attention to technological innovation and entrepreneurship as the driving force of economic growth. This was because the function of market dictated by the invisible hand, which was the central dogma of mainstream economics at the time, was focused on equilibrium and static analysis. It was thought to be insufficient to explain the dynamic economic growth in our reality. Innovation economics was born with *creative destruction*, which is coined by Schumpeter (1942), described the dynamism of industry where new skin sprouts and callus peels off.

Technological innovation is born in various ways, such as a new combination of existing resources or a combination of new resources. Firms that have achieved technological innovation face new opportunities by opening new markets. At this time, new technological innovation and diffusion of technology affect the growth and survival probability of heterogeneous firms in a different way, therewith, winners and losers are determined. As a result, it changes the structure of the existing industry and the distribution of capabilities of firms within the industry. (Dosi and Nelson, 2010). Entrepreneurs who can identify and develop new opportunities created by technological innovation survive in existing markets and industries that are being destroyed and act as protagonists of new creation, while firms that cannot do so are destroyed and eventually exit the market. Schumpeter (1942) argued that since 'all entrepreneurs have the dream and the will to found a private kingdom', technological innovation is born through the voluntary efforts of entrepreneurs. Schumpeter believed that the economy grows through the process of breaking out of the egg with creative destruction.

As a result, innovation economics considers technological innovation and the accumulation of technological knowledge, more than any other input, as the main driving force for economic growth. Romer's endogenous growth model (discussed in Section 2.1.1) also emphasizes the importance of technological knowledge accumulation. However, this model assumes that there is an externality of technological knowledge accumulation, and the cost is expected to decrease over time as a result of the economy of scale of R&D investment. In addition, it assumes representative producers and pays attention to the state of equilibrium derived in the process of solving the profit maximization problem. Simplified approaches in traditional economics fail to explain the *productivity paradox*, which is the gap between innovation activities and productivity growth (안상훈, 2018). Innovation economics, which overcomes and supplements the limitations of traditional economics, is firm dynamics that focuses on the heterogeneity of firms and understands the accumulation of technological knowledge within firms in various contexts such as countries, industries, producers, and consumers.

2.1.2.1 Resource based theory

Resource-based theory focuses on the internal elements of a firm, rather than the environment surrounding the firm or the structure of the market or industry (Porter, 1980b, 1997; Schmalensee, 1985). It considers a firm as a unique bundle of disparate resources and capabilities (Penrose et al., 2009). Resource-based theory was created to explain the reality that firms earn rent by leveraging resources, which are difficult to trade in the market (Amit and Schoemaker, 1993; Teece, 2010). While traditional economics considers all firms to be the same in terms of their ability to access information, resource-based theory considers this to be a firm-specific property.

In the resource-based theory, a resource is a specific asset for each firm. Firms gain a comparative advantage by owning tangible and intangible assets that are valuable, rare, inimitable, and non-substitutable, resulting in long-term returns in competitive markets (Wernerfelt, 1984; Barney, 1991). If these assets can be traded on the market, this means they can be owned by the purchaser. However, intangible assets such as technological knowledge are particularly difficult to transact as they become costly when the tacit level of the knowledge to be transferred is high or the absorptive capacity of the firm to which it is transferred is low. Therefore, the transferability of resources and capabilities is one of the key factors for a firm to sustain its comparative advantage (Barney, 1986).

If an asset among resources is bricks for building a house, one of the other types of resources, dynamics capability, can be referred to the ability to draw blueprints and lay bricks. In other words, dynamic capability, one of the resources of a firm, is the ability to integrate, build, and reorganize internal and external resources to react to fast evolving environments (Teece et al., 1997; Amit and Schoemaker, 1993; Teece, 2010). It is essential for optimal deployment of capabilities and resources, which are the main management tasks of a firm to make the best profit (Grant, 1996).

The dynamic capability is subdivided into three actions. Sensing is the ability to seize opportunities and identify 'what to accumulate technological knowledge for'. Next, seizing refers to the act of concentrating on accumulating technological knowledge in order to catch the opportunities. Lastly, transformation refers to an effort to break away from unfavorable existing organizational structures.

Dynamic capabilities that can be acquired through seizing, which is the accumulation of technology-related resources and technological knowledge that are difficult to trade, cannot be easily purchased and can only be built and secured by a firm's own efforts (Teece, 2010). Therefore, the resource-based theory regards the accumulation of technological knowledge as an essential process for a firm to secure a comparative advantage.

2.1.2.1.1 Knowledge based view

Knowledge is one of the many resources of a firm, but in this study, it (especially technology knowledge) is regarded as the most important resource for a firm's survival and growth. Therefore, this section examines the knowledge-based view (hereinafter referred to as *KBV*), a research area which regards all knowledge including technological knowledge as a firm's special asset.[4]

Dierickx and Cool (1989), Kogut and Zander (1992), Nonaka et al. (1995), and Grant (1996) are representative studies that laid the foundation for the *KBV*. First, Dierickx and

[4] There is not yet a sufficient consensus regarding the knowledge as resource. Since various concepts and analysis results exist without convergence, it is considered as a *view* rather than a *theory* in this study.

Cool (1989) argued that, unlike other resources in the resource-based theory, a firm's knowledge cannot be traded and is created and accumulated in a different way. First, knowledge is not something that can be accumulated in a short period of time and helps to secure a firm's comparative advantage, because it shows diseconomies in time compression. Diseconomies in time compression means that the result of investing *K* in learning over a time interval of *2T* is better than that of investing *2K* in learning over a time interval of *T*. This means that knowledge is not a resource whose total amount is determined by simply adding all amounts of investment like other assets, but its process of accumulation also is important. Second, unlike asset stock that is depreciated without proper maintenance, such as physical production facilities or equipment, if new knowledge is not additionally accumulated through R&D (which is a flow), existing knowledge (which is a stock) is isolated technically and depreciated. This means that knowledge is depreciated for a different reason than other existing resources, and that the amount of depreciation can be reduced through additional effort. The study of Dierickx and Cool (1989) is significant and seminal in that it analyzed the characteristics of knowledge for the first time and judged knowledge as a resource divided into stock and flow.

Next, Kogut and Zander (1992) emphasized the importance of the type of knowledge a firm possesses and the firm's ability to combine it. Kogut and Zander (1992) first define knowledge and classified it into two categories as i) factual information related to who knows what and ii) know-how (how to organize a team) that must be learned and accumulated and includes the skills and competencies needed to perform a specific task.

This knowledge is not only possessed by individuals, but is also inherent in the social network of a firm, therewith Kogut and Zander (1992) perceived as the knowledge of a firm is greater than the sum of knowledge possessed by individuals. As a result, hiring a single individual does not change the knowledge of the entire firm. Therefore, new people must be transferred and should understand the firm's knowledge. But in this process, the replication of knowledge inevitably occurs. Kogut and Zander (1992) argued that there are combinative capabilities that can well combine existing knowledge, in the background where a firm can innovate beyond the limits of this contradiction of imitation. This is a new dynamic perspective, which is an attempt to explain how to overcome contradictions that inevitably arise in the process of efforts to deliver knowledge, unlike other resources, which are difficult to transfer.[5]

Nonaka et al. (1995) found the secret of Japanese firms' success after success in the international community in the late 1980s in their ability to create new knowledge, distribute it across the organization, and implement it into products, services, and systems. Nonaka et al. (1995) argued that there are two types of knowledge: explicit knowledge, which is externally expressed knowledge through language or text, and tacit knowledge, which is contextualized and internalized knowledge such as personal experience, know-how, and culture that are difficult to express verbally. Nonaka et al. (1995) presented a new concept, the SECI model to describe the process of growing a firm's knowledge base. It is

[5] Contrary to Kogut and Zander (1992), there is also a study by Grant (1996) that considers knowledge, which is a very important resource, is inherent only to individuals, and the role of organizations is not the creation of knowledge, but the integration and application of specialized knowledge possessed by individuals.

consists with i) Socialization, in which tacit knowledge is shared and created through direct experience with people with embedded tacit knowledge; ii) Externalization, which makes tacit knowledge clear as explicit knowledge through conversation and deliberation, iii) Combination, which applies information from explicit knowledge and systematizes it, and iv) Internalization, which learns new tacit knowledge through activities (Nonaka, 1994; Nonaka, and Takeuchi, 2007; Nonaka and Toyama, 2015). A firm's knowledge goes through two completely disparate knowledge domains (explicit & tacit knowledge) in the order of S, E, C, and I, repeating the expansion and repetition of conversion, thereby, the boundaries of knowledge expand.

Finally, knowledge is also regarded as a resource for dynamic strategy of the firm. Spender (1996) argued that knowledge is a key driving force as a strategic action for a firm's comparative advantage. Applying the SWOT (Strengths, Weaknesses, Opportunities, and Threats) model proposed by Porter (1980b; 2008) that analyzes the internal capabilities of a firm from its environment, Zack (1999) presented a firm's knowledge management strategy. Among other things, identifying gaps between the knowledge resources a firm currently has and the knowledge it needs to achieve its strategic objectives helps to understand the strengths and weaknesses of its knowledge assets (Zack, 1999).

2.1.3 Evolutionary economics

While the traditional economics (in Section 2.1.1) explained economic development as a process of finding equilibrium and steady state, Nelson and Winter (1982/2014) interpreted economic development through the lens of evolutionary theory. Microeconomics concerns the quantity of inputs needed to maximize profits assuming that firms follow the same production function. The production set is assumed to be given from the beginning, constant over time, and the same for all firms in a theoretical framework. On the other hand, Nelson and Winter (1982) argued that the economy evolves through ceaseless change and adaptation. In particular, firms are not passive beings who have no choice but to select the most suitable technology for a given environment, but Nelson and Winter (1982) saw them as active beings who control the demand for their products and continuously develop new technologies in the ever-changing industrial environment,

Nelson and Winter (1982/2014), in particular, believed that both the input factor and the firm's production function (or production set) can be varied by the firm's exploration and exploitation efforts. Exploration is an act that does not follow the repetitive and predictable behavioral pattern of a firm, that is, the routine of genes (Cattani and Malerba, 2021). Exploration corresponds to a mutation to a living organism. In the contrary exploitation is information imprinted in genes, and means to act according to a routine. Cohen et al. (1996) defined routine as the ability to repeatedly execute actions in a specific context learned by an organization. In the theory of evolutionary economy, the input, output, and price of the industry can change dynamically through the exploration process of the firm and the firm is a dynamic entity that can change the production set through exploration and exploitation. Thus, technological knowledge can be seen as accumulating within a firm through the tension between the occasional exploration against routine and the predominant exploitation by gene following a probability distribution.

Also, unlike traditional economics, which presupposes that the production set is changed by external technological progress, the production function of a firm in evolutionary economics can be extended to technological progress through internal R&D as well as external technological progress. Investing in R&D is an intentional activity, like paying for the input of knowledge. This is in line with the interpretation of viewing the boundaries of a firm's technological knowledge as a flexible element that can change through exploration.

Then, where is the technological knowledge obtained through R&D located in the firm? In evolutionary economic theory, technological knowledge refers to the entire system of a firm itself, including the documents related to technological knowledge and the person who holds it (Nelson and Winter, 1982/2014). In other words, beyond the simple sum of the two types of components, the document and the person, technological knowledge is a concept that includes both the ability to interpret a document and the ability to harmonize the individual tasks of people with specialized knowledge. Since this system is the cumulative result of a firm's exploitation, the technological knowledge of a firm can be seen as the source of determining the pattern of the next selection as a firm's genes.

2.1.4 Complexity economics

Based on strong premises such as the law of diminishing returns and profit/utility maximization through rational choice, traditional economics' efforts to explain economic phenomena through the same representative producers/consumers can explain the main mechanism of economic phenomena, but have limitations in describing the overall economy. This is because the actual economy we live in is much more diverse than the traditional economics' strong premise that standardizes the same agent, and the relationship between them is complex (Bloch et al., 2011). Complexity economics was born to comprehensively explain the complex, disordered, diverse and unbalanced realities that cannot be explained in the traditional economics of the reductionist methodology. Regarding the accumulation of technological knowledge, the core aspects of complexity economics are as follows.

First, complexity economics views systems such as technologies or organizations as evolving objects. When the elements that make up technology are newly changed, one change occurs like a cascade due to evolutionary exaptive bootstrapping (Lane, 2011). Similarly, due to the implicit and special nature of technological knowledge, once technological knowledge is accumulated within a firm, the accumulated knowledge in the past affects the next accumulation of technological knowledge, resulting in a synergism (Colombelli and von Tunzelmann, 2011). Therefore, the accumulation of technological knowledge can be said to be the result of a firm-specific collective process that begins with the firm's intentional efforts.

Next, complexity economics presupposes technological interactions between firms. Complexity economics views a system by dividing it into distinguishable components and interactions between components. On a network, components are represented by nodes and interactions by links. Any sub-component of the system, such as a component of technological knowledge or a firm within an industry, can be considered as a node of the network. If the elements constituting technological knowledge are nodes and all the nodes are connected, we can be said to have understood the complete knowledge about the external environment (Saviotti, 2011). However, reality is more incompletely connected rather than a perfect connected network, and as a result, exploration plays an important role.

If the firms constituting the industry are regarded as nodes of the network, it can be seen that the links are formed due to the externality effect of the technological knowledge accumulated by the firms. Even if a firm develops a certain technology, it is impossible to completely appropriate that technological knowledge, and therefore, the spill-over effect occurs. Understanding interactions through networks provides a window into understanding various phenomena related to technology accumulation, such as the diffusion of new technological knowledge (Feldman and Kogler, 2010) and the importance of a geographic location (Stoneman and Battisti, 2010).

2.1.5 Interpretation in empirical study

Measuring technological knowledge in firm-level empirical analysis is still under discussion without a unified methodology, and various measurements are being used. Information related to R&D and patents is being used as measurements for traditional proxies for technology.[6] R&D-related information is regarded as input and effort as direct

[6] In addition, various information is used to determine and measure the accumulation of technological

activities for the accumulation of technological knowledge or outcomes of the accumulation of technological knowledge. On the other hand, patents, as a means to protect technological knowledge, are mostly regarded as the result of accumulation of technological knowledge, because the patent is a knowledge created by itself (Crépon et al., 1998; Nagaoka et al., 2010). The main interest of this study is the technological knowledge of firms located at the very bottom and the financial growth of firms located at ideologically on the outermost fringes. Therefore, this study investigates and focuses on the literatures which set the firm's technology-related measures as independent or dependent variables and the firm's financial measures as dependent variables. The results are summarized in Table 2-1.

In this study, patent information filed by firms is utilized as a result of technological knowledge accumulation. The debate about whether patents can be regarded a firm's technological knowledge has existed for a long time. This is because there exist many applied patents that have less value, and not all technologies of firms are applied for as patents, and patents can also be utilized strategically (Somaya, 2012). Nevertheless, patents i) are positively correlated with R&D input, such as R&D expenditure (Griliches, 1984), ii) have a long and concrete history, iii) are based on laws and institutions, iv) and provide systematic information related to a firm's technological knowledge (Nagaoka et al., 2010). As a result, it can be said that a patent is the best technological knowledge related

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knowledge, such as whether a new product is developed and the sales ratio of the product, whether there is process improvement, and the performance change due to it. However, in this study, since technology and products are distinguished and classified as different levels of knowledge, only R&D and patents are considered as technology-related knowledge.

information (Nagaoka et al., 2010).

Among various bibliographical information provided by patents, the types and stocks of technological knowledge possessed by firms were measured through technology classification codes assigned to each patent. An inventor needs to clarify the technological field to which their invention belongs in order to assist the examination of the Patent Office where the invention has been filed and to facilitate the arrangement and search of patent documents. Accordingly, along with the invention of the patent system, methods for patent classification were devised and introduced for each country. Among them, International Patent Classification (hereafter, IPC) code, a unified classification method used in more than 100 countries, is the most representative since it has been developed in 1968.

Recently, the Corporate Patent Classification (hereafter, CPC) code of patents was jointly developed by the U.S. Patent and Trademark Office (hereafter, USPTO) and the European Patent Office (hereafter, EPO). CPC is a more subdivided patent classification system than IPC, and has been assigned along with the IPC code since 2012. Therefore, in this study, CPC code was used instead of IPC. All of the 'technological knowledge' to be mentioned in the empirical analysis in this study refers to the CPC code assigned to each patent of the firm.

Table 2-1. Measures for technological knowledge

Input / Output	Proxy	Aspect	Measures	Author
Input or effort for technological knowledge accumulation	R&D	Quantitative aspect	Total R&D expenditure	Pakes et al. (1980); Hall et al. (1984); Griliches (1985); Coad and Rao (2008)
			R&D Intensity (R&D expenditure / size)	Hall (1987); Filatotchev et al. (2009); Falk (2012); Nunes et al. (2012);
Outcome of technological knowledge accumulation	R&D	Quantitative aspect	R&D Intensity (R&D expenditure / size)	Morbey et al. (1990); Hitt et al. (1997); Garcia-Vega (2006)

Outcome of technological knowledge accumulation (continued)	Patent	Quantitative aspect	Total number of patents	Pakes et al. (1980); Hall et al. (1984); Garcia-Vega (2006); Leten et al. (2007); Coad and Rao (2008)
			Patent intensity (total number of patent / size)	Hitt et al. (1991);
		Qualitative aspect	Development of revealed technological advantage	Kim et al. (2022), Kim et al. (2023); Jun et al. (2023)

2.2 The nature of technological knowledge accumulation

We have yet to fully understand and explain the nature of technological knowledge (Arthur, 2009). Even if one understands technological knowledge, expressing it verbally is another challenge due to the ambiguity (Nelson and Winter, 1982/2014). The reasons why it is difficult to express technology in language can be summarized into five reasons, which are as follows; i) Technology is applied in various forms in various fields and industries, from tangible hammers to intangible Internet networks; ii) yesterday's technology is not the same as today's because it evolves over time; iii) As confirmed in Section 2.1, technology has an interdisciplinary nature, defined differently in various disciplines in their own way; iv) Even with the same technology, it has different contextual characteristics as the experience differs depending on culture, society, politics, and users; v) Through the development of new technology, it continuously expands beyond the boundaries of existing technology into uncharted territory.

Accordingly, various concepts were born to help understand the nature of the technological knowledge and its accumulation. Representative examples are path dependence (David, 1985; Arthur, 1989, 1994; Rosenberg et al. 1994); relatedness (Christensen et al., 1981; Hitt et al, 1997; Hidalgo et al., 2007); exploration and exploitation (March, 1991; Levinthal and March, 1993); ambidexterity (Tushman and O'Reilly, 1996) and punctuated equilibrium (Tushman and Romanelli, 1985; Levinthal et al., 1998); diversification and specialization (or focus) (Markowitz et al., 1952); breadth and depth (Prencipe, 2000). Each theory describes the essence of technological knowledge through a single concept, and all of them help understanding through concise and clear idea. In particular, the concepts proposed by each study are generally complementary in understanding the multifaceted phenomenon of accumulation of technological knowledge.

However, various terms presented in various studies are used differently depending on each context. For example, the concept of capability can be defined in various dimensions such as process, utility, level, feature, source, and situation (Zou et al., 2019). Therefore, in Section 2.2, we tried to classify concepts related to the nature of technological knowledge and its accumulation that have been used in various contexts into a unified standard.

Various concepts related to the nature of technological knowledge and its accumulation are largely classified into i) methods, ii) processes, and iii) aspects. The criteria for classifying each follow the subsequent definitions. The method of accumulation of technological knowledge indicates how to use the accumulation strategy of technological knowledge, and means the purpose or direction. Next, the process of accumulation of technological knowledge represents a strategic choice that changes the composition of accumulated technological knowledge, and means actions or efforts to implement methods. Finally, the aspect of accumulation of technological knowledge refers to features or characteristics related to configuration that have changed as a result of strategic selection.

In this section, we will first look at the standardized facts of technological knowledge accumulation used in various academic fields through various empirical evidence. Next, various terms devised for the accumulation of technological knowledge will be categorized into methods, processes, and aspects. By understanding the limitations of static and cross-sectional approaches of existing studies related to the accumulation of technological knowledge, the necessity of research to overcome them is suggested.

2.2.1 Stylized facts on technological knowledge accumulation

In this section, the standardized facts about technological knowledge and its accumulation, which are commonly found in various academic fields and theories, will be summarized. Standardized facts refer to a converged theory in which the results of various studies conducted over a long period of time have generally reached the same conclusion. Until a new concept is accepted as a standardized fact, it goes through the following process. First, a theory corresponding to the *thesis* is born, and a new field of research is opened. Following that, the opposite, the logic of *antithesis* is born. The constructive discussion between *thesis* and *antithesis* continued for a long time, and the field of research grew. Afterwards, the field of research reached a unified conclusion, *synthesis*, without disagreement, and the standardized facts were accepted as facts beyond theory, representing a concept of unified congruity.

The philosopher Bernard de Mandeville looked at the Man of War, the most innovative invention of the time, and admired, 'Human genius and profound insight are the product of the accumulated experience of many generations, and these products are hardly different from each other.' (Dosi and Nelson, 2010). In this anecdote, we can find several characteristics about technological knowledge. The fact is that new technology is the product of the accumulated experience of many generations and differs little from the technology of the past.

First of all, three concepts commonly dealt with in all studies and theories, which are considered to have reached a *synthesis* about the accumulation of technological knowledge in firms, were summarized as standardized facts. Representative standardized facts about the accumulation of technological knowledge include i) cumulativeness, ii) the principle of relatedness, and iii) path dependence.

2.2.1.1 Cumulativeness

In Section 2.1, we investigate the basic concept of technological knowledge and its accumulation in various theoretical contexts. Summarizing the foregoing discussions, it can be said that various characteristics of technological knowledge ultimately originate from its implicit characteristics. Because of this tacitness, technological knowledge is not easily tradable, and tends to stay in person, space, and time, and thus, the same technological knowledge yields different results depending on the agent or organization's ability to digest it. The reason why technological knowledge is especially emphasized as a source of comparative advantage in the KBV. The tacit knowledge of a firm is difficult to imitate and transfer easily because of its stickiness.

As a result of trials and error resulting from the firm's intentional choice, which is accumulated and embodied in the firm, tacit knowledge is born. Therefore, saying that technological knowledge has tacit characteristics is equivalent to saying that the accumulation of technological knowledge has cumulative characteristics. This is because the technological knowledge of a firm does not arise by itself even if the firm is standing still. Resources must be invested to create new knowledge. According to Dierick and Cool (1989), knowledge accumulation takes place under a consistent policy over a long period of time. Since knowledge, the stock of a strategic asset depreciates, an appropriate flow must be continuously accumulated over a long period of time (Dierick and Cool, 1989).

The importance of accumulating technological knowledge is identified at various levels of analysis. First, as a way to overcome the trend of declining growth rate in Korea, Lee et al. (2015), Lee (2017), and Lee (2022) emphasized the need for continuous and sufficient accumulation of technological knowledge. Lee et al. (2015) argued that Korea should go beyond the imitative implementation strategy, which Korea has been based on to overcome the declined trend. To this end, a new concept of conceptual design capability was suggested, which newly defined the problem and creatively suggested the direction of the solution. According to the Lee et al. (2015), conceptual design capability can only be developed through long-term and continuous accumulation of trials and error. Next, Lee (2017) presented a method for accumulating trials and error. He emphasized the importance of the small betting & scale-up strategy, which confirms the possibility through pilots and develops ideas based on the results, rather than the big betting strategy based on selection and concentration. From past successes and failures, the stages for efforts and achievements at the current situation are determined (Dosi and Nelson, 2010) and Lee (2022) introduced what firms should do with small betting scale-up from their current situation. Lee (2022) suggested that firms should do small betting & scale-up with their own first question. Lee

(2022) saw that the accumulation of meaningful technological knowledge begins only when firms ask the first questions.

The cumulative nature of technological knowledge can also be found in the educational psychological theories of humans, which of a smaller size compared with industry or firm. 『Outliers』 by Gladwell (2009) emphasized through case studies that at least 10,000 hours of experience are required in a field in order to become an expert in the field. Simonton (1991) surveyed the lives and works of 120 classical composers. One of the factors influencing their talents was the development and honing of skills through practice. Their peak creative results begin in the middle or late stages of their careers. Kaufman and Kaufman (2007) traced the development of professional from 24 prominent writers, and found that time and commitment were required as elements during a complex and multifaceted process. In addition, Frick (2014) investigated the age distribution of the top 100 venture entrepreneurs in Silicon Valley. Contrary to the prejudice that successful entrepreneurs are young, their average age was 31.9 years old, and most were in their 30s or 40s. The Frick (2014) emphasized that accumulated experience, wisdom and network according to age are also valuable assets of entrepreneurs.

Determinants of technological knowledge accumulation have been actively identified from various perspectives, but there is no generalized discussion yet. The existence of various scattered discussions on the determinants of technological knowledge accumulation means that the optimal process of technological knowledge accumulation may vary depending on the physical environment of each firm or the context of the times.[7] However, what is commonly presupposed and undeniable in all various topics such as luck, flexibility, and persistency is the fact that the accumulation of technological knowledge is formed through the accumulation of tangible and intangible assets such as time, endeavor and experience.

2.2.1.1.1 Trials and error

Trials and error are inevitably involved in the process of the accumulation or being embodied of technological knowledge within a firm. This is because the choice of a firm is myopia (Levinthal and March, 1993). In other words, since firms make choices at every moment based on their own experiences and resources, the local maximum based on limited rationality is the best result that can be expected. Therefore, it is impossible to expect firms to find the global maximum, which is an exact solution to the problem, all at once.

Firms' strategic choices are like doing a hill-climbing search toward a global maximum (Levinthal, 1997). In a landscape determined by the combination of all decision-making choices, a firm's goal is to find the combination of choices that provides the highest value.

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[7] There are still various discussions about the determinants that affect the accumulation of technological knowledge. First, Denrell (2004) saw that the accumulation of technological knowledge is determined by *luck*. Even if a firm randomly invests resources, it is revealed that the degree of accumulation and, furthermore, the difference in competitive advantage can be occurred by *luck*. Next, Mudambi and Swift (2011) argued that a firm's strategy for accumulating technological knowledge should be aligned with the firm's growth strategy, which varies depending on market conditions, technology advances, and competitors' behavior. This is because continuing with only one single strategy may not be able to respond nimbly to changes. This means that a firm's technological knowledge accumulation can be constantly fluctuated by operational R&D activity. In the opposite context, Kang et al. (2017) found that stable and steady R&D investment is necessary for firms to gain the ability to secure comparative advantage and, as a result, to achieve greater financial growth.

The process of finding this combination can be viewed as trials and error. The accumulation of technological knowledge is also one of the strategic choices of firms, so in the process of accumulating experience during accumulating technological knowledge, firms will inevitably experience trials and error.

Because technological knowledge has a different nature from other resources, trials and error is essential to utilize it when introduced from outside. Tangible assets such as labor can be traded through the factor market, and they can be directly accumulated and used within the firm right after being imported or acquired from outside. While, intangible resources such as technological knowledge are not only acquired through intentional learning and trials and error, but also require a higher level of understanding that can combine them with accumulated knowledge to use them. One of the reasons why technological M&A (Mergers and Acquisitions) fails is that they blindly introduce outside technology without any internal trials and error. Sears and Hoetker (2014) found that even if technological knowledge is introduced from outside through technology acquisition, the firm cannot use external knowledge effectively when i) the acquiring firm does not have knowledge related to the acquired firm's knowledge, ii) the acquiring firm does not have the technological capabilities, and, iii) the acquiring firm cannot recombine the acquired firm's knowledge.

Therefore, we can say that the accumulation of technological knowledge is the process and result of trials and error itself. The judgment that enables firms to make better choices about what to accumulate is also formed through trials and error, and deciding how to accumulate it is also based on trials and error. In the previous section, it was confirmed that the cumulative characteristic of technological knowledge accumulation is another expression of implicit characteristic. Therefore, the accumulation of technological knowledge within a firm to become tacit knowledge can also be said to be a process and result of trials and error.

Trials and error is inevitable in accumulating technological knowledge, but it is not unconditional. Since the firm is not absolute, it inevitably chooses the local maximum, which is a good enough choice (Callander, 2011). A firm always pursues the global maximum, which is the best choice like *Ideas*. Therefore, the result of choice by trials and error is always inefficient when compared to the global maximum, therewith, firms with limited resources need to learn in a sophisticated way (Zollo and Winter, 2002). Accordingly, Lee (2017) argued that small betting & scale-up strategies, which activate pilot investment when solving problems with high uncertainty without any hints, and simultaneously invest in stages, are the most efficient and safe methods for dealing with trials and error.

2.2.1.1.2 Increasing returns to scale

In the process of accumulating technological knowledge within a firm through trials and error, know-how on how to accumulate is also created. Unlike simply doing R&D, Arrow (1962b) defined the process of being embodied in and accumulating experience and knowledge within a firm as learning by doing. Embodied past experience and accumulated knowledge cause a learning effect, and as a result, firms experience increasing returns of scale for additional inputs of production factors (Le Bas and Scellato, 2014). This means that even if a firm makes the same effort, the result can be different depending on the technological knowledge accumulated in the past.

In various academic fields and theories, the phenomenon of increasing returns of technological knowledge accumulation was analyzed. In the neo-classical school of traditional economics, it was revealed that productivity can be improved even with the same input factors and level of technology through external effects of accumulated technological knowledge. Arrow (1962a) defined technological change $A(t)$ as a function of input factors in Equation (2.1). In this case, the average value of the region or industry to which the firm belongs is used for the input factors, not the inputs from an individual firm. This means that the accumulation of collective experiences in the industry or region to which each firm belongs can affect the productivity of a firm.

Next, in Resource-based theory, the larger the existing stock of technological knowledge, the greater the incentive to add additional increments to the asset. Dierickx and Cool (1989) defined this as asset mass efficiency, and saw that firms who already possess important assets, such as R&D know-how, are more advantageous in accumulating knowledge in the future than those that do not. Absorptive capability, one of the capabilities of a firm, is also interpreted in the same context as increasing returns of scale. Absorptive capacity refers to a firm's ability to identify, assimilate, and apply new information from outside of the firm (Cohen and Levinthal, 1990; Zahra and George, 2002). The greater the absorptive capacity, the more efficiently a firm can exploit additional external knowledge, resulting in improved innovation outcomes (Cohen and Levinthal, 1990; Zahra and George, 2002).

Finally, discussions related to increasing returns to scale can also be found in Complexity economics. In Complexity economics, one new thing causes another new thing, and called these phenomena as a *cascade* of innovation or *Schumpeterian gales of creative destruction* (Schilling et al, 1998; Lane, 2011). According to Lane (2011), one innovation triggers a chain reaction, and new innovations pour like a *cascade* through the process of positive feedback. This aligns precisely with the definition of increasing returns, in that when one new innovation becomes an additional input, a greater amount of new innovation is created.

2.2.1.2 Principle of relatedness

Efforts to understand the aspects of technological knowledge and its accumulation have recently been discussed in the field of Complexity economics. The field of complexity economics is largely divided into two pillars, one is about the principle of relatedness and the other is about the Economies of Complexity.

In this section, we will first look at the principle of relatedness. The principle of relatedness refers to a phenomenon in which an organization's initiation of a new economic activity is greatly influenced by its capabilities related to the existing economic activity. This is a phenomenon that is also observed in the fact that people usually feel more comfortable with new things they are familiar with. This principle of relatedness starts with the assumption that 1) the absorptive capacity of a firm is associated with the related knowledge it possesses in advance, and 2) economic activity, such as producing new products and entering new industries, is related to knowledge diffusion, which is constrained by relatedness (Cohen et al., 1990; Jaffe et al., 1993; Audretsch et al., 1996; Boschma, 2005; Frenken et al., 2007).

Hidalgo et al. (2007), in their seminal paper, uses a country's product export data to build a product space, and then, visualized that countries expand their production portfolio to products related to existing products as a country's economy develops. Hidalgo et al. (2007) first calculate the proximity (or similarity) between products through the conditional probability of co-occurrence, which is an agnostic method.[8] The formula for calculating the proximity between economic activity α (product, technology, industry, occupation, etc.) and economic activity β is as follows.

$$\varphi_{\alpha,\beta} = \min\{\Pr\left(RTA_{\alpha} \middle| RTA_{\beta}\right), \Pr(RTA_{\beta}|RTA_{\alpha})\} \cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots \text{Eq. (2.4)}$$

Here, Revealed Technological Advantage (hereafter, *RTA*) is obtained through the following Eq. (2.5) (Balassa, 1965).

[8] This methodology assumes that similar institutions, infrastructures, physical factors, technologies, or a combination of these are used together in the background, when two products are related. Therefore, there is a high probability that both products will be found together 'consequently', if two products are related. By this way of interpretation, the agnostic way is also referred to as outcomes-based measures.

$$RTA_{i,\alpha,t} = \frac{P_{i,\alpha,t}}{\sum_\alpha P_{i,\alpha,t}} \bigg/ \frac{\sum_i P_{i,\alpha,t}}{\sum_i \sum_\alpha P_{i,\alpha,t}} \quad \cdots\cdots \text{Eq. (2.5)}$$

$P_{i,\alpha,t}$ indicates how many patents assigned to technology classification α are owned by firm i at time t. $RTA_{i,\alpha,t}$ is a measure of how much firm i owns, relative to the average of all firms in the industry, for technology α over all other technologies within the firm. If $RTA_{i,\alpha,t}$ is greater than or equal to 1, it means that the share of technology α within firm i is higher than the average for the entire industry.

Hidalgo et al. (2007) built a product space based on the proximity between product α and product β. A network is a tool to visualize the relationship between n number of subjects (nodes) of interest, and helps to understand the overall picture by expressing the relationship between them ($n * (n-1)/2$) as a single figure. In addition to the conditional probability of co-occurrence, various approaches have been developed to calculate proximity regarding economic activities. Figure 2-1 shows the networks built through different methods, and Table 2-2 summarizes the equations and interpretation of each methodology.

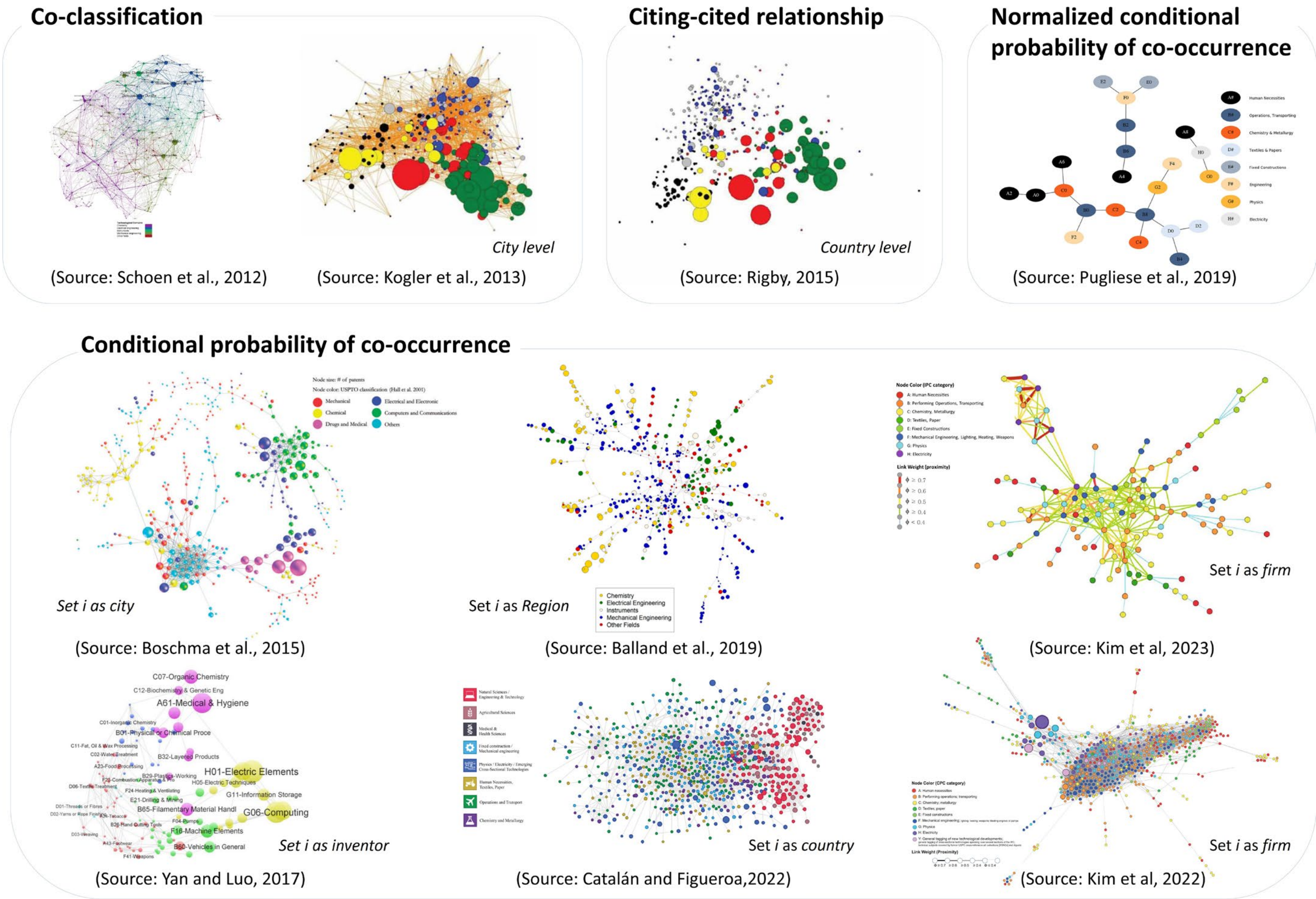

Figure 2-1. Technology network constructed by various methodologies

Table 2-2. Methods for calculating proximity (or similarity) between technologies

Name		Measure	Interpretation	Authors
Bibliometric mapping	Co-reference	$$\varphi_{\alpha,\beta} = \frac{\lvert C_\alpha \cap C_\beta \rvert}{\lvert C_\alpha \cup C_\beta \rvert}$$ ● Where C_α is the number of backward citation of technology classification α	The total number of patents cited by patents of technology α or β comparing with the number of patents cited by both technology simultaneously	Jaccard (1901); Yan and Luo (2017); Song et al. (2019)
	Co-classification cosine similarity	$$\varphi_{\alpha,\beta} = \frac{\sum_p C_{p,\alpha} C_{p,\beta}}{\sqrt{\sum_p C_{p,\alpha}^2}\sqrt{\sum_p C_{p,\beta}^2}}$$ ● $C_{p,\alpha}$ is the number of patents (p) assigned to technology classification α	The dot product of the vectors of technology α and β divided by the product of their lengths of the documents	Jaffe (1986); Hussinger et al. (2010)
	Co-classification	$$\varphi_{\alpha,\beta} = \sum_p C_{p,\alpha} C_{p,\beta}$$ ● Where $C_{p,\alpha}$ is 1 when a patent p is assigned to technology classification α, or 0, otherwise.	The number of patents (p) that are assigned to both technology classifications, α & β	Engelsman and Van Raan (1994); Schoen et al. (2012); Kogler et al. (2013)
	Co-word	$$\varphi_{\alpha,\beta} = \sum_p C_{p,\alpha} C_{p,\beta}$$ ● Where $C_{p,\alpha}$ is 1 when a patent p is assigned to technology classification α, or 0, otherwise.	The number of patents (p) that contain both keywords related to technology α & β in their abstract	Engelsman and Van Raan (1994)

	Co-citation	$$\varphi_{\alpha,\beta} = \sum_{p} C_{p,\alpha} C_{p,\beta}$$ • Where $C_{p,\alpha}$ is 1 when a patent p is assigned to technology classification α, or 0, otherwise.	The number of patents (p) (assigned to both technology classifications, α & β) that are cited together	Engelsman and Van Raan (1994)
	Actual-expected citation ratio	$$\varphi_{\alpha,\beta} = \frac{(\mathrm{O}_{\alpha,\beta} + \mathrm{O}_{\beta,\alpha})}{(\mathrm{E}_{\alpha,\beta} + \mathrm{E}_{\beta,\alpha})}$$ • Where $\mathrm{O}_{\alpha,\beta}$ is observed number of patents of technology classification β cited by patents of technology α • $\mathrm{E}_{\alpha,\beta}$ $(= (\sum_{\beta} \mathrm{O}_{\alpha,\beta}) * {}^{p_{\beta}}/_{\sum_{\beta} p_{\beta}})$ is expected (random) number of patents of technology β cited by patents (p) of technology α	Excess ratio of actual citation to expected citation between two different technologies, α & β	Leten et al. (2007); Leten et al. (2016); Ning et al. (2022)
	Citing-cited relationship	$$\varphi_{\alpha,\beta} = C_{\alpha,\beta}$$ • $C_{\alpha,\beta}$ is normalized by the number of patents in technology classification β	The number of patents made by citing patents of technology classification α to cited patents of classification β	Rigby (2015)
Joint co-occurrence ($t_{i,j}$)		$$\varphi_{\alpha,\beta} = \frac{J_{\alpha,\beta} - \mu_{\alpha,\beta}}{\sigma_{\alpha,\beta}}$$ • Where $J_{\alpha,\beta}(= \sum_i C_{i,\alpha} C_{i,\beta})$ is the number of firms (i) that are active in both technologies α & β • $\mu_{\alpha,\beta}$ $(= \frac{\sum_i P_{i,\alpha} \sum_i P_{i,\beta}}{I})$ is expected number • $\sigma^2_{\alpha,\beta} = \mu_{\alpha,\beta}(1 - \frac{\sum_i P_{i,\alpha}}{I})(\frac{I - \sum_i P_{i,\beta}}{I-1})$	The degree where the observed linkage between the actual two different technologies, α & β exceeds that which would be expected were the random assignments of technologies to firms	Teece et al. (1994); Breschi et al. (2003); Nesta and Saviotti (2005); Colombelli et al. (2013)

Conditional probability of co-occurrence	$$\varphi_{\alpha,\beta} = \frac{M_{i,\alpha}M_{i,\beta}}{\max(u_{\alpha}, u_{\beta})}$$ ● $M_{i,\alpha}$ is a binary matrix that has value 1 if firm i has RTA in technology α which is calculated by Eq. (2.5) ● u_{α} is the ubiquity of technology α $(=\sum_{i} M_{i,\alpha})$	The minimum likelihood of the pairwise conditional probability that two different technologies α and β with RTA are found within the same firm.	● i as city, region or country: Boschma et al. (2013, 2015); Balland et al. (2019, 2021); Catalán and Figueroa (2022) ● i as inventor: Yan and Luo (2017) ● i as firm: Kim et al. (2022); Kim et al. (2023); Dosi et al. (2022) (α as product)
Normalized conditional probability of co-occurrence	$$\varphi_{\alpha,\beta} = \frac{1}{\max(u_{\alpha}, u_{\beta})}\sum_{i}\frac{M_{i,\alpha}M_{i,\beta}}{d_i}$$ ● $M_{i,\alpha}$ is a binary matrix that has value 1 if firm i has RTA in technology α which is calculated by Eq. (2.5) ● d_i is the diversification of firm i $(=\sum_{\alpha} M_{i,\alpha})$ ● u_{α} is the ubiquity of technology α $(=\sum_{i} M_{i,\alpha})$	Normalized value of *Conditional probability of co-occurrence* to both the maximum ubiquity value between technologies α and β, and the technological diversification level of firm	Pugliese et al. (2019)

The principle of relatedness is empirically revealed through relatedness density, a variable calculated based on the structure of the network. The variable devised by Hidalgo et al. (2007) measures the relatedness between an economic activity and the economic activities in which a specific organization has a comparative advantage already. It centers a specific economic activity on the network and considers proximity with all other economic activities except the economic activity centered on. The relatedness density ($\omega_{i,\alpha}$) for the undeveloped economic activity α of organization i is calculated as follows.

$$\omega_{i,\alpha} = \frac{\sum_{\beta} \varphi_{\alpha,\beta} U_{i,\beta}}{\sum_{\beta} \varphi_{\alpha,\beta}} \cdots\cdots \text{Eq. (2.6)}$$

Here, $U_{i,\beta}$ is a binary variable that is expressed as 1 if firm i has a comparative advantage in economic activity β, and as 0 otherwise. When $RTA_{i,\beta,t}$ is greater than 1, the corresponding economic activity β is judged to have a comparative advantage. $\varphi_{\alpha,\beta}$ represents the proximity between economic activity α and economic activity β. The value of this relatedness density ($\omega_{i,\alpha}$) indicates how closely the set of economic activities β in which organization i has a comparative advantage is related to the new economic activity α that has not yet been developed. For a more detailed explanation of variables through examples, see Appendix 1.

Various results from empirical analysis have proven the existence of the principle of relatedness, the higher the value of the relatedness density ($\omega_{i,\alpha}$), the higher the probability that organization i will secure a comparative advantage ($U_{i,\alpha}$) in economic activity α in which it has not yet secured a comparative advantage. Hidalgo et al. (2007) confirmed that relatedness density has a huge explanatory power for predicting the probability that a country will successfully develop a new product from country's product export data. Beginning with the study of Hidalgo et al. (2007), an empirical analysis of various economic activities under various economic organizations was conducted. The results of empirical analysis have been proven in various economic activities; i) technology (Kogler et al., 2013; Boschma et al., 2015; Rigby, 2015; Balland and Rigby, 2017; Balland et al., 2021; Juhász et al., 2021; Kim et al, 2022, 2023; Jun et al., 2023); ii) product (Hidalgo et al., 2007; Jun et al., 2020); iii) industry (Boschma et al., 2013; Neffke et al., 2011; Jara-Figueroa et al., 2018; Gao et al., 2021) ; iv) occupation (Muneepeerakul et al., 2013); v) task (or skill) (Neffke and Henning, 2013; Alabdulkareem et al., 2018); vi) amenity (The results of empirical analysis proven in various economic activities, including Hidalgo et al., 2020; Jun et al., 2022) ; and vii) research fields (Guevara et al., 2016) at country, regional or city, firm level have established the principle of relatedness as a general rule.

The results of research that empirically revealed the principle of relatedness can be organized as shown in Table 2-3 according to the level of the economic agents and the type of economic activity to be analyzed.

Table 2-3. Previous studies on 'Principle of relatedness'

	Country	Region	City	Firm	Individual (including Occupation, Labor flow)
Product	● Hidalgo et al. (2007), Jun et al. (2022)				
Industry		● Sweden: Neffke et al. (2011) ● Spain: Boschma et al. (2013) ● Brazil: Jara-Figueroa et al. (2018) ● China: Gao et al. (2021)			
Technology		● EU: Balland et al. (2019), Juhász et al. (2021)	● 336 cities in US: Boschma et al. (2015), Rigby	● Korea: Kim et al.,(2022), Kim et al.(2023), Jun et al. (2023)	

Technology (continued)			(2015), Balland and Rigby, 2017 ● US: Kogler et al., 2013		
Skill					● Alabdulkareem et al. (2018) ● Neffke and Henning (2013)
Occupation			● US MSA (Metropolitan Statistical Areas): Muneepeerakul et al. (2013)		
Amenity			● Seoul in Korea: Jun et al. (2020) ● 47 cities in US: Hidalgo et al.(2020)		
Research					● Guevara et al. (2016)

2.2.1.3 Path dependence

If the results of choices made by individuals and organizations are traced over time, a trajectory, the traces left by each individual and organization, can be found. A certain direction is observed in this trajectory, and although it is not an *Idea* or a global optimum by today's standards, the direction determined in the past usually remains unchanged over time. This phenomenon in which a path is observed because current decisions are influenced by past decisions is called path dependence. The main reason why path dependence is found is that we find alternatives locally from accumulated past knowledge (Helfat, 1997), not from all possible alternatives due to limited rationality (Simon, 1978).

Path dependence is observed in all aspects of a firms' technology and product, a way of accumulating technological knowledge, and the strategic choices they make. First, in terms of product design, path dependence is related to the dominant design, which is a stage of the cyclical model of technological change devised by Anderson and Tushman (1990). Once the dominant design accepted as the standard of the industry, incremental innovation rather than radical innovation occurs until the next technological change occurs, and the innovation occurs in the process while maintaining the product rather than additional innovation in the product. (Utterback and Abernathy, 1975; Abernathy and Utterback, 1978; Suarez and Utterback, 1995).

A prime example can be found in the QWERTY keyboard. When the keyboard is arranged in alphabetical order, the problem of keys getting tangled often occurred as adjacent keys are hit consecutively. so the random separation of alphabets is the background of the development of the QWERTY keyboard. David (1985) argues that despite the development of the more scientific and efficient Dvorak keyboard, the historical coincidence that the QWERTY keyboard was chosen by the public led to increasing returns to adoption of the technology. The early access to the QWERTY keyboard cannot deviate from the path by self-reinforcing process.

In terms of the accumulation of technological knowledge within the firm, new knowledge creation is also made based on the accumulated knowledge of the past and is accumulated while forming a specific trajectory (Malerba and Orsenigo, 2000). Arthur (1989) confirmed through a simulation analysis that, in a situation where technologies with increasing returns are competing, an initial accidental historical event locks in a firm's selection to one specific technology. In addition, Bergek and Onufrey (2013) expanded the existing concept of path dependence, revealing that several types of paths coexist within a firm and a firm is developed through the interaction between these paths.

The various theoretical backgrounds introduced in section 2.1 are looking for the cause of path dependence, focusing on their own interests. Hidalgo (2021) argued that the path dependence of economic agents arises as a result of the principle of relatedness, and Arthur (1994) argued that the causes of path dependence in a firm's technological selection are economies of scale, learning effects, and positive feedback from network externalities. Sydow et al. (2009) argued that self-reinforcing mechanisms such as increasing returns, positive feedback loops, and network effects make organizational pathways entrenched.

Path dependence is a standardized fact found in the process of product evolution and the accumulation of technological knowledge within individuals or firms. But when its degree increases, it negatively affects individuals or organizations. This is because it is not easy to change individuals or organizations out of the original trajectory due to lock-in when they are trapped in a particular trajectory (Arthur, 1989; Burgelman, 2002). In other words, it can be assumed that the relationship between path dependence and the efficiency of technological knowledge accumulation is an inverted U-shaped relationship. However, as the environment surrounding firms, such as market situation or technological environment, is constantly changing, firms also need to deviate from their routes from time to time marching the line with the current atmosphere.

Therefore, the factors necessary for organizations to escape from excessive path dependence were also investigated. Teece et al. (1997) argued that dynamic capability plays an important role in maintaining a comparative advantage by escaping the existing path dependence in a rapidly changing environment. Garud and Karnøe (2001) presented a new perspective that firms can achieve path creation through conscious efforts to deviate from the path. As a way for local economies to overcome path dependence, Hassink (2005) suggested the need for learning clusters in which various organizations, such as firms and institutions, can connect to each other to exchange knowledge and enjoy the spillovers effect.

2.2.2 Method of technological knowledge accumulation

The method of accumulating technological knowledge means 'how to use the strategy for accumulating technological knowledge' (Kang et al., 2019). The keywords related to the method of technological knowledge accumulation include activity, mode, and direction. Methods of technological knowledge accumulation include exploration and exploration, experimentation and experience.

2.2.2.1 Exploration vs. Exploitation

The terminology of exploration and exploitation has been studied in various fields includes i) management (e.g. Sitkin et al., 1994; Benner and Tushman, 2002; Tsang et al., 2007; Harreld et al., 2007; Ireland and Webb, 2007; Andriopoulos and Lewis, 2009; Kauppila, 2010; Donate and Guadamillas, 2011); ii) learning (e.g. March, 1991; Levinthal and March, 1993; Sitkin et al., 1994; Danneels, 2002; He and Wong, 2004; Grant et al., 2004; Schildt, Maula, and Keil, 2005; Auh et al, 2005; Uotila et al., 2009; Fang et al., 2010); iii) design (e.g. Tushman and O 'Reilly, 1996; Katila and Ahuja, 2002; Fang et al., 2010); and iv) innovation (e.g. Katila and Ahuja, 2002; Danneels, 2002; He and Wong, 2004; Jansen et al., 2006; Belderbos et al., 2010; Donate and Guadamillas, 2011).

At the same time, studies on various contexts in each field were conducted, for example i) inter-organizational structure (e.g. Tushman and O'Reilly, 1996; O'Reilly and Tushman, 2004; Beckman et al., 2006; Andriopoulos and Lewis, 2009; Lavie et al., 2010; Fang et al., 2010; Stettner and Lavie, 2014); ii) organizational relationships (e.g. Koza and Lewin, 1998; Grant et al., 2004; Beckman, Haunschild, and Phillips, 2004; Rothaermel and Deeds, 2004; Schildt, Maula, and Keil, 2005; Lavie and Rosenkopf, 2006; Im et al., 2008; Lavie et al., 2010; Kauppila, 2010; Belderbos et al., 2010; Stettner and Lavie, 2014; Guan and Liu, 2016); iii) resources including capabilities (e.g. Tsang et al., 2007; Harreld et al., 2007); iv) product innovation (e.g. Tushman and O'Reilly, 1996; Katila and Ahuja, 2002; Danneels, 2002; He and Wong, 2004; Donate and Guadamillas, 2011), and; technology innovation (e.g. Tushman and O'Reilly, 1996; Benner and Tushman, 2002; Belderbos et al. al., 2010). In this section, previous studies focusing on knowledge learning and studies focusing product innovation and technological innovation contextually were summarized.

First, the concepts of exploration and exploitation were first coined by March (1991). March (1991) largely divided methods of learning into exploration and exploitation. The heart of exploration lies in experimentation with novel options, and the essence of exploitation is refinement or extension of existing capability, technology, and paradigm. In his follow-up study, Levinthal and March (1993) confined the earlier broad definition to knowledge only, defining exploration as a method for future viability and exploitation as a method for current viability. Since then, the concepts of exploration and exploitation have been definitized through several seminal papers. Sitkin et al. (1994) defined exploration as a learning activity that causes the addition of new resources, and exploitation as a learning activity related to the use of existing resources that a firm already possesses. Belderbos et al. (2010) defined the technological exploration when a patent is expanded into a new technological area that has not been previously applied for, and the technological exploitation when an additional patent is applied in a technological area for which a patent has been applied for previously.

The various keywords that have been suggested to describe exploration. March (1991) introduces keywords such as search, variation, risk taking, experimentation, play, flexibility, discovery, and innovation. Nonaka et al. (2002) expressed exploration as creativity, time-consuming resource building. He and Wong (2004) added the keywords path breaking, improvisation, chaos, emerging technology, and new possibility. Grant et al. (2004) called generation and creation.

On the other hand, as keywords related to exploitation, March (1991) selects refinement, choice, production, efficiency, selection, implementation, execution. He and Wong (2004) use the keywords of path dependence, routinization, control, stable technology, and old certainty. Spender (1992) explain exploitation as application and Donate and Guadamillas (2011) express it as leveraging.

The characteristics of exploration and exploitation are essentially different. Exploration is something takes longer in time, is more distant from current status, and is more uncertain about the result than exploitation (He and Wong, 2004). It is also distinguished characteristic that there is a large variation between the success and failure of exploration, and that radical innovation can be expected as a positive result of exploration (Lin et al., 2013). Exploration also gives firms the flexibility to adapt to new environments (McGrath, 2001). On the other hand, results of exploitation are certain and immediate (He and Wong, 2004). The difference between success and failure of exploitation is not large and relatively stable, and incremental innovation can be expected as a result of exploitation (Lin et al., 2013).

2.2.2.1.1 Experimentation vs. Experience

March (1991) defined exploration as 'experimentation with new alternatives for which the return is uncertain, distant, and often negative.' Since then, various studies on experimentation, one of the methods of exploration, have been conducted, and the concept of experience corresponding to exploitation as a concept opposite to experimentation was coined. Experimentation refers to the direction of decision on how to try something new (Kang et al., 2019). In other words, experimentation means deliberate learning to overcome limitations by intentionally using energy.[9] So experimentation can go beyond repetitive learning in which certain results can be obtained with little energy, as firms have previously conducted. On the other hand, experience, one of the methods of exploitation, means how to accumulate and configure technology, that is, how deeply and repeatedly the accumulated technology was performed (Kang et al., 2019).

Empirical evidences on experience have been conducted mainly with studies that analyze the cumulativeness of technological knowledge and the composition of the knowledge base within a firm. On the other hand, as the technology of the industrial ecosystem becomes complex and rapidly changes, many researches related to experimentation on new execution have been conducted. In particular, experimentation are used with the concept of recombination, this is because new knowledge is created as a result

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[9] A discussion of *deliberate learning* can also be found in the educational psychology theory. Jeff Colvin's book, 『Talent is overrated』 insists that the success of individuals and organizations does not come from investing just 10,000 hours. Successful individuals invested about 10,000 hours of their time, but in addition they exercised great concentration during these 10,000 hours. In other words, successful individuals did 10,000 hours of focused, dense training of 'deliberately planned practice'.

of exploring and identifying a new knowledge that can be combined among sporadic knowledge based on existing knowledge, and as a result of experiments newly recombined the new knowledge with existing knowledge. (Fleming, 2001; Colombelli et al., 2013; Strumsky and Lobo, 2015). Experimentation for knowledge recombination are also important in terms of firm's survival, as incumbent firms may be at risk of failure due to their established expertise and approaches. This is because, for incumbent firms it is not easy to identify an architectural innovation, an innovation initiated by of a new entrant, in which the core design remains unchanged and only the components are slightly different (Henderson and Clark, 1990).

There are representative researches of West and Iansiti (2003) and Kang et al. (2019) focusing specifically on the concept of experimentation and experience of knowledge of the firm in the empirical study. West and Iansiti (2003) found that the generation of technological knowledge through experimentation has a positive and significant effect on the firm's R&D performance, and the absence of retention of technological knowledge through experience has a negative effect on R&D performance. These two methods of technological knowledge accumulation functioned as alternatives to each other, and played a more important role than the commitment or deployment of resources. Kang et al. (2019) defined experience through the composition of accumulated technological knowledge and experimentation through how new combinations occur with new technological knowledge. From the Korean manufacturing industry, Kang et al. (2019) argued that persistent experience in a technological field is important in the accumulation of technological knowledge, but that learning strategies should change according to the degree of experience. When the depth of experience is less, experimentation should be minimized, while depth of experience is more, firms can grow more only when they try various combinations with new technology based on their core technology.

2.2.3 Process of technological knowledge accumulation

The process of technological knowledge accumulation is the cumulative result of efforts to implement a method, and means a strategic choice that affects the construction of technological knowledge (Moorthy and Polley, 2010). The reason why firms have no choice but to make strategic choices is that they have limited resources. A firm's limited resources force a firm to make deliberate and conscious choices to make the most efficient use of them. Keywords related to the process of technological knowledge accumulation include implementation, phenomenon, strategy, strategic choice, means, action, and procedure.

It has been found that methods for technological knowledge accumulation are carried out through various processes. According to Lavie et al. (2010), experimentation with new knowledge through firm's diversification effort is a phenomenon that emerges as a result of exploration, and the concepts of focus or experience are explained through exploitation. The concept of ambidexterity and punctuated equilibrium is also a matter of strategic choice in determining how to balance exploration and exploitation (Tushman and O'Reilly, 1996). Therefore, in this study, two conflicting strategic choices named 'diversification vs.

specialization' and 'ambidexterity vs. punctual equilibrium' were summarized as representative processes of technological knowledge accumulation.

2.2.3.1 Diversification vs. Specialization[10]

In a competitive technology environment, firms are faced with fundamental decisions about how to accumulate technological knowledge. In particular, to deal with uncertainty, firms must decide whether to specialize in a few technologies or spread their bets in diverse technologies (McGrath 1997). As a firm's resources are limited (Conner and Prahalad, 1996), it is impossible to choose everything.

The strategy to expand the scope (or area) of technological portfolio into various domains is called diversification of technological knowledge (Granstrand and Oskarsson 1994). As a result of firms choosing exploration as their technology accumulation method, the firm's strategy of technological diversification is manifested (Lavie et al., 2010). The main reason firms diversify their technologies is to secure flexibility. This is because, within the technological uncertainty, if a firm accumulates experience across multiple technologies through distributed betting, it can quickly adapt to dominant technologies emerging in the market. This phenomenon has actually been confirmed in firms such as Airbus and Intel (Pacheco-de-Almeida et al., 2008; Toh and Kim, 2013).

On the other hand, specialization of technological knowledge refers to a strategy that

[10] Various indexes designed to measure technological diversification and specialization strategies are covered in Section 2.3.1, and results of various empirical analysis related to technological diversification are summarized in Section 2.3.2. Accordingly, in this section, the concept of diversification, the concept and results of empirical analysis related to specialization strategy are summarized.

limits a firm's area of interest to few technological knowledge, concentrates resources, and reduces the possibility of developing and acquiring various technology (Madhok, 1996). This definition aligns with the firm's exploitative activity of technological knowledge. Studies emphasizing the importance of specialization strategies presuppose that the purpose of firms' technological knowledge accumulation is eventually technological standardization within the industry through securing dominant technologies (Khazam and Mowery, 1994). It can be seen that diversification is just a process of finding one dominant technology for technological standardization in high uncertainty, and firm eventually secure a comparative advantage by specialization of one technology (Heney, 1985). Also, since uncertainty arises from competitors who are already dominant in a particular technology (Clarkson and Toh 2010), the role of diversification strategy is overestimated and cannot be the ultimate solution (Toh and Kim, 2013). Therefore, studies emphasizing the importance of technological specialization argue that technological or market uncertainty rather increases the force toward specialization of technological knowledge within a firm, not diversification of technological knowledge.

The advantages of technological specialization are as follows. First of all, specialized and focused efforts provide the basis for stable development of a firm even in the face of rapidly changing market or customer preferences (Bloch, 1995). Next, the specialized resources, knowledge and know-how possessed by specialized firms help them make better selection decisions (Schwartz and Hornych, 2008).

The importance of the specialization strategy can also be found in the educational psychology theory studying people, which are smaller units than firm. Successful individual such as famous composers, writers, scientists and sports stars emphasize the importance of specialization. They all developed their own style, mastering to do one thing exceptionally well in a narrow field (Bloch, 1995).

The effect of the specialization strategy on the increase in performance was empirically analyzed at the firm level. Berger and Ofek (1995) and Comment and Jarrell (1995) investigated US firms in the 1980s and confirmed that technological diversification reduces firm's value. The causes of this result could be found in the phenomenon of overinvestment in diversified segments under limited amount of investment and the phenomenon of cross-subsidization from departments with good performance to departments with poor performance. Rocha (1999) measured technological specialization by calculating the ratio of how much patents are concentrated in a specific industry to the total number of patents. As a result of analyzing 72 firms within high-tech industries in Japan, Europe, and North America, it was confirmed that the technological specialization of firms had a positive and significant effect on the technological performance (in terms of technological cooperation). Toh and Kim (2013) argued that technological specialization helps to resolve technological uncertainty. As a result of surveying firms active in R&D within the US telecommunications equipment industry from 1996 to 2006, firms responded by specializing in narrow technology area when technological uncertainty is increased due to policy shock caused by government support.

2.2.3.2 Ambidexterity vs. Punctuated equilibrium

March (1991) perceive that maintaining the proper balance between exploration and exploitation is a key factor for a system to survive and thrive. Efforts for continuously exploiting current knowledge help firms maximize short run profits, and efforts to continuously explore unknown knowledge help firms maximize long run profits. In the same vein, Levinthal and March (1993) saw that the long-term survival of a firm is determined by both sufficient exploration for future viability and sufficient exploitation for current viability. This is because when a firm only conducts exploitation, it falls into core rigidity, loses their flexibility, and, as a result, gets trapped in a competency trap that reduces its long-term growth rate. (Leonard-Barton, 1992; Levinthal and March, 1993). On the other hand, if the firm only conducts exploration, it becomes oversensitive to short-term variance and local error, and it wastes resources by revising routines of the firm too often. (Volberda and Lewin, 2003; Siggelkow and Rivkin, 2006).

So, there is no research denying that firms should do both. However, the interpretation of the proper balance between exploration and exploration is divided into two main interpretations, depending on how these two methods are performed. One is ambidexterity, a strategy that simultaneously explores and exploits, and the other is punctuated equilibrium, a strategy that alternates exploration and exploitation.

First, the concept of the ambidextrous strategy was firstly presented by Tushman and O'Reilly (1996). Tushman and O'Reilly (1996), through the metaphor of a 'juggler' who handles several balls at once, argued that firms should have the ability to compete in existing mature markets and new markets at the same time. Floyd and Lane (2000) argued that firms should maintain both the exploitation of existing capabilities and the exploration to new areas for strategic renewal. In other words, the firm's ambidextrous strategy means a strategic choice to find a balance between exploration and exploitation, which are located at the two extremes of both technology accumulation methods, by performing both at the same time.

Keywords associated with ambidexterity include complementarity (Revilla et al., 2010; Revilla et al., 2018), simultaneity (Tushman and O'Reilly, 1997), and duality (Turner et al., 2013), etc. it is also called as exploration-exploitation paradox (O'reilly and Tushman, 2008), or exploitation-exploration tensions (Knott, 2002; Andriopoulos and Lewis, 2009) in the sense that exploration and exploitation both have to be balanced, but it's not easy. Because ambidextrous firms must overcome the paradox of destroying existing strategic choices that yield short-term success in order to achieve long-term success.

Various empirical analyses demonstrate that ambidextrous strategies have a positive effect on firm performance.[11] He and Wong (2004) revealed the reality of the ambidextrous strategy through an empirical analysis for the first time. He and Wong (2004) surveyed the innovation performance from CEOs of 137 manufacturing firms in Singapore and 69 firms in Penang, Malaysia between 1999 and 2000. It was confirmed that ambidextrous strategy helps the financial growth. Lin et al. (2013) investigated 214 Strategic Business Units in

[11] Many studies not only analyze the *methods* of technological accumulation, such as *exploration* and *exploration*, but analyze the *process* of technological accumulation, the *ambidextrous strategy* together. Although there are many studies that investigate factors that affect ambidextrous strategy as a dependent variable, this study only focuses on the study considering ambidextrous strategy as an independent variable.

Taiwan and found that the innovation ambidexterity (The sum of radical innovation and incremental innovation, which are proxy indicators of exploration and exploitation, respectively.) had a positive and significant effect on the firm's financial growth as a mediating role. Knott (2002) saw the reduction in production cost due to the learning curve as evidence of exploitation, and the improvement in quality due to new product development as evidence of exploration, and found that exploitation and exploration were discovered in Toyota at the same time.

As a contrast to ambidexterity, there is punctuated equilibrium[12]. A punctuated equilibrium is a term originally developed in evolutionary biology, which refers to a phenomenon in which rapid evolution occurring over a short period of time is followed by a long stasis period where only small changes exist. The concept of punctuated equilibrium was first introduced in firm-level research through the theory of organizational evolution by seminal work of Tushman and Romanelli (1985). Tushman and Romanelli (1985) argued that organizations evolve through a process in which reorientation (or recreation) is punctuated between one convergent period and the next convergent period[13]. Here, the convergent period is a relatively long period of incremental change and adaptation, and a reorientation (or recreation) refers to a relatively brief period of discrete change in which

[12] Keywords related to *punctuated equilibrium* include *temporal separation* (Gibson and Birkinshaw, 2004), *mutual exclusivity* (Gupta et al., 2006), and *substitutability*.

[13] In addition to organizational evolution, it is possible to interpret various phenomena through *punctuated equilibrium*. First, if *punctuated equilibrium* is applied to technology, the principle of *creative destruction* can be explained. This is because the invasion into a new technological domain through the application of antecedent generates rapid and discontinuous technological changes (Levinthal et al., 1998). If the concept of *punctuated equilibrium* is applied to the technological knowledge accumulation, it is possible to explain a phenomenon in which discrete strategic choices are observed in a series. Here, strategic choice refers to maximally exploiting a given opportunity or maximally exploring a future opportunity.

strategy, power, structure, and control are retooled and transformed into a fundamentally new alignment.

The punctuated equilibrium considers exploitation and exploration as having an opposite concept, that is, a reciprocal relationship. In other words, punctuated equilibrium is considered that the exploitation of technology knowledge naturally decreases when the proportion of exploration increases, and vice versa. This is because focusing exclusively on new technological knowledge and focusing solely on existing technological knowledge require different types of culture, capabilities and structures for firms (Bierly and Daly, 2007). A firm that does both can be seen as lacking in focus or internal fit (Miller and Friesen, 1986).

Several studies substantiate the punctuated equilibrium strategy of firms through case studies or the finding that exploiting and exploring at the same time has nothing to do with a firm's financial performance. Romanelli and Tushman (1994) confirmed that strategic changes, structural changes, and power distribution changes, measured quantitatively and qualitatively, occurred rapidly in 25 US small computer manufacturing firms in a very short period of time. The author argues that revolutionary transformation through punctuated equilibrium is the driving force that fundamentally changes firms. Bierly and Daly (2007) conducted a survey of 98 Small and Medium-sized Enterprises (hereafter, SME) in the US and found that exploitation and exploration have a high correlation, indicating that firms pursue both strategies at the same time. However, The author cannot find any significant effect of performing the two strategies simultaneously on the firm's financial performance

(Each had an impact, with exploitation in an inverted U-shape and exploration in a positive linear way on financial performance.)

2.2.4 Aspect of technological knowledge accumulation

Lastly, the aspect of technology accumulation represents the feature of the technological portfolio accumulated as a result of strategic choice. Keywords related to aspect include composition, feature, shape, form, structure, and content. Aspects of technology accumulation include 'breadth and depth' and 'coherence'.

2.2.4.1 Breadth vs. Depth

The terminology of breadth and depth is used in various topics; i) searching (e.g., Laursen and Salter, 2006; Chiang et al. 2010; Garriga et al.,2013; Ferreras-Méndez et al., 2015; D'Ambrosio et al. al., 2017; Zobel et al., 2017; Flor et al., 2018) ; ii) learning (e.g., Zahra et al., 2000; Zahra, 2012), experience (e.g., Gavetti et al. al., 2005; Wang et al., 2010; Eggers et al., 2012; Godart et al., 2015; Maitland et al., 2015), and expertise (e.g., Haynes et al., 2010; Boh et al., 2014) ; iii) operating countries (e.g., Allen, 1996), export (e.g., Filipescu et al., 2013), investment (e.g., Lee et al., 2009) and relationships including collaboration (e.g., Garcia Martinez et al., 2014; Kobarg et al., 2019; Shi et al., 2019) ; iv) resources (e.g., Miller et al., 2008; Sirmon et al., 2011; Jourdan et al., 2017) and sources (e.g., Ghisetti et al., 2015; Mei et al., 2021). In this study, we are interested in the breadth and depth of a firm's technological knowledge that can be considered through its technological portfolio (e.g., Brusoni et al., 2005; Zhang et al. 2007; Moorthy and Polley, 2010; Van Wijk et al., 2012; Zhou et al., 2012; Xu, 2015; Farazi et al., 2019; Yao et al., 2021; Zhu et al., 2021; Nguyen, 2022).

The breadth of a firm's technological portfolio refers to how diverse or heterogeneous the compositions of technological portfolio are (Zou et al., 2019). In particular, the breadth of a technological portfolio can be seen as a characteristic of a technological portfolio that is determined by a diversification strategy (Acha et al., 2007). In many studies, the word diversity is used interchangeably, and as diversity increases, the breadth also increases. On the other hand, depth refers to the degree to which a firm is specialized and mastered in a specific technology field (Zou et al., 2019). The depth is a characteristic of a technological portfolio that is determined by a firm's specialization strategy (Acha et al., 2007).

Indexes that measure the breadth and depth of a firm's technological portfolio have been introduced through various studies. The method of measuring the breadth and depth of a technological portfolio is using a survey (Van Wijk et al., 2012; Zhou et al., 2012; Yao et al., 2021; Nguyen, 2022) or interpretive analysis. (Brusoni et al., 2005), or indirect measurement through proxy indicators. This study focuses on studies that measure the breadth and depth of technological portfolios through proxy indicators based on patent data.

Breadth or depth, an aspect of accumulated technological knowledge, was measured primarily on an absolute number. Absolute number-based measures are directly affected by the absolute values of the components in the formula.[14] The most basic absolute numbers

[14] In contrast, measures for *strategy* of technology accumulation are calculated based on a concentrated (or scaled) ratio. This is because the relative ratio of each classification should be considered along with the number

that can measure a firm's breadth or depth include the total number of patents, the number of patents in a specific technology classification, and the number of technology classification.

Various methodologies for measuring breadth of a firm's technological portfolio are summarized in Table 2-4, and depth are summarized in Table 2-5. In addition to the firm's technological knowledge, various keywords such as 'capability' were selected according to the purpose and context of each study.

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of technology classifications within the firm in order to include both concepts, the *breadth* and *depth* of the technological portfolio, in a single value. Measures about *strategies* for technology accumulation are discussed in detail in Section 2.3.1.

Table 2-4. Measure for the breadth of firm's accumulated knowledge

Terminology	Method	Features	Reference
Breadth of technological knowledge	$1 - 1/n$ ● where n is the total number of patent classes	● Range: [0,1] ● The breadth does not increase linearly with n.	Jose et al., (1986); Moorthy and Polley (2010)
Breadth capability	The total number of patent subclasses (n)	● Range: [1, Maximum number of existing classification codes] ● The breadth increases linearly with n.	George et al. (2008), Kotha et al., (2011)
Breadth of knowledge base			Zhang et al. (2007)
Knowledge breadth			Xu (2015)
Technological breadth			Farazi et al. (2019); Zhu et al. (2021)
Breadth capability	$\max_{j \in P}$(combination within an CPC subclass j) ● where P is firm's technological portfolio	● Based on absolute CPC number ● Free from underestimation or distortion comparing with scaled index	Ning and Guo (2022)

Table 2-5. Measure for the depth of firm's accumulated knowledge

Term	Method	Features	Reference
Depth of technological knowledge	$$\sum_{\alpha}[\left(\frac{P_{i,\alpha}}{P_i}\right)^2 - \left(\frac{1}{n_i}\right)^2]$$ ● where $\left(\frac{P_{i,\alpha}}{P_i}\right)$ is the fraction of patents assigned in class α ● n is the total number of patent classes	● The depth increases as the share of patents of a particular subclass (x_i) increases. ● Increasing values of the number of classes, n imply an increasing asymmetry in share across technology classes.	Jose et al., (1986); Moorthy and Polley (2010)
Depth capability	Maximum number of approved patents in any patent subclass for each firm i	● The depth increases linearly with the maximum number of patents in the subclass.	George et al. (2008), Kotha et al., (2011)
Knowledge depth			Xu (2015)
Concentration of knowledge base	$\frac{\sigma_{RTA}}{\mu_{RTA}}$ (coefficient of variation) ● where RTA is calculated by eq (2.5)	● The depth increases when a firm has a high RTA in one or few technology subclasses.	Zhang et al. (2007)
Technological depth			Farazi et al. (2019)

Technological depth	$\frac{\sum_{i=1}^{5} p_i}{5}$ The average number of patents (p_i) in top 5 deepest technology subclass	● The depth increases linearly with the total number of patents in the top 5 subclasses.	Zhu et al. (2021)
Depth capability	$\sum_{j\in P}\sum_{k\in P}(\mathit{combination}$ cross CPC subclasses j and k) ● where P is firm's technological portfolio	● Based on absolute CPC number ● Free from underestimation or distortion comparing with scaled index	Ning and Guo (2022)

2.2.4.2 Coherence

Another aspect of accumulated technological knowledge within a firm is coherence among technological knowledge. Coherence between technology means proximity, distance, cohesion, or relatedness between all constituent components in a technological portfolio. In the case of high coherence, higher synergy can be exploited by sharing common technological knowledge. (Breschi et al., 2003; Nesta and Saviotti, 2006). Therefore, even if a firm has a large number of technology classification, if the coherence between technologies is poor, firms may lose technological specialization (Rigby, 2015).

Various measurements are devised to calculate the overall coherence among all technologies in the technological portfolio, and the results are summarized in Table 2-6. First, Nesta and Saviotti (2006) and Leten et al. (2007) calculate the average proximity between the entire technologies within portfolio of the firm based on the Weighted-Average Relatedness [15] developed by Teece et al. (1994). Rigby (2015) measured regional technology coherence through average proximity between technologies obtained through citing-cited relationships in patents. Pugliese et al. (2019) take weighted average the number of technologies with a comparative advantage compared to the total number of technology classifications in the firm.

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[15] The *Weighted-Average Relatedness* is proposed by Teece et al. (1994) and *related density* by Hidalgo et al. (2007) has a similar formula structure in that they calculate the weighted sum of *proximity* centering on one technology. *Weighted-Average Relatedness* is multiplied by the ratio of the number of patents in a specific technology classification to the total number of patents owned by the frim. In the case of *related density*, the *RTA* of a specific technology classification owned by the firm divided by *RTA* of all existing technologies is multiplied.

Table 2-6. Measure for the coherence of firm's accumulated knowledge

Term	Method	Interpretation	Reference
Coherence (*COH*)	$COH = \sum_i WAR_i * f_i$ ● where, $WAR_i = \sum_{j \neq i} \varphi_{ij} * p_j \Big/ \sum_{j \neq i} p_j$, which is suggested by Teece et al. (1994) • p_j is number of patents in classification *j* and φ_{ij} is proximity value between technology *i* & *j* ● $f_i (= p_i / \sum_i p_i)$ is the fraction of technology classification *i*	● Weighted-Average of Weighted-Average Relatedness (WAR_i) ● Average proximity of any technology randomly chosen in a firm's technological portfolio with respect to any other technology.	Nesta and Saviotti (2005); Nesta and Saviotti (2006); Leten et al. (2007)
Average Relatedness ($AR^{t,r}$)	$AR^{t,r} = \frac{\sum_i \sum_j \varphi_{ij}^t * D_{ij}^{t,r} + \sum_i \varphi_{ii}^t * 2D_{ii}^{t,r}}{P^{t,r} * (P^{t,r} - 1)}$ for $i \neq j$ ● where φ_{ij}^t is technological proximity between technology classification *i* & *j* ● $N^{t,r}$ is total number of patents in region r in year t ● $D_{ij}^{t,r}$ is the total number of pairs of patents that are located in technology classes *i* & *j* in region r in year t.	● The average of all proximity values between technology i & j ● If the Average Relatedness value ($AR^{t,r}$) is high, the patents in region r are distributed over technology classes that are, on average, close from one another in the technology space.	Rigby (2015)

Coherent Technological Diversification (*CTD*)	$$CTD_f = \frac{\sum_\alpha M_{f,\alpha} * \gamma_{f,\alpha}}{d_f}$$ ● where $\gamma_{f,\alpha}$ is the sum of proximity value ($\varphi_{\alpha,\beta}$) of all technologies (β) which has *RTA* around technology α ($= \sum_\beta \varphi_{\alpha,\beta} * M_{f,\beta}$) ● $M_{f,\alpha}$ is a binary matrix that has value 1 if firm *f* has *RTA* in technology α, which is calculated by Eq. (2.5) ● d_f is the diversification of firm f $\left(= \sum_\alpha M_{f,\alpha}\right)$	● *CTD* is the average of *proximity value ($\sum_\beta \varphi_{\alpha,\beta}$)* assigned to each technology (α), which is the summation of all proximity linked with other technologies (β).	Pugliese et al. (2019)

2.2.5 Limitations of previous studies

As mentioned above, various academic fields have tried to understand the nature of technological knowledge and its accumulation in firms, and as a result, various concepts related to them have been devised. The fact that various subjects about technological knowledge accumulation is covered in various academic fields means that understanding the nature of technological knowledge is just as important. As can be seen from a series of causal relationships; technological innovation; product innovation through technological innovation; and financial growth through selling innovative product, the accumulation of technological knowledge is a major driving force for firm growth, which lies at the very bottom.

The seminal studies introduced above concisely and clearly explain and help understand the nature of technological knowledge and its accumulation based on a unique concept. However, the definitions of various concepts designed to express the nature of technological knowledge are not unified and their use has been mixed differently depending on the context. Consequently, in Section 2.2 of this study, efforts were made to classify the various concepts into methods, processes, and aspects.

Stylized facts reached a consensus in interdisciplinary field were also found; i) technological knowledge is cumulative result which is not easily; ii) a firm accumulate new technological knowledge related to existing one; iii) a technology to be acquired in the future will be influenced by the technological knowledge accumulated from the past to the present. This is supported by empirical evidence derived from a variety of data and methodologies, from traditional economics to evolutionary and complexity economics, which are currently being actively researched.

But still, there are not many concepts about the nature of technological knowledge and its accumulation that are accepted without objection as a stylized fact. The primary reason may be that technological knowledge is multifaceted and intangible. Long discussions related to technological knowledge presuppose that technology is an n-dimensional and intangible that is difficult to explain. We have no choice but to do effort to understand through a single window, because each devised theory cannot explain all aspects of technology accumulation. As expressed by Arthur (2009), we can explain what each technology is, but paradoxically, we cannot understand and describe what technology is in general.

The second reason is that both the technological knowledge to be accumulated and the firms that perform the accumulation evolve over time. Both of them are beings whose characteristics change. According to the discussion so far, a technology is a set of several sub-technologies and is made up of interactions between them. So, an evolution of technology has occurred through interactions between past and present sub-technologies. Therefore, the accumulation of technological knowledge within firms is needed to fully understand in a more sophisticated way. Going one step further from the existing discussions, we will be able to more delicately understand the accumulation of technological knowledge, which is the driving force of firm's growth, when 1) the multifaceted aspects of technology accumulation and 2) the dynamics of technology accumulation are considered.

2.3 Technological diversification, complexity and firm's performance

A firm's resources and technological capabilities are the sources of its comparative advantage (Barney, 2001). Accordingly, firms accumulate technological knowledge in order to increase the resources they can utilize, therewith, enhance their technological capabilities. At this time, it is possible to judge the 'technological knowledge accumulation strategy selected by the firm' through 'which process a firm choose to accumulate their technological knowledge' as discussed in Chapter 2.2.3.

Firms mainly expand the boundary of their knowledge base through technological diversification or specialization strategies. Among them, a firm's technological diversification strategy has been a key research topic in explaining various phenomena (financial performance, innovation performance, product diversification and relationships between firms, etc.) from the 1990s (Ceipek et al., 2019). In particular, since a strategy to reduce technological diversification is synonymous with a strategy to focus on the few technologies, more empirical studies are concentrating on firms' technological diversification strategies.

In this section, we first look at the index that quantifies the firm's technological knowledge accumulation strategy. Three indices (e.g. Gini-Simpson's diversity (Herfindahl-Hirschman Index), Shannon's Entropy, Concentric measure of diversification

(Rao-Stirling index) for technological diversification, and the core competence developed by Kim et al. (2016) will be introduced, and then confirm the characteristics and limitations of each indices. Next, the results of empirical analysis examining the relationship between a firm's technological diversification strategy and its performance are summarized. Since this study is particularly interested in the dimensions of a firm's technological knowledge and financial performance, it only focuses on the studies that set innovation performance and financial performance as independent variables. Finally, after examining the moderating variables that affect technological diversification, the complexity of the technological portfolio is introduced as one of the moderating variables.

2.3.1 The measure for technological knowledge accumulation strategy

There are two main strategies for accumulating technological knowledge that firms can choose. One is a technological diversification strategy that leverages existing resources to expand into new technology areas. The other is a technological specialization strategy that enhances the competitiveness of the specific technology area to which the resource belongs by exploiting existing resources.

In various fields such as physics, ecology, sociology, and anthropology, indices have been devised to quantify the composition of analysis objects. Since these indices have an interdisciplinary nature, they are borrowed and used in business administration and economics. In addition to the various interdisciplinary indices, there are also indices developed specifically for business and economics. In this section, both interdisciplinary indices and various indices designed for the purpose of business research and economics are studied. In particular, the concepts and pros and cons of each indices are also examined.

The indices introduced in this section are all used in studies examining the composition or strategy of a firm's technological portfolio. An index calculated in a particular year indicates what the composition of the technological portfolio was in that year. On the other hand, it is regarded as a strategy in regression analysis that analyzes the causal relationship. Because regression analysis is to find out the effect of independent variable when the component is changed by one unit. So it can be recognized as an effort to change the composition, that is, as a strategy.

Indices that measure the composition or strategy of a technological portfolio are calculated through i) the diversity of each technology classification in a firm's technological portfolio and ii) the relative proportion of each technology classification to the total number of technologies. Calculation method based on relative proportions of each components is called a scaled ratio-based measure. Scaled ratio-based measures include both the concept of breadth (the number of technology classification) and the concept of relative depth (the proportion of each technology classification within a firm) to express that the measures are affected by two factors simultaneously.[16]

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[16] The *scaled ratio-based measurement* differs from the *absolute number-based measurement* discussed in Section 2.2.4.1 in that it is not directly affected by the increase or decrease in the number of elements related to patents. This is also the criterion for distinguishing the *process* of technological knowledge accumulation from the *aspect* of accumulated technological knowledge. Since the *aspect* of the accumulated technological knowledge considers *breadth* and *depth* as independent characteristics, there is no need to consider both factors

Table 2-7 shows the results of summarizing the indices to be introduced in Section 2.3.1. $P_{i,\alpha,t}$, a symbol commonly used in this section, indicates how many patents related to technology classification α are owned by firm *i* at time *t*. $P_{i,t}$ $(= \sum_{\alpha} P_{i,\alpha,t})$ means the sum of the patents number held by firm *i* for all technology classifications. Thus, $(\frac{P_{i,\alpha,t}}{\sum_{\alpha} P_{i,\alpha,t}})$ is the ratio of the number of patents related to technology classification α, compared to all patents within the firm *i* at time *t*.

simultaneously as one single variable. On the other hand, the *process* of accumulated technological knowledge explains the accumulation *strategy* (or accumulated *composition*) of technological knowledge through one variable in which the *breadth* and *depth* of the technological portfolio are simultaneously considered.

Table 2-7. Measures for technological knowledge accumulating strategy based on scaled ratio

Term	Objectives	Origin	Equation	Element	Related research
Gini-Simpson's diversity or Herfindahl-Hirschman Index	Diversification	Gini (1912), Hirschman (1945), Simpson (1949)	$1 - \sum_{\alpha} \left(\frac{P_{i,\alpha,t}}{P_{i,t}}\right)^2$	• Variety • Balance	Berry (1975), Hirschman (1980), Miller (2004)
Entropy	Diversification	Shannon (1948)	$\sum_{\alpha} P_{i,\alpha,t} \cdot \ln(\frac{1}{P_{i,\alpha,t}})$	• Variety • Balance	Zander (1997), Ricotta et al. (2006)
Concentric measure or Rao-Stirling	Diversification	Caves et al. (1980), Rao (1982), Stirling (2007)	$\sum_{\alpha,\beta} (1 - \phi_{\alpha,\beta}) \left(\frac{P_{i,\alpha,t}}{P_{i,t}}\right) \left(\frac{P_{i,\beta,t}}{P_{i,t}}\right)$	• Variety • Balance • Disparity	Argyres (1996), Ricotta et al. (2006), Rafols and Meyer (2010), Leydesdorff et al.(2019)
Core competence	Specialization	Kim et al. (2016)	$\ln[\max\{RTA_{i,\alpha,t} \cdot P_{i,\alpha,t}\}]$ where RTA is calculated by eq (2.5)	• Comparative advantage • Technology stock	Patel and Pavitt (1997)

2.3.1.1 Gini-Simpson's diversity (Herfindahl-Hirschman Index)

Gini-Simpson's diversity is a index developed by Gini (1912) and Simpson (1949) to measure the degree of evenness or concentration in economics (Stirling, 2007). Afterwards, the Herschman-Herfindahl Index (hereinafter referred to as HHI) was developed by Herfindal and introduced through Hirschman's (1945) thesis to regulate market share in the US. Simpson's Index, or HHI, is the sum of the squares of each market share (%) of all firms in the market, and captures market concentration between 0 and 1 (Hirschman, 1980). Berry (1975) was the first to measure how diversified a firm's technological knowledge was using HHI.

The diversity index expresses how distributed a technology is within a firm, with a slight transformation of subtracting the degree of concentration of a technology by classification from 1, which is the overall technology of a firm. The diversity index value of firm *i* is expressed as follows.

$$Diversity_{HHI_{i,t}} \quad = \quad 1 - \sum_{\alpha} \left(\frac{P_{i,\alpha,t}}{P_{i,t}} \right)^2 \cdots\cdots\cdots\cdots \text{Eq. (2.7)}$$

The diversity index is affected by variety (the number of technology classification within a firm) and balance (the ratio of the number of patents in each technology classification to the total number of patents). The greater the variety, and the more balance, the higher the value of the diversity index (firms should have more than one technology classification). Notionally, it can be seen that there is an inverse relationship with specialization strategy in a particular technology. Because the diversity index decreases when a specific technology classification within a firm's technological portfolio accounts for a large portion.

The diversity index has a disadvantage that it cannot perfectly explain the causal relationship observed in our reality (the lower the classification level, the higher the diversity index should appear), because the more systematized a technological classification is (the higher the classification level), the higher diversity index (Jacquemin et al., 1979). In addition, since all technology classification codes are considered as the same, the distance between different technologies, that is, the proximity between technologies is not considered (Rao, 1982).

2.3.1.2 Shannon's Entropy

Entropy was devised in information theory to measure the inherent potential uncertainty of any outcome with respect to a particular variable (Shannon, 1948). Unlike Gini-Simpson's diversity or Herfindahl-Hirschman Index, the entropy index can decompose the classification in different level and express them through a linear sum of the different contributions of each diversification effects by element. A typical example is a modified formula that reflects both the degree of diversification within each technology classification and the degree of diversification among technology classification within a firm (Jacquemin et al., 1979). The entropy index in its basic form is:

$$Diversity_{Entropy_{i,t}} = \sum_{\alpha} P_{i,\alpha,t} \cdot \ln(\frac{1}{P_{i,\alpha,t}}) \cdots\cdots\cdots\cdots \text{Eq. (2.8)}$$

Like HHI, the entropy index is also affected by variety and balance. The larger the number of technology classifications owned by a firm with more than one technology classification, and the more even the ratio between technology classifications, the higher the entropy index.

Also, the entropy index shares the inherent disadvantage of scaled ratio-based measures. First, since the relative ratio between technology classifications is used, there may be distortion in the result depending on the level of technology classification (Robins et al., 2003). Next, since it is based on the ratio of each technology classification within a firm, relative comparison between firms is impossible. In addition, if the number of technology classifications and the ratio of patents for each technology classification are the same, the result of the entropy index does not change, even if the technology stock (the number of patents) changes. Finally, diversity index and entropy indices do not consider heterogeneity between technologies. As a result of considering all technologies to be the same, proximity between technologies, which is the distance between technologies, is not considered (Ricotta et al., 2006).

2.3.1.3 Concentric measure of diversification (Rao-Stirling index)

Gini-Simpson diversity (or HHI) assumes that each technology classification belongs to the same category, and the distance between all technologies is zero. By transforming the Gini-Simpson diversity (or HHI), the concept of distance between technologies can be included by adding disparity (or similarity) to the product of the proportions of two different technologies within a firm. We call it as concentric measure (or Rao-Stirling index) (hereafter, Rao-Stirling index) and understand is as the improved version of the Gini-Simpson diversity (or HHI).

The first study to use the Rao-Stirling index was Caves et al. (1980). The authors calculated the degree of industrial diversification of the Canadian economy based on the ratio of the number of workers by industry. Later, it was used by Argyres (1996) to measure the technological diversification of multidivisional firms. In the interdisciplinary research, the index of the same concept was devised. Based on the research of Rao (1982), Rafols and Meyer (2010) name the index as the Rao-Stirling index improved by Stirling (2007) to overcome the problems of existing diversification indices (Leydesdorff et al., 2019).

While The Diversity & entropy index, which have been mainly used, consider only the variety and the balance, Rao-Stirling index improves these two indices by additionally considering disparity (or similarity), which measures how different each item is (or how similar each item is). The expression of the Rao-Stirling index is:

$$Diversity_{Rao-stirling_{i,t}} = \sum_{\alpha,\beta}(\lambda_{\alpha,\beta})\left(\frac{P_{i,\alpha,t}}{P_{i,t}}\right)\left(\frac{P_{i,\beta,t}}{P_{i,t}}\right) = 1 - \sum_{\alpha,\beta}(\varphi_{\alpha,\beta})\left(\frac{P_{i,\alpha,t}}{P_{i,t}}\right)\left(\frac{P_{i,\beta,t}}{P_{i,t}}\right) \cdots\cdots \text{Eq. (2.9)}$$

Here, β means a technology other than technology α. $\lambda_{\alpha,\beta}$ is the degree of disparity between technologies α and β, and $\varphi_{\alpha,\beta}$ is the degree of similarity (so far called, proximity) between technologies α and β, which is equal to 1-$\lambda_{\alpha,\beta}$. Therefore, as the number of classifications of technologies increases, the proportion of each technology is balanced, and the disparity between technologies increases, the value of Rao-Stirling index increases.

2.3.1.4 Core competence

We should not consider a firm's core technology simply as the technology classification that possesses the most quantity. Even if a small number of technology, if there are no other firms possessing the technology in the entire industry, it can be seen the technology has a comparative advantage comparing with other technologies. Conversely, even if a firm possesses the most patents in a technology classification in terms of quantity, it is difficult to say that it has relatively the advantage if all firms in the industry have a larger amount about that technology. Accordingly, Patel and Pavitt (1997) defined technology *j* corresponding to the largest value of $RTA_{i,j,t}$ as a core technology, and Kim et al. (2016) devised Equation 2.10 to measure core technology competence and defined technology α corresponding to $\max\{RTA_{i,\alpha,t} \cdot P_{i,\alpha,t}\}$ as the core technology of firm *i* in time *t*.

$$Specializaion_{core-competence_{i,t}} = \ln[\max\{RTA_{i,\alpha,t} \cdot P_{i,\alpha,t}\}] \cdots\cdots \text{Eq. (2.10)}$$

According to Equation 2.10, the technology j that maximizes the product of the number of patents and comparative advantage value becomes competence of core technology. Rearranging Equation 2.10 can be expressed in the following equation.

$$\ln[\max\left\{(P_{i,\alpha,t}^2 \Big/ \sum_j P_{i,\alpha,t}) \Big/ (\sum_i P_{i,\alpha,t} \Big/ \sum_i \sum_\alpha P_{i,\alpha,t})\right\}]$$

The core technology competence (Equation 2.10) is an index that logically better reflects our reality in that it simultaneously determines the core technology and measures its competence respectively. But numerically, there are two rooms for improvement. First, as mentioned earlier, there could be cases in which the entire industry did not accidentally develop a specific technology in a year while one firm accidentally develops a large number of the specific technology. Therefore, in order to determine the core technology, the $RTA_{i,\alpha,t}$ of a technology should be observed firstly and investigated continuously.

Next, Equation 2.10 is more influenced by the number of patents, $P_{i,\alpha,t}^2$, which is the numerator. It is an absolute value for each firm, not the relative value. As a result, even if the number of a technology classification is smaller than other firms compared to the industry as a whole, the technology classification that applied by the most within the firm is more likely to be judged as a core technology. For example, if firm i owns many patents related to technology α in time t, even if $RTA_{i,\alpha,t}$ is smaller than the average level of the entire industry, then technology α, a relatively uncompetitive technology can be judged as a core technology. Therefore, the influence of relative comparative advantage becomes lessen, and the result varies greatly with the number of patents which is absolute value.

2.3.2 Technological diversification and moderating variable

Technological diversification of firms is a long-studied topic. In most studies dealing with firm's technological knowledge accumulation strategies, technological diversification is considered as a factor that has a positive effect on firm's performance. Kim et al. (2016) summarized the purpose of technological diversification into the four following reasons. First, firms diversify their technologies to take advantage of the economies of scope of R&D. The diversified technological knowledge enables synergies between technological knowledge be used in various products, therewith can allocate their resources more efficiently. Second, firms diversify their technologies to secure technological competence by increasing their absorptive capacity. The third reason is that technological diversification reduces the uncertainty of a firm's R&D and increases its ability to adapt to a rapidly changing technological environment. Finally, technological capabilities in various fields accumulated through technological diversification help to secure larger rent in the market through the development of more complex products.

Ceipek et al. (2019) systematically summarized studies so far on firm's technological diversification in his seminal paper. According to Ceipek et al. (2019), research on technological diversification of firms has developed through four stages. First, the early research was conducted to establish a theoretical and conceptual foundation, and then, discussions on the effect of technological diversification on the financial performance of firms were mainly conducted in second stage. In the third stage, studies exploring other performance than financial performance were conducted, mainly the innovation performance of the firm. In recent years, efforts have been made to find moderating variables. Based on the research flow organized by Ceipek et al. (2019), this section focuses on the previous empirical studies about i) technological diversification and financial performance of firms, ii) technological diversification and innovation performance of firms, and ii) technological diversification and moderating variables of firms.

2.3.2.1 Technological diversification and financial performance

When we imagine the degree of technological diversification as the *x*-axis, It can be assumed that single, related, and unrelated diversification proceeds as the *x*-value increases. Studies that analyze the relationship between a firm's technological diversification and financial performance[17] can be classified into two types. First, a linear relationship in which the firm's financial performance increases as technological diversification increases. Next, there is an inverted-U-shaped relationship in which the financial performance of a firm increases as technological diversification increases until related technologies, but the

[17] Financial performance includes not only financial indicators such as sales, value added, return on equity, and return on assets, but also various variables related to growth such as the entry and exit productivity, growth rate, and survival rate of firms are included.

effect of technology diversification on financial performance begins to decrease when diversifying into unrelated technologies.

First, as a study arguing a linear relationship, Granstrand and Oskarsson (1994) conducted a survey targeting 12 Swedish, 14 Japanese, and 16 US large firms. The degree of technological diversification of a firm (measured by the technology field to which engineers belong) and the results of the survey showed a relationship between a firm's technological diversification and financial performance (sales growth rate). Gambardella and Torrisi (1998) surveyed 32 firms within the electronics industry in Europe and the US between 1984 and 1992 and found that, when technologically diversified, the firm's sales or profits or sales-per-employee ratio was confirmed to increase. Miller (2004) confirmed the endogenous relationship between technological diversification and firm's financial performance targeting 227 diversified large corporations in the US from 1980 to 1992. Later, Miller (2006) found a positive and significant causal relationship between a firm's technological diversification and its financial performance. Watanabe et al. (2007), as a result of analyzing Japan's leading electrical machinery firms, argued that technological diversification is a driving force in increasing sales of firms.

Next, Kim et al. (2016) confirmed the inverted-U-shaped relationship between technological diversification and financial performance through empirical analysis. Kim et al. (2016) found that when technological diversification is excessive, the cost of technological diversification becomes higher than the profit. This is because the more technological diversification is done, the more technological distance from the core technology, which lowers R&D productivity and increases costs due to additional input of R&D labor force and reallocation of resources within the firm.

On the other hand, there are studies that have argued that technological diversification has had a negative effect on or has no relevance to a firm's financial performance. Lin et al. (2006) surveyed technological diversification (broad technology diversity) and technological specialization (core field diversity) of 94 US firms from 1985 to 1999. The result showed technological diversification has a negative effect on the firm's financial performance. Technological diversification had a positively significant effect only on the profitability of firms with high technology stocks (firms that has a high number of patents as a percentage of total assets). Chen et al. (2013) also investigated smartphone manufacturers in Taiwan and confirmed that technological diversification has a negative effect on financial performance (measured by Tobin's q & Market Value Added). In particular, it was confirmed that the effect of technological diversification on financial performance (measured by Economic Value Added & Market Value Added) changed positively only when the absorbed organizational slack of the firm acted as a moderating effect. On the other hand, when unabsorbed organizational slack acts as a moderating effect, the effect of technological diversification on financial performance (measured by Economic Value Added & Market Value Added) is increased more significantly in a negative direction. Finally, as a result of study done by Nesta (2008), no statistically significant effect of technological diversification on the financial performance (measured by productivity) of 156 international conglomerates was observed.

2.3.2.2 Technological diversification and innovation performance

Studies that reveal the relationship between a firm's technological diversification and innovation performance[18] can also be classified into a linear relationship and an inverted-U shape relationship. First, Garcia-Vega (2006) and Quintana-García et al. (2008) found a linear relationship between a firm's technological diversification and innovation performance. Garcia-Vega (2006) analyzed 554 European firms from 1995 to 2000, and found that as the degree of technological diversification increases, the degree of innovation (represented by the R&D intensity and total number of patents) of the firm increases. Quintana-García et al. (2008) found that technological diversification investigated by biotechnology patents filed in the US between 1990 and 1998 has a positive effect on a firm's innovation capability (consisted with Exploratory innovative competence (number of patents registered in single year, number of patents not citing other papers) & Exploitation innovative competence (number of patents filed citing other patents))

An inverted-U shape relationship refers to a relationship in which innovation performance increases as a firm's technological diversification progresses, but decreases again when technological diversification progresses beyond related technologies to unrelated technologies. Leten et al. (2007), Huang and Chen (2010), Lee et al. (2012) and Aktamov (2014) found an inverted U-shaped relationship between technological diversification and innovation performance. Leten et al. (2007) surveyed 184 firms within

[18] Innovation performance includes various variables such as R&D expenditures, R&D intensity, number of applied patents or granted patents, number of CPC assigned to patents and number of patent citations. (see Table 2-1)

the top five industries with the highest R&D expenditures in the US, Japan, and Europe. As a result, technological diversification showed an inverted U-shaped relationship with technological performance. Huang and Chen (2010) perceive that patents are built defensively to protect the few core competence of firms when a firm's technological diversification is too low, while adjustment costs increase when technological diversification is too severe. So the authors argue that there would be an appropriate point in between both extremes. Huang and Chen (2010) investigated USPTO patents filed by 305 listed firms in Taiwan's IT industry and observed an inverted U-shaped relationship between technological diversification and firm's quantity and quality innovation performance. The same results are found by Lee et al. (2012) for US telecommunications firms and Aktamov (2014) for Chinese automotive firms.

On the other hand, some studies have found that a firm's technological diversification is not related to their innovation performance. Almeida and Phene (2004) investigated 58 US semiconductor multinational corporations and 374 subsidiaries belonging to them. The result shows that technological diversification of multinational corporations had a statistically non-significant effect on innovation performance of subsidiaries. Chan (2011) investigated US agricultural biotechnology firms and found that technological diversification did not have a significant effect on innovation performance (detected by development of new species diversity).

2.3.2.3 Moderating variable

Efforts have also been made to find variables that moderate the impact of technological diversification (TD) or excessive technological diversification (TD^2) on a firm's performance. So far, various moderating variables have been discovered, including i) technology stock (Lin et al., 2006; Kim et al., 2009), ii) organizational slack (Huang and Chen, 2010 ;Chen et al., 2013; Lee et al., 2017), iii) core technology competence (Kim et al., 2016), iv) complementary assets (Chiu et al., 2008; Pan et al., 2017), v) competitive behavior (Ndofor et al., 2011), vi) and technological coherence (Nesta and Saviotti, 2005; Leten et al., 2007).

Studies analyzing the moderating effect that affects technological diversification are largely classified by two criteria. First, it can be classified according to the type of dependent variable. It can be divided into a moderating variable that affects only innovation performance, a moderating variable that only affects financial performance, and a moderating variable that affects both outcomes (e.g. Organizational Slack). Next, it can be classified according to the degree of technological diversification that the moderating variable has an influence on. As we have seen in Section 2.3.2 so far, the effect of technological diversification on performance varies according to the degree of technological diversification. In particular, two conflicting views coexisted, interpreting the effect of excessive technological diversification (TD^2) on performance as either positive or negative. Therefore, in studies that assume that technological diversification has a linear effect on firm performance, the effect of a moderating effect on the linear term (TD)

is investigated. Studies that assume that the relationship between technological diversification and firm performance is inverted-U shape confirm the effect of moderating effects on the first-order (TD) or the second-order (TD^2) of technological diversification. Related previous studies are summarized in Table 2-8.

Table 2-8. Moderating variables for technological diversification

Moderating variable	Definition	Terms that are affected	Outcome variable	Effects	Reference
Technology stock	The accumulated number of patents for 3 years divided by firm's total assets	Technological diversification (TD)	Financial performance	The negative relation between broad-field technological diversification and financial performance is positively moderated by high-technology stocks for US firms.	Lin et al. (2006)
				The non-significant relation between broad-field technological diversification and financial performance becomes significant and positively moderated by technology stocks for KOR firms.	Kim et al. (2009)
Organizational Slack (OS)	● Absorbed OS: Sum of major repair fund, inventory fund, and accounts payable ● Unabsorbed OS: Sum of depreciation fund, reserve fund, loans, sales expenses, and retained earnings	Technological diversification (TD)	Innovation performance	● The inverted U-shaped relation between technological diversification and innovation performance is positively moderated by absorbed OS when the level of technological diversification is not high. ● The inverted U-shaped relation between technological diversification and innovation	Huang and Chen (2010)

Organizational Slack (continued)				performance is negatively moderated by unabsorbed OS when the level of technological diversification is not high.	
		Technological diversification (TD)	Financial performance	● The negative relation between technological diversification and financial performance is positively moderated by absorbed OS for TW smart phone firms. ● The negative relation between technological diversification and financial performance is negatively moderated by unabsorbed OS for TW smart phone firms.	Chen et al. (2013)
	Financial Slack: current assets, minus inventory, divided by current liabilities	Technological diversification (TD)	Financial performance	The positive relation between technological diversification and financial performance is positively moderated by financial slack for 168 firms belonging to Standard & Poor's (S&P) 500 index in 2008.	Lee et al. (2017)

Core technology competence	Maximum value of RTA multiplied by the number of patents of the same technology class (Eq. 2.10)	Excessive technological diversification (TD^2)	Financial performance	The inverted U-shaped relation between technological diversification and performance is positively moderated by core technological competence when the level of technological diversification is high.	Kim et al. (2016)
Complementary assets	Specialized Complementary Assets (SCA) = Marketing SCA + Production SCA + Human capital SCA	Technological diversification (TD)	Financial performance	The positive relation between technological diversification and financial performance is positively moderated by all types of SCAs for TW Electronic and Information Technology firms.	Chiu et al. (2008)
	The multiplication of intangible assets & value-added ratio (value added/sales) divided by firm's total assets	Technological diversification (TD)	Financial performance	The positive relation between technological diversification and financial performance is negatively moderated by complementary assets for CHN large firms.	Pan et al. (2017)
Competitive behavior	● Complexity of competitive behavior: The degree to which a firm's behavioral portfolio consists of a broad range of behaviors. (Eq. 2.7)	Technological diversification (TD)	Financial performance	The positive relation between technological diversification and financial performance (ROA) is positively moderated by competitive behavior of firms in in-vitro diagnostic substance manufacturing industry.	Ndofor et al. (2011)

Competitive behavior (continued)	● Deviance of a firm′s competitive behavior: Sum of squared differences in the proportions of competitive behavior categories between the firm of interest and the industry average				
Technological coherence	Average proximity of any technology randomly chosen in a firm's technological portfolio with respect to any other technology. (See table. 2-6)	Technological diversification (TD)	Innovation performance	The inverted U-shaped relation between technological diversification and innovation performance is positively moderated by technological coherence when the level of technological diversification is not high.	Nesta and Saviotti (2005), Leten et al. (2007)

2.3.3 Economic complexity

In Section 2.2.1.2, we looked at one of the two pillars of the Economics of complexity, the principle of relatedness. In this section, we will look at another pillar, economic complexity.

2.3.3.1 Theoretical background

A firm's technological capabilities are not simply influenced by a single factor stochastically, but are the result of various factors and their interactions (Weaver, 1948; Hidalgo, 2021). In particular, the accumulation of technological knowledge within a firm is influenced by the social network to which the firm belongs, and in particular, it depends on the area adjacent to the related firm that has already accumulated the relevant technology (Granovetter, 1985). Economics of complexity, which applies complex systems to economic analysis, goes further and gives us clues about how economic agents (country, region, or firm) equip the ability to carry out new economic activities (product production or technology development, etc.).

Hidalgo et al. (2009), the authority of Economics of complexity, introduced a new indicator called economic complexity, a structural measurement on the network. Among various characteristics of economic activities, or various characteristics of economic agents, Hidalgo et al. (2009) focused on the structural complexity found in networks. There are two types of economic complexity: complexity of activity and complexity of economy.

First, a complexity of activity expresses how many different economic agents perform one economic activity while preserving information about the level of capabilities possessed by each economic agent. Let's take technology as an economic activity and firm as an economic agent as an example. The complexity of a technology, which is not calculated absolutely but judged relatively, is determined by how many firms are developed, and by which firms develop. It can be inferred that the fewer firms that have developed and possess a particular technology, the more complex that technology is comparing with others, which have developed by many firms. In addition, even if the technology is developed by the same number of firms, it can be expected that the technology developed by a firm with higher technological capabilities will be relatively more complex. In other words, the complexity of activity expresses the degree of capacity required to carry out a specific economic activity.

Another is complexity of economy, which is an indicator that expresses how diversified the firm is while preserving information about the complexity of each economic activity. Continuing to take the firm's technology as an example, the complexity of a firm is determined by what technologies a firm possesses and by which technologies are developed by which firms. In the case of ubiquitous technology that can be developed by large number of firms, the level of required technological capabilities for developing it can be considered as low. Therefore, even if there is a diversified firm with the same number of technologies, the level of complexity can be relatively low, if a firm mainly develops generalized technologies with a low level of required technological capabilities. On the other hand, if there is a non-ubiquitous technology that can be developed by a small number of firms, the level of required technological capabilities for developing it can be considered as high. So, if the firm includes many non-ubiquitous technologies, the level of the complexity of firm will be higher. In other words, the complexity of an economic agent is expressed by the degree of capacity accumulated within the economic agent enabling them to engage in various economic activities.

Economic complexity is located between science of simplicity, which tries to explain the world with a trajectory obtained through differentiation and integration, and disorganized complexity, which tries to understand disorder as it is through probability (Hidalgo 2021). Between the two extremes lies organized complexity, the effort to understand the patterns that exist in interactions rather than ignoring them. Neither through aggregation (simplicity) nor through distribution (disorganized complexity), but through economic complexity, a dimensionality reduction technique, we can understand the interaction with each other while preserving the identity of the elements (Hidalgo, 2021).

2.3.3.2 Measure of complexity

In this section, we will look at Method of reflection, one of the various methodologies that preserves and reduces the information of one dimension in the data structure of a bipartite network and expresses it only with information about the other dimension, introduced by Hidalgo et al. (2009). Through this methodology, we can obtain respective information on 1) firm i and 2) technology α, which are symmetrically composed of a bipartite network. First, let's call a bipartite network a matrix $M_{i,\alpha}$. The elements of the matrix are values calculated through Equation 2.5, which are binary numbers equal to 1 if firm i has a comparative advantage in technology α and 0, otherwise.

This bipartite network contains two-dimensional information, one is information about technology directly expressed as a node to build a technology space, and the other is information about the firm that is used to form a link, but not directly expressed on the technology space. If we project the superficially observed technology space, we can think that information about the firm exists at the base of it. For example, if two different technologies are simultaneously possessed and utilized by a single firm, it was considered that the two technologies share the same technological background and knowledge. It also means there is information about the firm at the base of the two technologies expressed in technology space. Therefore, if we conversely reduce information about technology through a method of projecting the technology space and pay attention to information about firms located in the base, we can understand the firms based on information about technology that are owned by firms. The information on the technology and the information on the firm are expressed respectively in the following equations.

$$Complexity\ \ of\ \ firm\text{:}\quad K_{i,N} = \frac{1}{K_{i,0}} \sum_{\alpha} M_{i,\alpha} K_{\alpha,N-1} \cdots\cdots\cdots\cdots \text{Eq. (2.11)}$$

$$Complexity\ \ of\ \ technology\text{:}\quad K_{\alpha,N} = \frac{1}{K_{\alpha,0}} \sum_{i} M_{i,\alpha} K_{i,N-1} \cdots \text{Eq. (2.12)}$$

Equation 2.11 measures the level of complexity of the firm and Equation 2.12 measures the level of complexity of the technology. N is the number of iterations greater than or equal to 1. The reason why the name Method of reflection was given is that the dimension for firm *i* and the dimension for technology α are alternated in the bipartite network as *N* increases. The averaging value of the previous level features of neighboring note is computed iteratively *N* times. Therefore, we describe the firm as a vector $\overrightarrow{k_\iota} = (k_{i,0}, k_{i,1}, k_{i,2}, \dots, k_{i,20})$ and technology as a vector $\overrightarrow{k_\alpha} = (k_{\alpha,0}, k_{\alpha,1}, k_{\alpha,2}, \dots, k_{\alpha,20})$.

At this time, the meaning of the variable changes depending on what value *N* is. For information of the firm ($\overrightarrow{k_\iota}$), if *N* is an even number, then $\overrightarrow{k_\iota} = (k_{i,0}, k_{i,2}, k_{i,4}, \dots)$ means a generalized measure of technological diversification. Reversely, when *N* is odd, $\overrightarrow{k_\iota} = (k_{i,1}, k_{i,3}, k_{i,5}, \dots)$ means a generalized ubiquity of the technology possessed by the firm. Symmetrically, for information on technology ($\overrightarrow{k_\alpha}$), if *N* is an even number, $\overrightarrow{k_\alpha} = (k_{\alpha,0}, k_{\alpha,2}, k_{\alpha,4}, \dots)$ is a generalized measure of the technology's ubiquity, and if *N* is odd, $\overrightarrow{k_\alpha} = (k_{\alpha,1}, k_{\alpha,3}, k_{\alpha,5}, \dots)$ is a generalized measure of the degree to which a firm possessing a given technology is diversified.

$K_{i,0}$ and $K_{\alpha,0}$, which are the initial conditions when *N* is 0, mean the degree or number of links of firm *i* or technology α. Interpreted on a bipartite network, $K_{i,0}$ is the observed degree of diversification of the firm (the number of technologies in which the firm has a comparative advantage), and symmetrically $K_{\alpha,0}$ refers to the observed degree of ubiquity of the technology (the number of firms with a comparative advantage in a given technology). Expressed respectively as a mathematical formula, it is:

$$Diversification\ of\ \ firm\text{: } K_{i,0} = \sum_{\alpha} M_{i,\alpha} \cdots\cdots\cdots\cdots\cdots\cdots \text{ Eq. (2.13)}$$

$$Ubiquity\ of\ \ technology\text{: } K_{\alpha,0} = \sum_{i} M_{i,\alpha} \cdots\cdots\cdots\cdots\cdots\cdots \text{ Eq. (2.14)}$$

If N is 1, it is the average nearest neighbor degree value of the links connected to neighboring nodes. $K_{i,1}$ is the average ubiquity of technologies developed by firm i. Symmetrically, $K_{\alpha,1}$ represents the average diversification of firms that developed technology α.

Finally, the meaning of N is as follows. Let's start from one technology node and move to another technology node as a destination. But we cannot move directly to the node located in the same space, but must move through nodes in the opposite dimension. Then it is necessary to pass through nodes of different dimensions iteratively. At this time, the probability of all cases moved by random walk is weighted averaged, and then the total probability is calculated by linearly combining them. Therefore, N means how many times it iteratively passes through nodes of different dimensions to reach the end point. As a rule of thumb, when N is 20 for firm, $\overrightarrow{k_\iota}$ and N is 19 for technology $\overrightarrow{k_\alpha}$, it is considered that the iteration is sufficiently performed. For a more detailed explanation of Method of reflection through examples, see Appendix 2.

2.3.3.3 Empirical evidence

Earlier, it was mentioned that economic complexity is divided into two areas: the complexity of economic activity and the complexity of economic agents. Accordingly, various studies have been conducted for each variable. First, the studies about the complexity of economic activity about i) products (Felipe et al., 2012; Stojkoski et al., 2016); ii) occupation (Wohl, 2020); iii) technology (Balland et al., 2017; Petralia et al., 2017; Balland et al., 2019; Balland et al., 2020; Juhász et al., 2021; Kim et al., 2022; Jun et al., 2023) were analyzed at the country, regional, city, and firm level. Studies dealing with various economic activities have confirmed that the performance of each economic activity increases as the complexity of activity increases. Since the main focus of this study is the complexity of economy, studies related to the complexity of activity are briefly summarized in Table 2.9.

Table 2-9. Previous studies on the complexity of activity

The level of Economic Agent / Economic Activity (Our main interest)	**Country**	**Region**	**City**	**Firm**
Complexity of Product (including Services & goods)	● **Felipe et al. (2012)** - The share of the more complex products increases with the income of the countries and the opposite also holds. - Major exporters of the more complex products are usually high income countries, and the opposite also holds. ● **Stojkoski et al. (2016)** - The complexity of services is generally higher than the complexity of goods. - The inclusion of services generally			

	increases the ranking of the complexity of countries.			
Complexity of Industry				
Complexity of Technology	● **Petralia et al. (2017)** - The probability of diversifying to less complex and related technology is higher than more complex and unrelated technology - Low-income countries are more specialized at less complex technologies comparing the technologies produced by High-income countries.	● **Balland et al. (2019)** - EU regions are more likely to develop a new technology with the increase of complexity when they are related with the new technology. - An increase in technological complexity is associated with the future technological growth and its effect is much larger when regions are related with the complex technology	● **Balland and Rigby (2017)** - The increase of complexity increase knowledge flow (citation between two different patents) - If the inventors are in the same city, then the effects of complexity become large, which means more complex technology is more tacit. ● **Balland (2020)** - Urban concentration of activities is highly correlated with their complexity	● **Kim et al. (2022)** - The firms in Korea manufacturing industry are more likely to develop a new technology when the targeted technology is more complex. - The firms in Korea manufacturing industry are also more likely to develop an Industry 4.0 technology when i) there is a stronger relatedness between the new I4T and the firm's existing technologies and ii) there is more direct government support for the development of the I4T.

Complexity of Technology (Continued)		● **Juhász et al. (2021)** - As the difference in complexity between technology i and j increases, the probability of developing a new patent related to both i and j decreases. - The more complex technology has a positive and significant effect on the increase in the number of patents for related technologies.		● **Jun (et al. (2023)** - Manufacturing industry has been the foremost innovator in Korea in terms of both the number of patents filed and the diversity of technologies comparting with IT industry even in the era of 4IR. - The firms in IT industry of Korea are more likely to develop a new technology when the targeted technology is more complex comparing with the firms in manufacturing industry.
Complexity of Occupation			● **Wohl (2020)** - In US, the complexity of occupation is negatively correlated with the increase of wages.	

Next, studies analyzing the complexity of economy show that the complexity of economy at the level of a country, region, city, or firm is related to i) the financial growth (Hidalgo et al., 2009 Hausmann et al., 2014; Stojkoski et al., 2016; Chávez et al., 2017; Zhu et al., 2017; Gao et al., 2018; Sweet and Eterovic, 2019; Fritz et al., 2021; Domini , 2022), ii) solving income inequality (between countries: Hartmann et al., 2017; Lee and Vu, 2019, within countries: Sbardella et al., 2017; Gao et al., 2018) and iii) environmental issues (Positive impact: Romero et al., 2021; Boleti et al., 2021, Negative impact: Adebayo et al., 2022, inverted-U shape: Ahmad et al., 2021 on environmental improvement, including reduction of greenhouse gas emissions) at various economic activity such as product, technology, industry.

Since the main interest of this study is the effect of complexity of economy on financial growth, a literature review was conducted focusing on research related to this. Studies related to economic growth use the data about export product by country (Hidalgo et al., 2009; Hausmann et al., 2014; Zhu et al., 2017; Zhu et al., 2017; Domini, 2019), information with the addition of cross-border exchanges and overseas consumption related to services (Stojkoski et al., 2016), patents by country (Sweet and Eterovic, 2019), and number of workers by industry sector (Chávez et al., 2017; Fritz et al., 2021). Considering the data acquisition process, it can be seen that country-level studies are mainly conducted with product or patent data, and regional-level studies with industry data.

First, studies related to the effect of complexity of economy on country level economic growth are led by Hidalgo et al. (2009). Hidalgo et al. (2009) confirmed that a complexity of country is an indicator that well reflects our reality of having a very strong correlation with per capita income, and that it has better explanatory power than HHI or Entropy indices in predicting future economic growth. Hausmann et al. (2014) analyzed 128 countries and found that an increase in complexity predicts a country's financial growth (including per capita income and short-, mid-, and long-term annual per capita GDP). Stojkoski et al. (2016) considered services as products, integrated them with data on export product by country, and found that countries with higher complexity have experienced greater long-term economic growth. Zhu et al. (2017) found that the interaction between human capital and complexity of country also affects a country's short-term and long-term financial growth. Domini (2022) obtained the complexity of European countries through the data of inventions exhibited at universal exhibitions during the period 1855-1900. The higher a complexity of country, the higher their GDP per capita, that is, the wealthier they become (correlation), and the higher their long-term growth rate (causation). The fact that the same results as in the existing literature were obtained even when the analysis was extended to the 19th century data proves once again that the complexity of the production structure, which represents national capabilities, works as a key driving force for long-term growth.

Sweet and Eterovic (2019) compiled patent data from 70 countries and obtained complexity of each country. Sweet and Eterovic (2019) found that country-specific complexity, rather than a more robust patent system, had a more significant positive effect on a country's total factor productivity growth. The author argues that diffusion rather than protection through patents, adaptation in complex systems, and replication of the tacit knowledge of patents are more important within the international productive chain.

As a regional and city-level study, Chávez et al. (2017) calculated the number of workers in each industrial sector in all states of Mexico and then calculated the complexity of state. A positive correlation was observed between complexity of state and income per capita, and it was confirmed that it had a positive and significant effect on the state's growth rate. In particular, as a result of excluding the oil industry, which is influenced by geographical advantages such as natural resources and not based on complex knowledge, the statistical explanatory power of complexity has increased. Fritz et al. (2019) measured complexity of city based on industrial employment data by city in the US from 1998 to 2015. Similar to other studies, large cities and cities centered on trade industries had high complexity values on average. Also it was found that areas with high complexity had high income per capita in cross-sectional analysis. However, the effect of the increase in complexity on per capita income has decreased significantly since 2007, as a result of the panel analysis. The authors found that there was no additional increase in complexity after 2007 in more diversified cities, and resource extraction-centered areas, which had relatively low complexity, saw a rapid increase in complexity from 2007 due to the global boom. The table 2-10 below summarizes previous studies examining the effect of complexity of economy on economic growth.

Table 2-10. Previous studies on the complexity of economy

The types of economic activity / Economic agent (Our main interest)	Product (including Services & goods)	Industry	Technology	Occupation
Complexity of country	● Hidalgo and Hausmann (2009); Hausmann et al. (2014); Zhu et al.(2017); Domini (2022) - Economic complexity of country is a good predictor for the future economic growth of a country ● Stojkoski et al. (2016) - Increases of Economic complexity of country by diversifying to sophisticated services can be an additional source for economic growth.		● Sweet and Eterovic (2019) - Economic complexity of country has a more significant positive effect on the growth of a country's total factor productivity than a robust patent system	

Complexity of region		● Chávez et al. (2017) - Economic complexity is a good predictor for the future economic growth of a state in Mexico ● Gao et al. (2018) - Economic complexity is a good predictor for the future economic growth of provinces in China		
Complexity of city		● Fritz et al., (2021) - The relationship between Economic complexity and productive structure (Per capital income) should be understood in different socioeconomic backgrounds.		
Complexity of firm				

There has been no research to date that has revealed the effect of complexity of economy calculated from technology on economic growth at macro-scale (country, region, city) or micro-scale (firm, individual) economic agent level. This is because it is difficult to unify the applicant names of firms, which exist in various forms, into one unique applicant name. Also it is difficult to find trends in firm as the unit of analysis is small unlike the country or city level. In many cases, this is because the data structure is in-block nestedness (Laudati et al., 2022) as there are many firms that are specialized in few technologies. Therefore, micro-analysis of economic complexity, especially efforts to understand the complexity of firms calculated based on technology, is expected to open a new horizon for understanding the Economies of Complexity.

2.3.4 Linking technological diversification, complexity and firm growth

The results of empirical analysis related to technological diversification introduced in Chapter 2.3.2 assume that all technologies have the same difficulty without considering the level of heterogeneity between technologies. However, each of the different technologies has a different difficulty to develop, understand, and replicate. Also difficulty of R&D, retention, and security varies by technology. Even in our daily lives, we live by judging and comparing the difference between two. In addition, as a basic principle, the patent's classification codes are divided into mutually exclusive technologies (WIPO, 2023), which is based on the fact that each technology is developed from different theories and principles.

Existing technological diversification strategies that do not consider different difficulty of technology have limitations in explaining our real world. For example, a technology related to 'daily necessities' and a technology related to 'electricity/electronics' have different difficulties (or levels) for technological development. However, the HHI or entropy index generates the same value. When we consider the number of classification of patents and the proportion of each, it is calculated to have the same strategy regardless of which technologies are possessed by firm.

This fact means that the level of complexity of each technology must be reflected when analyzing and presenting a firm's technological diversification strategy. The concept, complexity will provide a window of understanding technological knowledge accumulation strategies more elaborately.

Chapter 3. The multifaceted nature of technological knowledge accumulation: Gradual migration with punctuated equilibrial expansion

3.1 Introduction

Polanyi's (1967) expression ' We know more than we can tell ' provides insight into the nature of technological knowledge. Even if technological knowledge exists, explaining it in words is a different level of problem, because it is difficult to express it explicitly. Paradoxically, although we live with technology, we have yet to fully understand and explain the nature of technological knowledge (Arthur, 2009). Even if we understand technological knowledge, putting it into words is another challenge (Nelson and Winter, 1982/2014).

The reasons why it is difficult to describe technological knowledge itself in language are as follows. First, this is because technology is a being that continuously evolves over time. Technology is not a static entity and is constantly changing. Numerous historical examples have demonstrated that modern versions of technology are descendants from earlier forms for better efficiency, better functionality, and better power (Dosi, 1982; Arthur, 2009). As a result, today's state-of-the-art technology becomes tomorrow's outdated technology.

Next, the fact that both technological knowledge and the firms that accumulate and use it change as they adapt to the environment adds complexity to explaining technological knowledge. Darwin argued that organisms must adapt to constantly changing environments in order to survive. In various environments such as rapidly changing technology and market, technology must also flexibly adapt to changed purposes and improvements (Dopfer, 2005; Arthur, 2009). Likewise, firms also need to overcome the pressures of adaptation in order to be selected and not forced out of the market (Nelson and Winter, 1982/2014). The situation in which both the object of interpretation (technological knowledge) and the entity that accumulate it (firm) are changing requires a new approach to explain its nature.

Finally, technological knowledge is multifaceted. In the meantime, various concepts have been devised to describe the characteristics of the technological knowledge and its accumulation. Concepts such as path dependence (David, 1985; Arthur, 1989, 1994; Rosenberg et al. 1994); relatedness (Christensen et al., 1981; Hitt et al, 1997; Hidalgo et al., 2007); exploration and exploitation (March, 1991; Levinthal and March, 1993); ambidexterity (Tushman and O'Reilly, 1996; Benner and Tushman, 2003) and punctuated equilibrium (Tushman and Romanelli, 1985; Levinthal et al., 1998); diversification and specialization (or focus) (Markowitz et al., 1952; Berger and Ofek, 1995); breadth and depth (Prencipe, 2000) are products of sheer efforts to understand and describe the nature of technological knowledge and its accumulation. Although only partial characteristics of technological knowledge can be described, we have tried to understand multifaceted technological knowledge through a single concept introduced earlier.

The accumulation of technological knowledge, an intangible resource within a firm that cannot be imagined because it has neither a fixed form nor a boundary like an amoeba, needs to be understood more elaborately. In this study, we tried to overcome the three difficulties for descriptions mentioned above by simultaneously applying the following three approaches. First, in this study, it was confirmed how the technological knowledge within the firm changes according to the firm's tenure. In other words, moving one step further from the earlier effort to capture and describe the phenomenon of a fixed point in time, dynamic changes according to the firm's business tenure were investigated. Next, in order to explain the disorganized complexity caused by changing technological knowledge and changing firms, an interpretation was attempted through distribution and its average by tenure (Hidalgo et al., 2021). In other words, the dynamic change of the average value by a firm's tenure was examined. Finally, by simultaneously applying various conceptual windows designed to understand the process of technological knowledge accumulation within a firm, its nature was viewed from multiple dimensions at the same time.

Coad and Guenther (2013) found the following five characteristics of a firm's product diversification through the German machine tool industry; i) firms do not carry out diversification consecutively; ii) firms diversify into related business fields; iii) The diversification rate of the firm decreased gradually as their tenure increases; iv) the size of the submarket increases as the size of the firm increases, and v) the probability of failure decreases as the firm diversifies. The finding of Coad and Guenther (2013) has important academic significance in that it analyzed the process of product knowledge accumulation within a firm in various aspects at the same time and analyzed their dynamic changes.

This study develops the work of Coad and Guenther (2013) in the following two aspects. First, in this study, efforts were made to understand the nature of technological knowledge within the firm. A firm's product-related knowledge should be distinguished from its technological knowledge. In particular, technological knowledge can be said to be the basis of all knowledge in that it is the basis for development and production of product. Helfat et al. (2000) argued that there are stages of activities such as value chains between technology and product, and that technology-related knowledge is the basis for product components used for product development. In addition, various studies (Patel and Pavitt 1997; Miller 2006; Dosi et al. 2017) distinguished between 'what a firm knows' and 'what a firm produces'. Moreover, Kang et al. (2020) empirically confirmed that technology-related strategic choices affect current product-related strategic choices. As far as we know, research that simultaneously explores the process of accumulating technological knowledge of the firm from various angles is still lacking.

Next, in this study, we tried to understand the nature of technological knowledge by expanding the limited awareness of current diversification strategies: 1) related diversification, 2) changes in the diversification rate, and 3) continuity (or discontinuity) of diversification, which are already examined by Coad and Guenther (2013). To this end, we first checked whether the changes in the core and periphery of technological knowledge in the firm follow the concept of relatedness. Next, it was confirmed whether the boundary of the firm's technological knowledge, including breadth and depth, is reduced or expanded according to the firm's tenure. Lastly, it was confirmed whether the efforts for diversification and specialization of technological knowledge within the firm are made in either ambidexterity or punctuated equilibrium.

To confirm the above three research questions, we investigated the average characteristics of technological portfolios of 3,074 firms belonging to the US manufacturing sector for 30 years from 1986 to 2015. The third-generation National Bureau of Economic Research (hereafter, NBER) applicant disambiguation project, DISCERN (Duke Innovation & SCientific Enterprises Research Network) dataset (Arora et al., 2020, 2021) was used for the analysis. The DISCERN dataset combined financial information for US firms by examining firm affiliate information (source: ORBIS), M&A information (source: SDC Platinum), and firm's name change information (source: WRDS's 'CRSP Monthly Stock') based on the gv-key, a firm-unique ID in US Compustat. Subsequently, disambiguation work (called dynamic reassignment) for matching all different patent applicant name with gv-key was performed. We considered the technological knowledge possessed by firms as the Cooperative Patent Classification (hereafter, CPC) code assigned to patents, and investigated three aspects related to the process of accumulating technological knowledge from the changes of the average value by a firm's tenure.

Ultimately, this study presents a new concept called 'gradual migration with punctuated equilibrial expansion', which describes the nature of the technological knowledge accumulation process in a firm by integrating the three aspects into one. As a result of the analysis, first of all, when a firm acquires a new technology, it acquires a related technology with a higher probability. At the same time, when core technologies change, the difference between them is does not change significantly regardless of a firm's tenure. In other words, the technological knowledge possessed by firms changed following the principle of relatedness at both the periphery and the core. In doing so, we argue for a gradual migration of the entire technological knowledge of a firm. Next, the diversification rate of technological knowledge steadily increases as the firm's tenure increases. In other words, as the firm's tenure increases, the accumulated technological knowledge gradually diversifies and the difference between the ratio by technological knowledge decreases, which means that the boundary of technology broadens according to their tenure. Finally, the firm did not perform both technological diversification and specialization into core technologies consecutively following the previous period. In other words, it can be seen that firms diversify or specialize in technological knowledge in the manner of punctuated equilibrium.

The structure of this chapter is as follows. First, in Section 3.2, the overall theoretical framework of the study and i) the principle of relatedness, ii) the process of expanding boundary according to diversification strategy, and iii) ambidexterity or punctuated equilibrium type of technology accumulation strategies are reviewed, and after that hypotheses are derived. In Section 3.3, we explain the data, the definition and explanation of the operational variables, and the model for the empirical analysis to verify the three hypotheses. Section 3.4 confirms the results of the analysis, and the last section 3.5 draws conclusions and implications of this study.

3.2 Literature review and hypotheses

3.2.1 Theoretical framework

In this chapter, we examine a framework that draws hypotheses to identify a new concept describing the nature of technological knowledge accumulation of the firm: *gradual migration with punctuated equilibrial expansion*. The gradual migration with punctuated equilibrial expansion refers to the independent and simultaneous observation of three characteristics of technological knowledge within a firm: 1) gradual migration of area, 2) extension of boundary, and 3) punctuated equilibrial way of accumulation. The new concept proposed in this study is an attempt to explain the more generalized feature as it can describe all the various concepts (e.g., path dependence, relatedness, exploration and exploration, ambidexterity and punctuated equilibrium, diversification and specialization, breadth and depth) designed to understand the characteristics of the technological knowledge and its accumulation. The framework of this study is summarized in Figure 3-1.

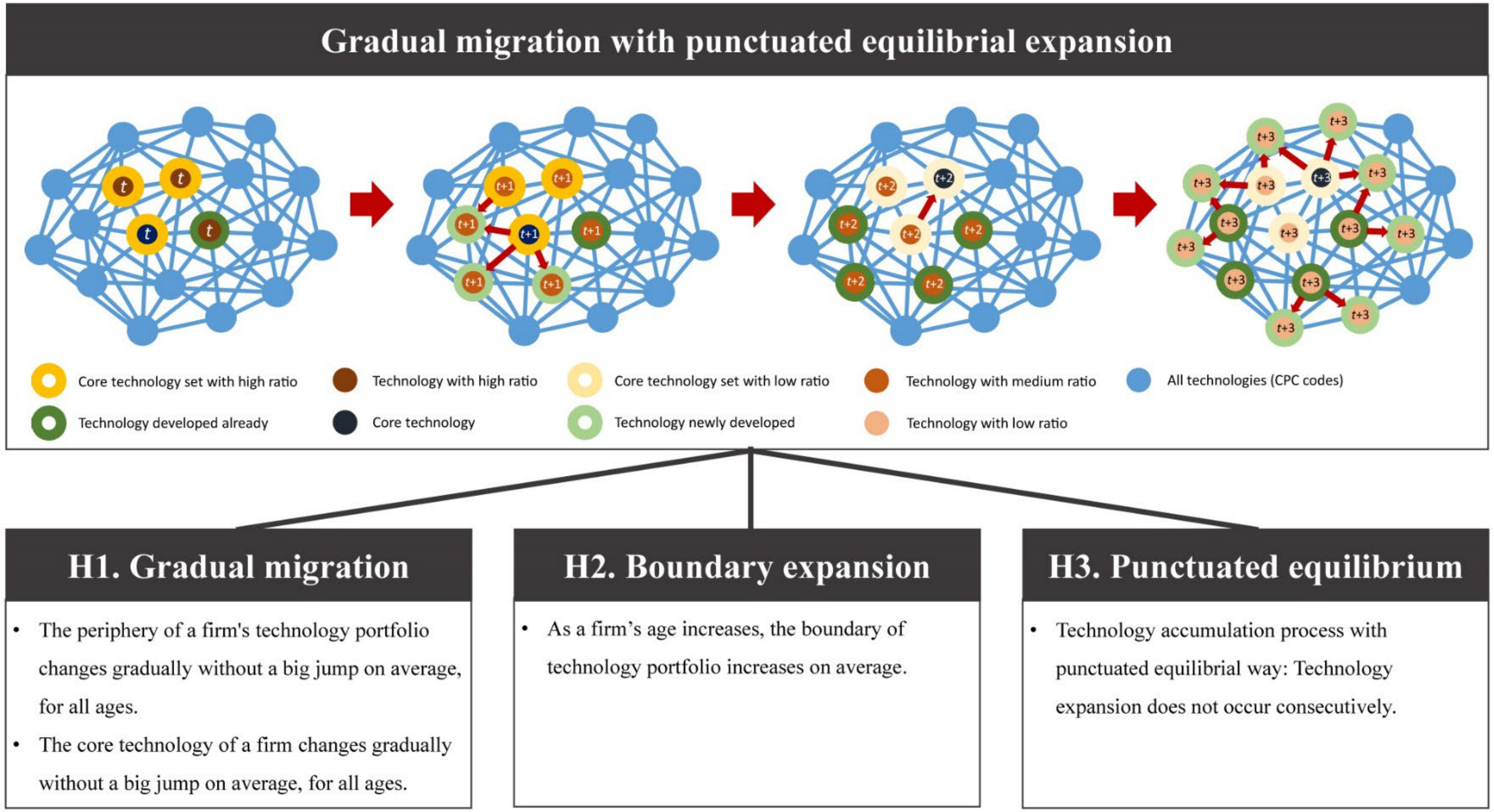

Figure 3-1. Framework for the research

3.2.2 Gradual migration

Suppose there is a technology space in which all types of technology classification codes are nodes and proximity between technologies is a link. Hidalgo et al. (2007), imagine each technology code as a tree, technology space as a forest, and firm as a monkey. There will be a limited area of trees (technologies) that monkeys (firms) can move in the forest (on technology space). The area widens or narrows over time, and the center of the area also can be changed over time. In the first hypothesis, the following two questions are thrown to find out the changes in the area of firm's technological knowledge over time.

First, in order to understand how the area of the technology knowledge varies depending on the tenure of the firm, it was confirmed whether developing new technological knowledge within the firm follows the principle of relatedness. As a result of various previous studies, it is already accepted as a stylized fact that the aspect of firms accumulating new technological knowledge follows the principle of relatedness. Some studies argue that the development of unrelated technologies sometimes leads to radical innovation (Castaldi et al., 2015), but most studies argue that a firm's technological diversification is mainly in related fields (Castaldi et al., 2015). Leten et al., 2016; Ning and Guo, 2022; Kim et al., 2022; Kim et al., 2023; Jun et al., 2023). This is because it can increase the efficiency of deploying and using existing resources (Teece, 1980; Teece, 1982), reduce the failure probability of new technology development, and create synergies with existing technologies (Tanriverdi and Venkatraman, 2005). In addition, by leveraging a firm's core competences, new technology development can be made easier.

If a firm develops a comparative advantage in new technological knowledge or un-develops existing technological knowledge according to the principle of relatedness, then the area of a firm's technological knowledge depends on the firm's accumulated technological knowledge, therewith, it will not undergo drastic changes. Hypothesis 1-1 describes the movement at the periphery of the technological knowledge by observing how the entire area of a firm's technological knowledge changes.

H.1-1: *When a firm acquires new technological knowledge, it acquires technological knowledge related to the existing technological knowledge. In other words, the overall area of a firm's technological portfolio follows the characteristics of the periphery changing according to the principle of relatedness, and as a result, it gradually changes.*

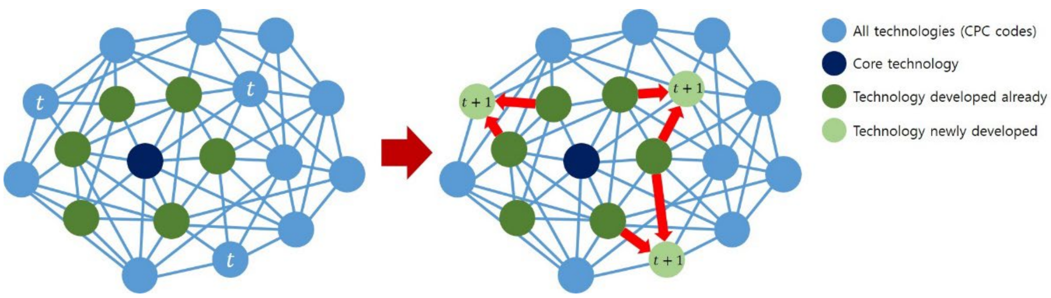

Figure 3-2. Graphical example for Hypothesis 1-1

Next, after defining core technology as the center of the area of technological knowledge possessed by the firm, how this core technology moved according to the firm's tenure was investigated. If the core technology is changed, the proximity between the two core technologies can be obtained. We describe the changes of the center of the area by identifying how the proximity value changes by firm's tenure.

There is no direction in the change in the area of technological knowledge interpreted through the principle of relatedness. Because related technological knowledge can be expanded or reduced in any direction based on the existing technological knowledge possessed by the firm. Therefore, in order to define the directionality, it is necessary to find the center of the intangible area. Observing how the core technology, which is the center of a firm's technological knowledge area, changes according to the firm's tenure, we will be able to describe the entire movement of the entire area beyond the explanation of changes at the periphery.

If changes in core technologies within the technological knowledge area of a firm also follow the principle of relatedness, then it can be inferred that the concept of direction exists even if the boundaries of technological portfolios change. This is because the whole area of technological knowledge is formed around core technologies. To confirm hypotheses 1-2, the center of the technological knowledge domain is first defined. Then, by observing how the change in the proximity value between core technologies varies according to firm's tenure, the movement of the technology knowledge area is described.

H.1-2 : *Even if the firm's tenure increases, the core technology of a firm changes gradually without a big jump on average. In other words, core technologies within a* *firm's technological portfolio also gradually move according to the principle of relatedness.*

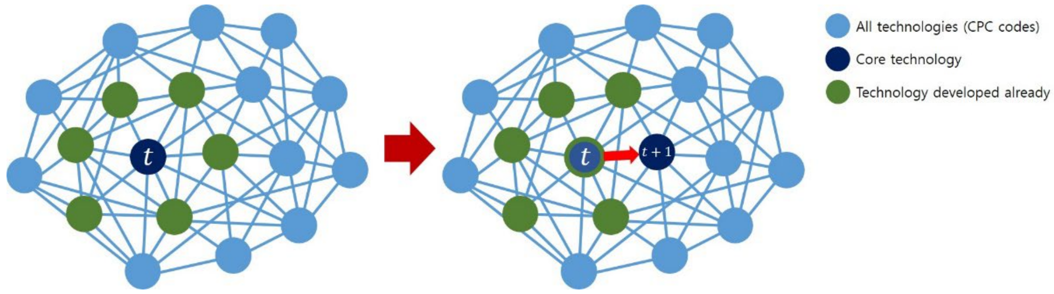

Figure 3-3. Graphical example for Hypothesis 1-2

Based on hypotheses 1-1 and 1-2, we investigated whether the principle of relatedness applies to changes in the firm's core technology and the entire technological knowledge area, respectively. If both hypotheses are supported, the periphery and the center of the firm's knowledge area will expand (or shrink) from existing technological knowledge to related technological knowledge without significant technological differences. We defined gradual migration as the case where both the periphery and the center of a firm's technological knowledge area follow principle of relatedness.

3.2.3 Expansion of boundary

Firms choose a technological diversification strategy for a variety of reasons (Kim et al., 2016). Possession of various technologies brings new technological opportunities

(Scherer, 1965b). Also, a diversified technology mix brings firms the advantage of economies of scale in R&D and technological knowledge (Teece, 1980). Through this, it is possible to derive synergy between technological knowledge used in various products and efficiently allocate resources (Tanriverdi and Venkatraman, 2005). In addition, technological diversification reduces uncertainty caused by a firm's R&D, increases adaptability to the rapidly changing technological environment, and makes it possible to secure greater rent in the market through the development of more complex products and diverse technologies. (Kim et al., 2016).

As a result, firms continue to pursue technological diversification strategies, and as a result, the composition of technological knowledge within the firm continues to be diversified as the firm increases. This can be explained as a change in the area of technological knowledge in the technology space, that is, the breadth. At the same time, an increase in the breadth of technological knowledge is associated with a decrease in the overall depth of technological knowledge. This is because the more diverse the composition, the smaller the share of each technological knowledge. Therefore, the increase in the degree of diversification of technological knowledge within a firm can be seen as the continuous expansion of the boundary, which expressed as both breadth and depth, of the technological portfolio.

Entropy and Hirschman-Herfindahl Index (hereafter, HHI), which are mainly used to measure the degree of diversification of technological knowledge within a firm, also reflect this conception. The value of the index is determined by two factors: variety and balance.

A firm's technological knowledge is considered more diversified when it has a shallow enlarged outer margin, which is broad in breadth, flat in depth.

This study aims to identify changes in the composition of technological knowledge through the degree of diversification of technological knowledge within a firm. The following hypothesis is set up to understand the dynamic changes in the composition of technological knowledge according to firm's tenure.

H.2 *As the firm's tenure increases, the boundary of technological knowledge within the firm continues to increase.*

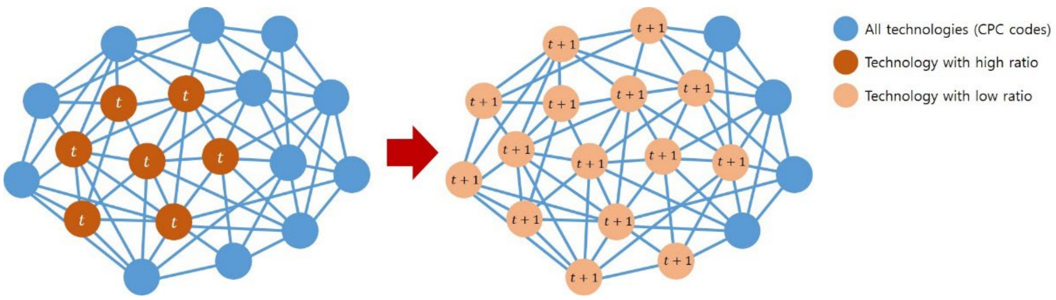

Figure 3-4. Graphical example for Hypothesis 2

3.2.4 Ambidexterity vs. Punctuated equilibrium

March (1991) argued that firms accumulate technological knowledge through two methods: exploration and exploitation. Exploration is the act of pursuing new ideas or developing new technologies. Exploration is done through experimentation that pays only for costs and has no benefits immediately, and includes meanings such as investigation, transformation, risk taking, experimentation, action, flexibility, discovery, and innovation (March, 1991). As a result of exploration, the breadth of technological knowledge a firm possesses is broadened. On the other hand, exploitation refers to the optimization and efficient use of already developed technologies. exploitation is a balance state of the next best, and includes meanings such as improvement, selection, production, efficiency, selection, implementation, and execution (March, 1991). As a result of the exploitation, the depth of specific technological knowledge is increased.

Exploration develops new technologies, therewith, becomes useful for future radical innovations, whereas exploitation develops existing technologies and is therefore useful for short-term, incremental innovations. Firms that only explore without exploitation pay a lot of costs for experiments and only get ideas, but cannot secure any differentiation. On the contrary, firms that only exploit without exploration fall into a success trap and reach the local optimum. (March, 1991; Leonard-Barton, 1992; Levinthal and March, 1993). As the two methods are complementary, March (1991) and Levinthal and March (1993) argue that striking the right balance between the two is essential for organizations to survive and grow.

A variety of strategies have been proposed to understand how to balance exploration and exploration to achieve efficient technological knowledge accumulation. Representative strategies are the ambidextrous strategy and the punctuated equilibrium strategy. First, the ambidextrous strategy refers to the process of technological knowledge accumulation in which exploration and exploitation, which are methods of accumulation, are performed simultaneously (Tushman and O'Reilly, 1996; Benner and Tushman, 2003). A contrasting concept, punctuated equilibrium strategy, refers to the process of accumulating technological knowledge by alternating exploration and exploration, one at a time (Tushman and Romanelli, 1985; Levinthal et al., 1998).

Various empirical studies have analyzed the process of ambidextrous accumulation. O'Reilly and Tushman (2004) found that some firms successfully explore for the present and explore for the future at the same time. These firms were operating in a way that tightly integrates the exploitation units, which were in charge of the existing ones, and the exploration units, which were in charge of discovering other processes, structures, and cultures. Uotila et al. (2009) measured exploration and exploration through information from newspaper articles published from 1989 to 2004 of firms in the 1989 Standard & Poor's 500 index. Through this, the impact of relative exploration, which is exploration compared to exploitation, on the financial performance of the firm was shown to be inverted-U shape, and an appropriate balance between the two methods was found.

The concept of punctuated equilibrium was first devised by Tushman and Romanelli (1985). Tushman and Romanelli (1985) argued that organizations evolve by alternating between convergent period and reorientation. The convergence period refers to a more stable, longer-term, gradual change in which an organization maintains the most effective strategies experienced through various strategic selection processes. In contrast, reorientation means a state in which internal inertia is reduced and competitive vigilant is high through extreme changes accompanied by discontinuous adjustment of core values.

Tushman and Romanelli (1985) argued that organizations evolve through a cyclical process in which one of these two processes ends and the other begins. Several empirical studies have revealed that firms' technology accumulation occurs in the way of punctuated equilibrium. Benner and Tushman (2002) investigated the firms in Photography and paint industry from 1980 to 1999 and found that when the weight of exploration increases, the expenditure of exploration is crowded out.

Regarding the two competing theories that are still controversial, Hypothesis 3 confirms how the accumulation of technological knowledge within firms occurs. Coad and Guenther (2013) analyzed firms about German machine tool from 1953 to 2002 (the post-war era), and found that product diversification strategies were not consistently implemented. In this study, we will examine how technological diversification and technological specialization occur in terms of technology knowledge within a firm.

If the cycles of a firm's technological diversification and specialization into core technologies are reversed, we can consider that the accumulation of technological knowledge occurs in a way of punctuated equilibrium. On the other hand, if the cycle of technological diversification and the cycle of specialization into core technologies are the same, we can say that ambidextrous accumulation of technological knowledge occurs. Regarding the two opposing strategies, this study identifies the process of average technology accumulation within a firm through the following hypotheses.

H.3-1. *The accumulation of technological knowledge in firms occurs in a punctuated equilibrium way. During the period when technological diversification through exploration is predominant, the strategy of technological specialization through exploitation is less selected.*

H.3-2. *The accumulation of technological knowledge in a firm is ambidextrous. During the period when technological knowledge diversification through exploration is predominant, the strategy of technological specialization through exploitation is also predominant.*

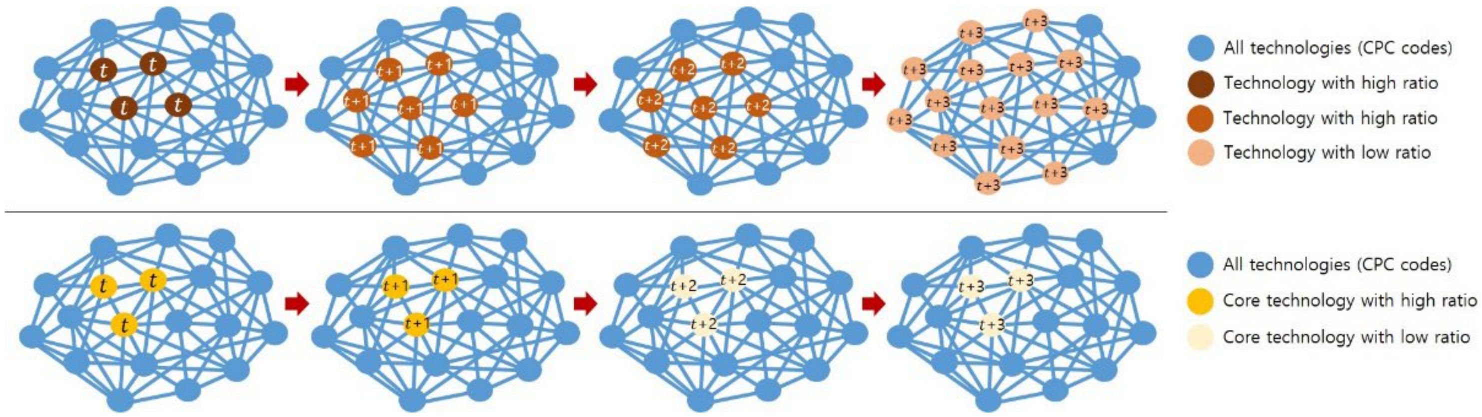

Figure 3-5. Graphical example for Hypothesis 3-1

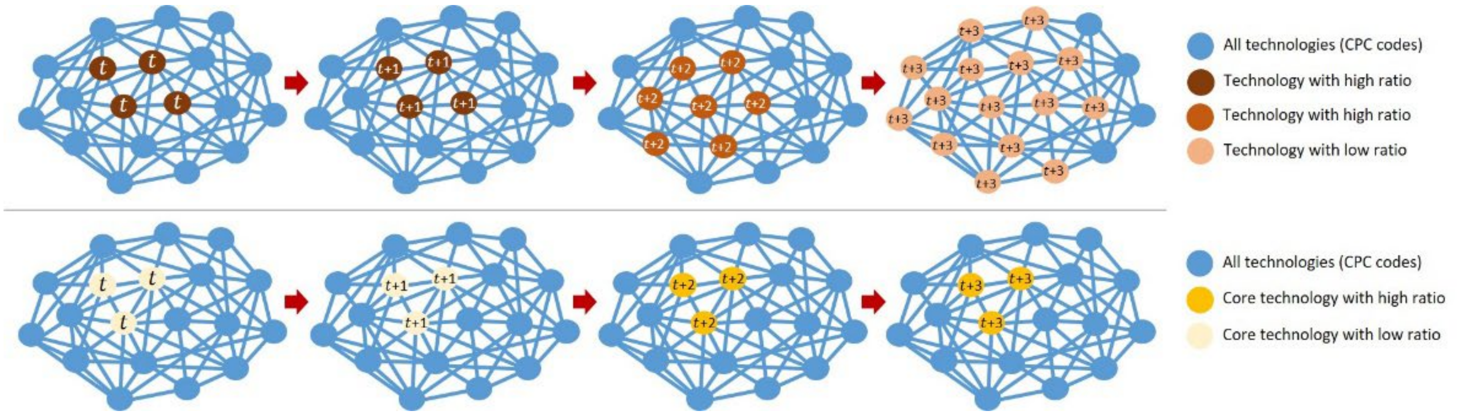

Figure 3-6. Graphical example for Hypothesis 3-2

3.3 Methodology

3.3.1 Data

In this study, the main interest is the information related to the technological knowledge developed and possessed by the firm. To understand the technological knowledge, this study used two types of datasets. First, we obtained firm patent information using the PATSTAT (Worldwide Patent Statistical Database) (2017 Autumn edition) dataset.[19]. In particular, we considered the Cooperative Patent Classification (hereafter, CPC) code assigned to each patent filed by firms with the US Patent and Trademark Office (hereafter, USPTO) as a proxy for technological knowledge. Due to its long history, the unified classification system, preservation and management by the national system, and the absence of alternative data other than patents, many studies have considered the classification code of patents as firm technology (Crépon et al., 1998; Nagaoka et al., 2010; Huang and Chen, 2010). In this study, the CPC code is used instead of the IPC code, which is used in many studies so far. The CPC code is the most accurate technology classification system in existence, classifying technologies into 250,000 categories (Balland and Boschma, 2021).

However, it is difficult to confirm that a patent is a firm's patent even if a patent is searched by a firm name as an applicant for the following reasons. First, the applicant

[19] PATSTAT is a patent data set that EPO started providing from 2016 at the request of the Organization for Economic Co-operation and Development (OECD), and is updated twice a year (Kang & Tarasconi, 2016). It also includes data on the legal status of the authorities, along with bibliographical information on more than 100 million patent documents held by more than 90 organizations worldwide.

information of the patent is written in the name rather than the unique ID. At this time, even if the same applicant, the name of the firm may be recorded differently due to spelling errors, abbreviations, or the use of unified names. Next, ownership of patents could be transferred due to M&A, disposition of patents, or when a subsidiary firm is separated from a parent firm. Finally, the firm name may be changed for reasons such as M&A or restructuring, change in focus business area, adoption of a brand name or affiliate name, or other reasons.

Since it is impossible to identify all patents owned by a firm with a just simple firm name, disambiguation to match the names of various forms of applicants has been attempted in several studies targeting various countries. Among them, the most historical and representative patent disambiguation work is the NBER patent dataset project. Hall et al. (2001) performed matching of applicants including all information related to 3 million US patents filed between 1963 and 1999, based on Compustat data, which is financial data related to firms traded in the US stock market. Later, the scope of the data set was expanded by Bessen (2006) from 1980 to 2005 with additional correction of the reassigned patent's owner name based on the work of Hall et al. (2001). As a recent 3rd generation NBER patent project, Arora et al. (2020, 2021) expanded the scope of the dataset from 1980 to 2015 based on the previous two datasets.

Arora et al. (2020, 2021)'s DISCERN dataset includes a firm's affiliate information (source: ORBIS), M&A information (source: SDC Platinum), and firm name change information (source: WRDS's 'CRSP Monthly Stock') and combines them with US

Compustat's gv-key. After that, dynamic reassignment of applicant information of various types of firm names in PATSTAT is done by combining them into the gv-key. As a result, the matching rate becomes about 20% higher than Bessen (2006)'s dataset, and it is confirmed that about 30% of the firms changed their firm name at least once. This dataset covers firms whose R&D expenditures from 1980 to 2015 have been positive at least one year, and firms who have at least one patent, and have active records in US Compustat.

In this study, by combining PATSTAT with the DISCERN dataset, we analyzed the technological portfolios of listed firms located in the US over 30 years (1986-2015). First, only patents filed with the USPTO between 1986 and 2015 were examined, and 3-digit CPC codes for each patent corresponding to a total of 128 technology classifications were considered as types of technologies.[20]. In particular, when multiple CPCs are assigned to a patent, all of the multiple CPCs are considered, not one representative CPC. That is, if firm i in time t has a patent corresponding to technology classification j, the combination of (i, j, t) was considered as one sample. (There can be multiple j in the same i.) About 1.71 million CPC codes (out of 1,062,751 patents) owned by 4,055 firms were investigated.

After building data on firm's technology (PATSTAT-DISCERN), we add financial information from Compustat (2019 file) provided by S&P Global in Wharton Research

[20] The optimal number of digits to measure technological diversification strategy has yet to be investigated. We can get an indirect clue from the work of Beaudry & Schiffauerova (2009) using industry classification codes. Beaudry & Schiffauerova (2009) summarized a large amount of previous studies about regional level specialization (Marshall–Arrow–Romer (MAR) externality) and diversification effects (Jacob externality). The result show that specialization and diversification strategies are represented most indiscriminately at a three-digit industry classification.

Data Services (WRDS). To do so (PATSTAT-DISCERN-COMPUSTAT), we can i) control industry-specific effects, ii) obtain information on firm tenure, and iii) control for variables affecting technology development. Our main target is manufacturing industry, belonging to the SIC code (D; 20-39), where company-sponsored R&D accounts for the largest portion among all industries (Bound et al., 1982). It is the backbone in charge of national technology development and economic growth as the industry applies for the most patents. A total of 3,048 firms and 780,567 patents (about 1.28 million CPCs) related to the manufacturing industry were investigated, and among them, a total of 758,656 patents (about 1.23 million CPCs) of 2,731 firms of which all financial information in Compustat was included without any omission, are selected. In particular, following the research of Griliches (1979) which show that knowledge capital depreciates very quickly and usually loses its value within 5 years, technological knowledge filed in year t was considered to exist as an accumulated stock in the firm until t+5.

3.3.2 Operational definition

Prior to the analysis, various concepts were defined for the purpose of this study. As relative technological advantage ($RTA_{i,\alpha,t}$) and proximity ($\phi_{\alpha,\beta,t}$) between technologies are basically used to calculate other variables, they are summarized as common notion. Operational definitions to be used in the analysis are summarized in Table 3-1. Here, $P_{i,\alpha,t}$ is the number of patents related to technology α owned by firm i at time t.

Table 3-1. Operational definition

Hypothesis	terminology	definition	Equation	Reference
Common	Relative Technological Advantage ($RTA_{i,\alpha,t}$)	The share of technology α possessed by firm i relative to the share of technology α possessed by firms with respect to the whole technologies of industry	$RTA_{i,\alpha,t} = \dfrac{P_{i,\alpha,t}}{\sum_\alpha P_{i,\alpha,t}} \bigg/ \dfrac{\sum_i P_{i,\alpha,t}}{\sum_i \sum_\alpha P_{i,\alpha,t}}$	Balassa (1965)
	Proximity ($\phi_{\alpha,\beta,t}$)	Proximity between technology α and β	$\phi_{\alpha\beta,t} = \min \{Pr(RTA_\alpha \vert RTA_\beta), Pr(RTA_\beta \vert RTA_\alpha)\}$	Hidalgo et al. (2007)
Hypothesis 1	core technology, j	Among all firm i's technologies that have RTA in all t-1, t, t+1 years, a technology j that has the highest $RTA_{i,j,t}$ value	Technology j s.t. $\max[RTA_{i,j,t}]$ for $\{RTA_{i,j,t-1} = 1\ \&\ RTA_{i,j,t} = 1\ \&\ RTA_{i,j,t+1} = 1\}$ (where $RTA_{i,j,t} = 1$ if $RTA_{i,j,t} \geq 0.8$ or 0, o.w.)	
	Changes of core technology ($\phi_{j,\mathrm{p,t}}$)	Proximity between core technology j in time t and core technology p in time t+1 of firm i	$\phi_{j,\mathrm{p,t}} = \phi_{i,\mathrm{p,t+1}} - \phi_{i,j,\mathrm{t}}$	
	Related density with peripheral technology ($\omega_{i,\alpha,t}$)	The degree of relatedness between firm i' s technological portfolio and a technology α that firm i has not yet developed	$\omega_{i,\alpha,t} = \dfrac{\sum_\beta \phi_{\alpha,\beta,t} \cdot U_{i,\beta,t}}{\sum_\beta \phi_{\alpha,\beta,t}}$	Hidalgo et al. (2007)

Hypothesis 2 & 3	Degree of diversification ($Tech\_Div_{it}$)	Degree of technological diversification of firm *i*'s technological portfolio	$Tech\_Div_{it} = \sum_{\alpha,\beta}(1-\phi_{\alpha,\beta})\left(\frac{P_{i,\alpha,t}}{P_{i,t}}\right)\left(\frac{P_{i,\beta,t}}{P_{i,t}}\right)$	Rafols and Meyer (2010)
Hypothesis 3	Degree of specialization ($Tech\_Conc_{i,t}$)	Degree of technological specialization of firm *i*'s core technology set (Top 3 technologies with the highest $RTA_{i,\alpha,t}$)	$Tech\_Conc_{i,t} = \sum_{\alpha=1,2,3}\left(\sum_{\beta(\neq\alpha)}\phi_{\alpha,\beta}\right)\left(\frac{P_{i,\alpha,t}}{P_{i,t}}\right)^2$	Hirschman (1945)

3.3.2.1 Common notion

3.3.2.1.1 Relative technological advantage

The revealed technological advantage (Hereafter, RTA) for technology α of firm i is calculated by measuring whether firm *i* had more technology α compared to the average of all technologies possessed by the entire industry (Balassa, 1965).

$$RTA_{i,\alpha,t} = \frac{P_{i,\alpha,t}}{\sum_{\alpha} P_{i,\alpha,t}} \Bigg/ \frac{\sum_{i} P_{i,\alpha,t}}{\sum_{i}\sum_{\alpha} P_{i,\alpha,t}} \quad \cdots\cdots \text{Eq. (3.1)}$$

If the $RTA_{i,\alpha,t}$ value is greater than 1, it means that the stock of technology α held by firm *i* is greater than the average stock of technology α in the entire industry. We converted to a binary variable, when $RTA_{i,\alpha,t} \geq 0.8$, $RTA_{i,\alpha,t}=1$, $RTA_{i,\alpha,t}<0.8$, $RTA_{i,\alpha,t} = 0$.[21] As a result, we can determine whether firm *i* has a comparative advantage in technology α or not. The reason why the threshold is set as 0.8 is to apply a more lenient criterion than the commonly used criterion of 1, which means that a firm with technology stock equivalent to about 80% of the industry average has a comparative advantage.

In addition, considering that it usually takes more than 3 years for a previously developed technology to have an impact on the development of a new technology, we also

[21] The technical reason is that the range of $RTA_{i,\alpha,t}$ is theoretically possible from 0 to infinity. In addition, since the value of $RTA_{i,\alpha,t}$ is a relative value calculated based on year *t*, it is impossible to compare it with values from other years. Therefore, to compare by year, we convert it to the binary variable asking whether or not.

looked at the 3 years before and after the development of technology α.[22] The sentence, firm i has a comparative advantage in technology α at time t means that firm i does not have comparative advantage at technology α before t, but becomes to have a comparative advantage in time t, and this comparative advantage is maintained thereafter. Therefore, in this study, we add conditions to define $RTA_{i,\alpha,t}$; i) There should be no comparative advantage (with an *RTA* value of less than 0.8) for consecutive periods t-2 and t-1 before time t ; ii) There should be comparative advantage (with an *RTA* value of greater than or equal to 0.8) at time t ; iii) The firm should maintain comparative advantage (with an *RTA* value of greater than or equal to 0.8) for next consecutive periods $t+1$ and $t+2$. It is assumed that the technology development of α in time t is not affected by the existing technology, α when the firm does not have the technology in time $t-2$ and $t-1$. At the same time, it is thought that the technology α at time t has an impact on the technology development of time $t+1$ and $t+2$, when the technology α has been developed already at time t. (Bahar et al., 2014). That is, to define the comparative advantage of firm i in technology α at time t, $[RTA_{t-2},\ RTA_{t-1},\ RTA_t,\ RTA_{t+1},\ RTA_{t+2}]$ must be [0, 0, 1, 1, 1].

The above strict conditions also have the effect of correcting the RTA of a specific technology that is measured accidentally in a specific year. For example, if one firm happened to develop a certain technology a lot in a certain year, but the whole industry did

[22] The influence of the previously developed technology within the firm on the firm's next technology is confirmed through patent self-citations. Aksnes (2003) confirmed that the rate of self-citation of patents attenuates rapidly within 3 years after the publication of patents.

not accidentally develop that technology, the RTA value can be calculated to very large value. By considering the five years before and after each year, it becomes possible to exclude technologies that have RTA by chance in a specific year.

3.3.2.1.2 Proximity

Proximity between technologies ($\phi_{\alpha\beta,t}$) represents the minimum value of a pair of conditional probabilities in which two technologies α and β will have RTA together within the same firm (Hidalgo et al., 2007). The proximity ($\phi_{\alpha\beta,t}$) is calculated through the following equation.

$$\phi_{\alpha\beta,t} = \min\{Pr(RTA_{\alpha} | RTA_{\beta}), Pr(RTA_{\beta} | RTA_{\alpha})\} \quad \cdots\cdots\cdots\cdots\cdots \text{Eq. (3.2)}$$

$Pr(RTA_{\alpha} | RTA_{\beta})$ is a conditional probability that means the number of firms that also have RTA in technology α among firms that have RTA in technology β. The fact that a large number of firms develop and possess two technologies α and β together means that the technological knowledge or infrastructure required to develop the two technologies is similar. Therefore, the chance to develop both becomes large by sharing the common technology knowledge or infrastructure.

Since $\phi_{\alpha\beta,t}$ is a probability, its value ranges from 0 to 1. The reason for using the minimum value of pairwise probability is to measure $\phi_{\alpha\beta,t}$ on a more conservative basis.

3.3.2.2 Gradual migration

3.3.2.2.1 Peripheral area: related density

Based on the proximity value between technologies ($\phi_{\alpha\beta,t}$), the related density ($\omega_{i,\alpha,t}$) that expresses how much the technological portfolio of firm i in time t is related to the newly technology α that has not yet been developed, was calculated (Hidalgo et al., 2007).

$$\omega_{i,\alpha,t} = \frac{\sum_{\beta} \phi_{\alpha,\beta,t} \cdot U_{i,\beta,t}}{\sum_{\beta} \phi_{\alpha,\beta,t}} \quad \cdots\cdots \text{Eq. (3.3)}$$

Movement of peripheral technologies in the area of technological portfolio can be described through a related density ($\omega_{i,\alpha,t}$). Here, $U_{i,\beta,t}$ is a binary variable expressed as 1 if firm i at time t has a RTA in technology β, and 0 otherwise. The denominator of the right term is the sum of the proximity ($\phi_{\alpha,\beta,t}$) about all technologies β around technology α. The numerator is the sum of the proximity ($\phi_{\alpha,\beta,t}$) between technology α which firm i has not yet developed and technologies β for which firm i has RTA already. Therefore, the related density ($\omega_{i,\alpha,t}$) can be regarded as a variable that reflects the accumulated technological capabilities of each firm while considering the technological distance ($\phi_{\alpha,\beta,t}$) between technologies.

An explanation about the variable with an example can be found in Appendix 1.

3.3.2.2.2 Core technology

In this study, a core technology at time *t* is defined by technology *j* with the largest value of $RTA_{i,j,t}$, among all technologies that has RTA in all periods *t-1*, *t*, and *t+1* ($RTA_{i,j,t-1} \geq 0.8$ & $RTA_{i,j,t} \geq 0.8$ & $RTA_{i,j,t+1} \geq 0.8$) within the technological portfolio of firm *i*. It is reasonable to regard core technology *j* of the firm *i* in time *t* as a technology whose RTA is observed in 3 consecutive years (to avoid accidental discovery of one year) with the largest stock compared to the industry average and the firm's entire technology. The core technology can be said to be the center of the intangible technological portfolio, and can be likened to the nucleus of an amoeba whose boundaries and shapes cannot be specified.

Core technologies can be changed over time. According to the definition, the core technology changes from *j* to *p* when the maximum RTA value in time *t* is technology *j*, and the maximum RTA value in time *t+1* becomes technology *p*. This is because i) firm *i* increases their share of technology *p* within the firm during the time to t+1, or ii) increases the share of technology *p* above the industry average. If the core technology changes from *j* at time *t* to *p* at time *t+1*, then it can be seen that the core technology has a difference by $\phi_{j,p,t}$. This is equal to the distance traveled on the technology space. If the core technology of time *t* and time *t+1* is equal to *j*, the movement distance becomes $\phi_{j,p=j,t}$ whose value is 0.

Next, we calculated the average value ($\overline{\phi_{J,\mathrm{p,t}}}$) of the change of firms' core technology

($\phi_{j,\mathrm{p,t}}$) by firm's tenure. In other words, average change of proximity between core technologies ($\overline{\phi_{J,p,t}}$) means the average proximity between core technologies *j* and *p* of all firms whose tenure correspond to *t* and *t+1*.

Lastly, we measured average value ($\overline{\overline{\phi_{\alpha,\beta,t}}}$) of the all technologies by firm's tenure. To this end, all technological proximity ($\phi_{\alpha,\beta,T}$) between α and β in time T was firstly calculated. Then, the average ($\overline{\phi_{\alpha,\beta,T}}$) of the proximity at time T ($\phi_{\alpha,\beta,T}$) is obtained (let's call $\overline{\phi_{\alpha,\beta,T}}$ as the average proximity at time T). Then, the average value of $\overline{\phi_{\alpha,\beta,T}}$ applied to firms belonging to a specific tenure *t* is calculated. For all firms with tenure *t*, the average value of $\overline{\phi_{\alpha,\beta,T}}$ corresponding to the year *T* to which the firm belonged is called 'average proximity ($\overline{\overline{\phi_{\alpha,\beta,t}}}$)'.

If the average change of proximity between core technologies ($\overline{\phi_{J,p,t}}$) is smaller than the value of average proximity ($\overline{\overline{\phi_{\alpha,\beta,t}}}$) ($0 \leq \overline{\phi_{J,p,t}} \leq \overline{\overline{\phi_{\alpha,\beta,t}}}$), then core technology is defined as gradual change. Conversely, if the average change of proximity between core technologies ($\overline{\phi_{J,p,t}}$) is greater than the value of average proximity ($\overline{\overline{\phi_{\alpha,\beta,t}}}$) ($\overline{\phi_{J,p,t}} > \overline{\overline{\phi_{\alpha,\beta,t}}}$), core technology is defined as radical change.

3.3.2.3 Expansion of boundary

3.3.2.3.1 Degree of diversification

Various indices have been developed to measure the composition of a firm's technological portfolio (see Section 2.3.1). The representative index, entropy or HHI is determined by the variety and balance of the elements constituting the technological portfolio. (Let's use entropy index as an example) First, the entropy index is increased when diversity increases, and it means that the types of technology classifications that make up the technological portfolio are diversified. The increase in the number of types of technology can be regarded as broadening the breadth of technological knowledge. Second, as the deviation between the ratio of the number of patents allocated to each technology classification to the total number of patents decreases, the entropy index increases. A small deviation between the ratios of each technology means that the firm is not concentrated in a specific technology. This can be regarded as a decrease in the depth of technological knowledge. Thus, the denotation of the technological knowledge expansion is described as increasing in breadth and at the same time flattening in depth rather than being particularly deep for a specific technology.

However, indices such as entropy or HHI do not consider the proximity between technologies. Since all technologies are considered equal, no matter which technology is added, the same variety and balance will yield the same result. However, even if diversity is increased by adding one technology, if more heterogeneous technologies with little similarity (is synonymous with cognitive distance) among existing technologies are added, the expansion of the technological portfolio will have to increase significantly. [23]

[23] For example, let's assume that firm A has the number of 100 technologies at *a* and 100 technologies *b* that is different from *a*. While, firm B has the number of 100 technologies *a* and 100 technologies *a'* that is similar to *a*. If the proximity between technology *a* and technology *b* and between technology *a* and technology *a'* are considered heterogeneous, the entropy of firm A and firm B will be different. This is because the technology portfolio of firm A which has technology *a* and *b* that are less similar to each other, can be considered to have

Therefore, in this study, The Rao-Stirling index (Rafols and Meyer, 2010), which additionally considers the technology proximity ($\phi_{\alpha,\beta,t}$) among the constituent technologies in addition to diversity and balance, is used.

$$Tech\_Div_{it} = \sum_{\alpha,\beta}(1 - \phi_{\alpha,\beta}) \left(\frac{x_{i,\alpha,t}}{x_{i,t}}\right)\left(\frac{x_{i,\beta,t}}{x_{i,t}}\right) \quad \cdots\cdots\cdots\cdots\cdots\cdots \text{Eq. (3.4)}$$

The Rao-stirling index is affected by the value of '1 - technology proximity ($\phi_{\alpha,\beta,t}$)', which represents the disparity between technologies. The larger the value (i.e., the smaller the technological similarity), the greater the expansion of the technological portfolio. We obtained the average value ($\overline{Tech\_Div_{it}}$) of technology boundaries of all firms by firm's tenure, and observed the dynamic change of boundary of technology portfolio according to firm's tenure.

3.3.2.3.2 Degree of specialization

$RTA_{i,j,t}$ has been used to determine core technologies within a firm. Patel and Pavitt (1997) judged the technology classification with the largest $RTA_{i,j,t}$ as the core technology of the firm. Kim et al. (2016) defines technology j, in which the product of $RTA_{i,j,t}$ and the number of patents in that technology is the largest, as the core technology.

However, the indices introduced above have room for improvement for the following reasons. First, it is appropriate to consider a firm's core technology as a set of technologies

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higher entropy.

rather than just one technology. Second, $RTA_{i,j,t}$ can be observed to exist by chance, if all firms in the industry do not develop the technology j in a year or when a firm i develops a lot of specific technology j in that year. Third, the formula used in Kim et al. (2016) is proportional to the square of the number of patents mathematically, therewith, is dominantly influenced by the number of patents. Fourth, a two-step approach is needed to calculate the capability of the technology, after determining the core technology firstly.

In this study, after defining core technologies, the degree of concentration was calculated based on this core technology set. The degree of concentration was calculated through the original HHI (Hirschman, 1945).

$$Tech\_Conc_{i,t} = \sum_{\alpha=1,2,3}\left(\sum_{\beta(\neq\alpha)} \boldsymbol{\phi_{\alpha,\beta,t}}\right)\left(\frac{x_{i,\alpha,t}}{x_{i,t}}\right)^2 \quad \cdots\cdots\cdots\cdots \text{Eq. (3.5)}$$

The HHI is used to determine the existence of a monopoly through the market share occupied by firms in an industry. We defined the proportion of the three core technologies in the entire technological portfolio as the degree of concentration and used it to identify the depth of technological knowledge. The three core technologies are the set of three technologies j with the largest $RTA_{i,j,t}$ in the firm's technological portfolio among the technologies in which comparative advantage exists in all periods t-1, t, and t+1. Since $RTA_{i,j,t}$ is a relative value calculated every year, it is inappropriate to observe absolute changes over time. Therefore, it is just used as a criterion for judging whether or not it was a core technology. Afterwards, the degree of concentration of the firm's technological portfolio was confirmed over time through HHI of core technology set.

In this study, we further added the concept of technological similarity ($\phi_{\alpha,\beta,t}$) to the existing HHI formula. If the similarity between technologies is high, it is thought that synergy will occur between core technologies and the degree of concentration will further increase. Accordingly, the technological similarity ($\phi_{\alpha,\beta,t}$) between the two different technologies is weighted. We consider a maximum of three core technologies, but some firms have only one or two technologies with a higher than average $RTA_{i,j,t}$. When there is only one core technology in time *t*, the correlation between technologies is set to the maximum value of 1.

3.3.3 Empirical Model

3.3.3.1 Gradual migration of peripheral area

The following multivariate probit model is established to investigate the statistical causal relationship of whether the technological portfolio of a firm highly related to α affects the development of newly acquired technology α.

$$U_{i,\alpha,t+2} = \beta_0 + \beta_1 \omega_{i,\alpha,t} + \boldsymbol{\beta_2 Tech_{\alpha,t}} + \boldsymbol{\beta_3 Firm_{i,t}} + year_t + \varepsilon_{i,\alpha,t} \quad \cdots\cdots\cdots\cdots\cdots\cdots \text{Eq. (3.6)}$$

First, $U_{i,\alpha,t+2}$ shows whether firm *i* has secured RTA for technology α at *t+2* or not.

It is a binary variable expressed as 1 if the RTA is possessed and 0, otherwise. Since we are only interested in whether RTA is developed or not, we convert the dependent variable into binary variable. The main explanatory variable, $\omega_{i,\alpha,t}$, means how related the existing technological portfolio is to technology α not yet developed. $\boldsymbol{Tech_{\alpha,t}}$ and $\boldsymbol{Firm_{i,t}}$ is a control variable vector related to technology α and firm i, respectively. The technology-related control variable vector $\boldsymbol{Tech_{\alpha,t}}$ includes the number of other firms with RTA in technology α ($number\ \ RTA\ \ industry_{\alpha,t}$) to investigate the technological environment where the firm locates. The firm-related control variable vector $\boldsymbol{Firm_{i,t}}$ includes the firm's tenure ($age_{i,t}$)[24], the size of the firm as measured by the number of employees ($emp_{i,t}$), profit to sales ($Profit\ \ ratio_{i,t}$), total debt to total assets ($Debt\ \ ratio_{i,t}$) considering the qualitative aspects of financial structure, and the number of all technologies with comparative advantage in firm i ($num\ \ RTA_{i,t}$). $year_t$ is the effect of each year, and $\varepsilon_{i,\alpha,t}$ is the error term.

3.3.3.2 Diversification cycle

We set up the following pooled quantile autoregression equation to find out whether a firm that diversifies from one period (year *t* to *t+1*) continues to diversify next period (after *T* years).

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[24] The date of birth of the firm is regarded as the listing year, which is the year in which data was first recorded in Compustat. Therefore, the firm's tenure is regarded as the listing age, subtracting the listing year from the current year (Fama & French, 2001).

$$Div\_Growth_{i,T\sim T+1} = \beta_4 Div\_Growth_{i,t\sim t+1} + \boldsymbol{\beta_5 Firm_{i,t}} + \varepsilon_{i,\alpha,t} \quad \cdots\cdots \text{Eq. (3.7)}$$

$$where,\ Div\_Growth_{i,t\sim t+1} = {(Tech\_Div_{i,t+1} - Tech\_Div_{i,t})}/{Tech\_Div_{i,t}} \quad \cdots\cdots\cdots \text{Eq. (3.8)}$$

The independent variable $Div\_Growth_{i,t\sim t+1}$ means the rate of change (increase rate) between year t and year $t+1$ of the technological diversification index ($Tech\_Div_{i,t}$). The larger this value is, the more technological diversification can be seen from firm i between year t and year $t+1$. The dependent variable $Div\_Growth_{i,T\sim T+1}$ means the rate of change between year T and year $T+1$ of the diversification index ($Tech\_Div_{i,t}$). Lagged time T is investigated in a total of 5 cases ($t+2$, $t+3$, $t+4$, $t+5$, $t+6$), which is increase rate of technological diversification of the firm after 2 years, 3 years, 4 years, 5 years, and 6 years. The larger this value is, the more the firm diversify their technologies between year T and year $T+1$. The control variable $\boldsymbol{Firm_{i,t}}$ includes the firm's tenure ($age_{i,t}$), the size of the firm measured by the number of employees ($Size_{i,t}$), and the firm's financial structure information ($Profit\ ratio_{i,t}, Debt\ ratio_{i,t}$) are included. $\varepsilon_{i,\alpha,t}$ is an error term.

3.4 Empirical results

The analysis of this study focuses on the changes of the average value according to the firm's tenure. There could be point out that the number of firms entering and exiting the market may differ depending on the historical events of a particular year. However, since the x-axis we set up is the tenure of the firm, the effect of a specific historical event does not need to be considered. For example, at the 2nd year of business, firms that starts their management in various years from 1986 to 2015 are all included if a firm have been in business for two years. In addition, considering the phenomenon that the number of firms continuing to operate naturally decreases as firm's tenure increases, this study analyzes the tenure of more than 30 firms, as a minimum number of samples that satisfy the normal distribution. Since Compustat provides data that has been recorded since 1950, 252 firms that have existed before 1950 are excluded from the analysis because the listing age is unknown.

3.4.1 Gradual migration

3.4.1.1 Peripheral area

The basic statistics for variables are as follows. Box-Cox transformation (Box and Cox, 1964) on the basis of each year was applied to all variables except for the dependent variable for normalization. Table 3-2 summarizes the results of analyzing the basic statistics and correlations between variables used in quantitative analysis to clarify Hypothesis 1-1.

The related density ($\omega_{\mathrm{i,\alpha,t}}$) showed a high correlation with the size of the firm ($emp_{i,t}$) and the number of all technologies with RTA within firm i ($num\ \ RTA_{i,t}$). A high correlation was also observed between size ($emp_{i,t}$) and the number of all technologies with RTA within firm i ($num\ \ RTA_{i,t}$). The reason for this is as follows. When we look at Equation (3.3), if the number of technologies with RTA increases, the numerator increases even with a small value of technological proximity ($\phi_{\alpha,\beta,t}$), therewith the related density ($\omega_{i,\alpha,t}$) becomes high. Also, as the size of the firm ($emp_{i,t}$) increases, the number of accumulated technologies also increases, hence, the number of all technologies with RTA ($num\ RTA_{i,t}$) also increases (Kim et al., 2023). As a result, the size of the firm ($emp_{i,t}$) and the number of all technologies with RTA ($num\ RTA_{i,t}$) and related density ($\omega_{i,\alpha,t}$) show a high correlation.

However, since the related density ($\omega_{i,\alpha,t}$) is a structural variable calculated through the technology space, it is difficult to simply consider that there is a multicollinearity problem although the correlation coefficient is high. To confirm this, we measure VIF (Variance Inflation Factor) between independent variables. The results of the VIF test between the related density ($\omega_{i,\alpha,t}$) and the number of all technologies with RTA ($num\ RTA_{i,t}$), related density ($\omega_{i,\alpha,t}$) and the size of the firm ($emp_{i,t}$), the size of the firm ($emp_{i,t}$) and the number of all technologies with RTA ($num\ RTA_{i,t}$) are not significant. The results of the VIF test for all three relationships do not exceed 10 (based on the rule of thumb), suggesting that all variables can be considered together in our regression model.

Table 3-2. Descriptive statistics and correlations

Statistic	N	Mean	St. Dev.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) $Dependent\_RTA_{t+2}$	2,356,377	0.004	0.062	1							
(2) $\omega_{i,\alpha,t}$	2,356,377	0.0001	1.113	0.069	1						
(3) $age_{i,t}$	2,356,377	0.0004	11.734	0.022	0.274	1					
(4) $num\_RTA\_industry_{\alpha,t}$	2,356,377	−0.000	4.868	0.033	0.139	0	1				
(5) $num\_RTA_{i,t}$	2,356,377	0.0002	0.712	0.059	0.887	0.313	0	1			
(6) $emp_{i,t}$	2,356,377	0.001	2.152	0.056	0.628	0.378	0	0.676	1		
(7) $Profit\_ratio_{i,t}$	2,356,377	0.104	22.798	0.006	0.086	0.039	0	0.091	0.163	1	
(8) $Debt\_ratio_{i,t}$	2,356,377	0.0002	0.528	0.012	0.211	0.112	0	0.234	0.307	0.021	1

Table 3-3. Result of gradual migration at peripheral area

	Dependent variable:				
	$Dependent\_RTA_{t+2}$				$Dependent\_RTA_{t+5}$
	(1)	(2)	(3)	(4)	(5)
$\omega_{i,\alpha,t}$	0.348792^{***}	0.346003^{***}	0.369791^{***}	0.360260^{***}	0.274726^{***}
	(0.003367)	(0.003433)	(0.010502)	(0.010835)	(0.011889)
$num\_RTA\_industry_{\alpha,t}$		0.037034^{***}	0.037221^{***}	0.037150^{***}	0.035062^{***}
		(0.000837)	(0.000866)	(0.000871)	(0.000952)
$age_{i,t}$			0.001071^{***}	-0.001128^{***}	-0.001990^{***}
			(0.000405)	(0.000387)	(0.000414)
$num\_RTA_{i,t}$			-0.196074^{***}	-0.172385^{***}	-0.046777^{**}
			(0.016788)	(0.017406)	(0.019975)
$emp_{i,t}$			0.059198^{***}	0.061373^{***}	0.068085^{***}
			(0.003090)	(0.003123)	(0.003466)
$Profit\_ratio_{i,t}$			0.001295^{***}	0.001776^{***}	0.004653^{***}
			(0.000454)	(0.000531)	(0.000870)
$Debt\_ratio_{i,t}$			-0.100680^{***}	-0.098059^{***}	-0.094869^{***}
			(0.009940)	(0.010239)	(0.011920)
Constant	-2.901668^{***}	-2.953134^{***}	-2.914128^{***}	-2.793142^{***}	-2.861309^{***}
	(0.005077)	(0.005519)	(0.005548)	(0.019806)	(0.021518)
Observations	2,625,207	2,625,207	2,356,377	2,356,377	2,156,621
Log Likelihood	-54,887.11	-53,865.68	-52,646.68	-52,337.32	-42,678.26
McFadden R^2	0.09745254	0.1142486	0.1135725	0.1187813	0.1168254
Note:					*p<0.1; **p<0.05; ***p<0.01

The results of regression analysis drawn in Section 3.3.3.1 are shown in Table 3-3. In column (1), we consider only the main variable of our interest, the related density ($\omega_{i,\alpha,t}$). In column (2), only related density ($\omega_{i,\alpha,t}$) and technology-related control variable vector ($\boldsymbol{Tech_{\alpha,t}}$) are included in the analysis, and in column (3), the firm-related control variable vector ($\boldsymbol{Firm_{i,t}}$) is added. In column (4), we control the year effect ($year_t$). In column (5), the effect of related density ($\omega_{i,\alpha,t}$) on $U_{i,\alpha,t+5}$, which means developing long-term RTA, is additionally analyzed.

The related density ($\omega_{i,\alpha,t}$), a main variable, have a positive and significant effect on developing RTA. As shown in columns (3) and (4), the significant effect of the related density ($\omega_{i,\alpha,t}$) is maintained even after controlling for the year. Based on column (4), when the related density ($\omega_{i,\alpha,t}$) increases by 1 unit, the odds of developing the comparative advantage in technology α after 2 years increase by 36% . This means that firms are more likely to develop a new technology related to those technologies that the firm already possesses. Finally, through column (5), it is found that the related density ($\omega_{i,\alpha,t}$) have a positive and significant effect on developing long-term RTA in technology α after t+5 years.

Although the influence is smaller than the related density ($\omega_{i,\alpha,t}$), the sign and statistical significance of the control variables are remained the same for all models, except for firm's tenure ($age_{i,t}$). The results indicate that the greater the number of firms possessing the same technology α ($number\ RTA\ industry_{\alpha,t}$), the more positive it is for firm i to develop a comparative advantage in technology α. This means that the effect of learning is greater than the loss from competition (Kim et al., 2023). On the other hand, the larger the size of the firm ($emp_{i,t}$), the more positive it is for developing RTA in technology α, because more R&D resources such as human capital and external investment can be utilized by firm's size (Shefer and Frenkel , 2005). Finally, the lower the debt ratio ($Debt\ \ ratio_{i,t}$) and the higher the profit ratio ($Profit\ \ ratio_{i,t}$), the more positive the firm is in developing RTA in technology α.

The results of the above econometric analysis are found to support Hypothesis 1-1. The periphery of a firm's technological portfolio changes according to the principle of relatedness, as a result, the periphery of technological portfolio changes gradually. However, it is impossible to define the direction of expansion to related technologies. Because it is possible to expand in any direction if the technology is related to the existing technologies. This can be likened to the cytoplasm of an amoeba, which has a free form and can extend in any directions. This is why it is necessary to look at the center of the area and examine the changes of core technologies, along with the expansion of the peripheral area.

3.4.1.2 Core technology

In order to confirm Hypothesis 1-2, firstly, average change of proximity between core technologies ($\overline{\phi_{J,\mathrm{p,t}}}$) and average proximity ($\overline{\overline{\phi_{\alpha,\beta,t}}}$) by tenure are obtained respectively according to the operational definition in Section 3.3.2.2.2. Next, the changes of the two values are examined according to the firm's tenure. The result is shown in Figure 3-7.

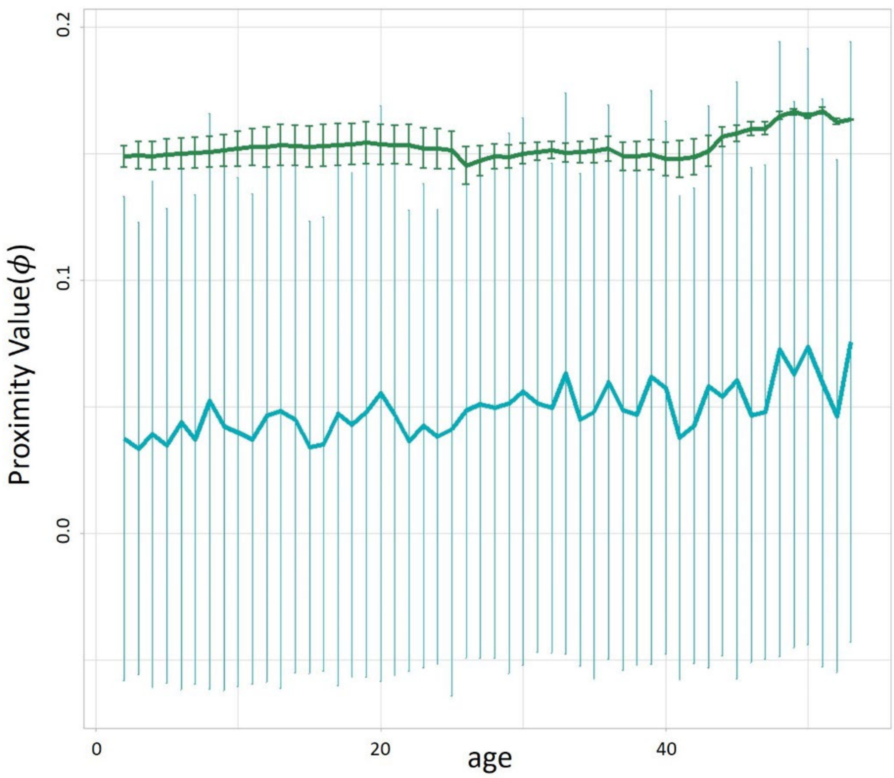

Figure 3-7. Comparison average change of proximity between core technologies ($\overline{\phi_{J,p,t}}$, light blue) with average proximity ($\overline{\overline{\phi_{\alpha,\beta,t}}}$, green) according to firm's age

The x-axis in Figure 3-7 represents the firm's tenure. The Y axis means the value of similarity (ϕ). The light blue dots mean the average amount of change of the proximity between two different core technologies of the firms ($\overline{\phi_{J,\mathrm{p,t}}} = \phi_{p,t+1} - \phi_{j,t}$). The light blue line is the result of connecting the average value ($\overline{\phi_{J,\mathrm{p,t}}}$) by tenure. The average value of change of core technologies by tenure ($\overline{\phi_{J,\mathrm{p,t}}}$) records the minimum value of 0.0336 in the 3rd year of business and the maximum value of 0.0756 in the 53rd year of business, and is increased by 0.0004 (***) over time. The fact that the slope with tenure is not 0 means that the firm's core technology changes according to their age, and the average technology proximity between core technologies increases by 0.04% on average per one year (in other words, the degree to which the core technology changes has increased as the firm has grown).

The green dot is the average value ($\overline{\overline{\phi_{\alpha,\beta,t}}}$) of the average proximity at time *T* ($\overline{\phi_{\alpha,\beta,T}}$) by firm's tenure *t*. The green line is the result of connecting the average proximity ($\overline{\overline{\phi_{\alpha,\beta,t}}}$) by firm's tenure with the minimum value of 0.1454 and the maximum value of 0.1669. Compared to the average change in core technology ($\overline{\phi_{J,\mathrm{p,t}}}$), it is larger than at least about 2.16 times (52 years of business) and up to 4.49 times (14 years of business). The fact that the average change in core technology ($\overline{\phi_{J,\mathrm{p,t}}}$) is smaller than the average value ($\overline{\overline{\phi_{\alpha,\beta,t}}}$) for all firm's history indicates that the degree of change in the firm's core technology is not large. In other words, the firm's core technology has changed to a related technology with a small difference in proximity comparing with relationships (ϕ) between all possible combinations about technologies (α, β). Through this, it is found that core technologies change gradually without a big Jump, and as a result, Hypothesis 1-2 is supported.

Appendix 4 shows how the core technologies of firms in each industry change on average according to their business tenure.

3.4.2 Expansion of boundary

In order to confirm Hypothesis 2, the degree of technological diversification of firm i at age t is calculated according to the methodology introduced in Section 3.3.2.3.1. Afterwards, we draw a time series graph with the x-axis as firm's tenure, and the y-axis as the value of Rao-Stirling index ($\overline{Tech\_Div_{it}}$). The result is shown in Figure 3-8.

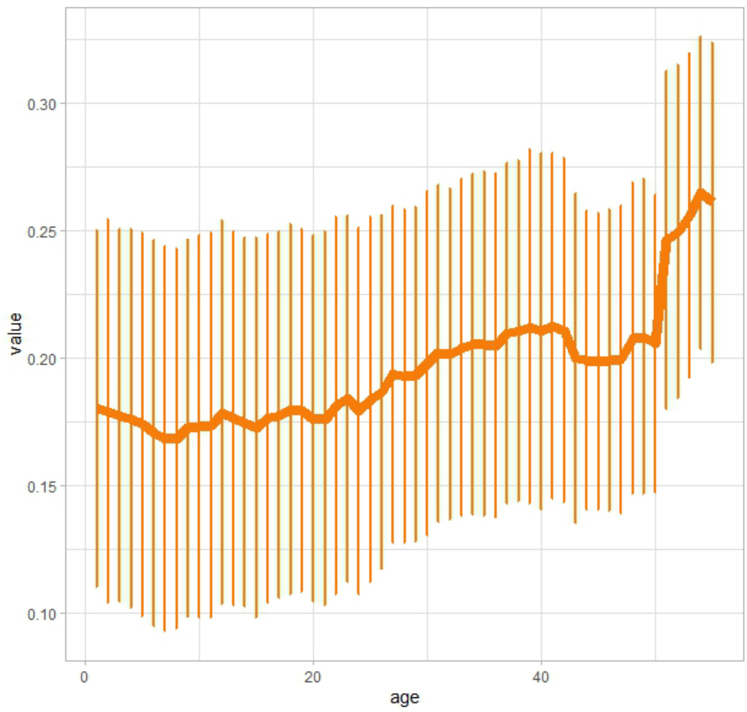

Figure 3-8. Average degree of technological diversification ($\overline{Tech\_Div_{it}}$) according to firm's age

The orange dot in Figure 3-8 is the average value ($\overline{Tech\_Div_{it}}$) of the technological diversification ($Tech\_Div_{it}$) of a firm's technological portfolio. The vertical line means the standard deviation, and if the number of samples for each business tenure is less than 30, it was excluded from the analysis. By connecting the average degree of technological diversification ($\overline{Tech\_Div_{it}}$), dynamic changes according to business tenure can be observed.

As a firm's tenure increases, $\overline{Tech\_Div_{it}}$ increases (slope: 0.001***). In particular, $\overline{Tech\_Div_{it}}$ increases rapidly from 45 to 55 years (slope: 0.007***). Through this, it is found that the average degree of technological diversification of a firm's technological portfolio, that is, the boundary of technological knowledge increases as the firm's tenure increases. In particular, when a firm's age exceeds 45 years, the composition of its technological portfolio has rapidly diversified. This is because the amount of accumulated technology stock increases as the firm's business tenure increases, which is consistent with a study of Dosi et al. (2017). The author found that the more the amount of technology stock, the more diverse the types of technology classifications held.

Appendix 5 shows how the average degree of technological diversification of firms by industry changes according to their business tenure.

3.4.3 Punctuated equilibrial way of technological knowledge accumulation

In order to answer the question, 'Does a firm that diversified technology from one period (from *t* to *t+1*) continue to diversify technology in next period with 2 to 6 years later?', pooled quantile autoregression analysis is performed. The confidence interval was obtained with 100 bootstrap replications.

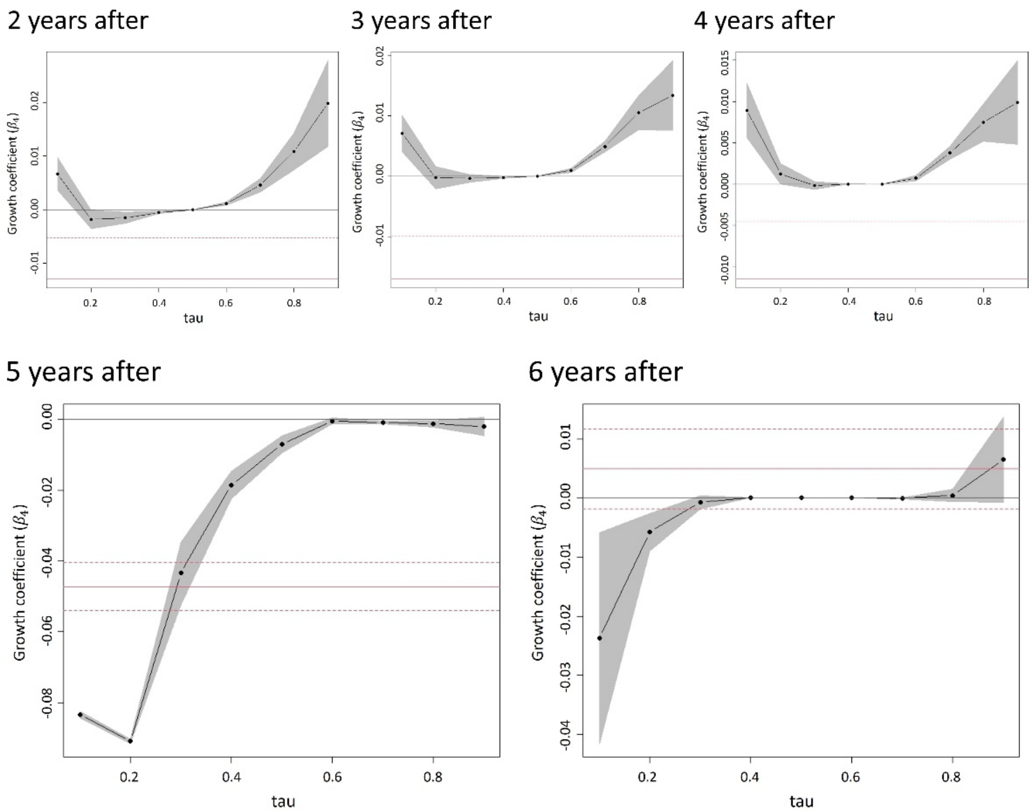

Figure 3-9. Quantile autoregression results of the dynamics of technological diversification

Figure 3-9 shows only β_4 among the results of the regression model established in Section 3.3.3.2. The x-axis represents the 10th percentile of the technological diversification rate for one period, from *t* to *t+1*, and the y-axis represents the value of β_4, the effect of technological diversification rate of each quintile at time *t* to *t+1* on the technological diversification rate after lagged time *T*.

Firms with the top 30% of technological diversification rate from *t* to *t+1*, continues to diversify 2, 3, and 4 years later (i.e. $\beta_4 > 0$). Through this, it can be seen that technological diversification occurs continuously for 2 to 4 years. On the other hand, for most firms in the top 30% to 70%, efforts to diversify technology in periods *t* to *t+1* had no effect on technological diversification after 2, 3, and 4 years (i.e., $\beta_4 = 0$). Firms that did not diversify technology (i.e., the bottom 10% of technological diversification rate) in time period *t* to *t+1* are found to diversify technology again 2, 3, and 4 years later (i.e., $\beta_4 > 0$). From the above results, the following conclusions can be drawn. If technological diversification occurs in one period, there is a high probability that technological diversification will occur consecutively as the following period, later 2 to 4 years. In the case of the bottom 10%, the technological diversification rate in the lagged time T period is calculated to be high even if only a little technological diversification is achieved, since the technological diversification rate in the *t* to *t+1* period is low.

It is confirmed whether the firms that diversified their technology in the *t* to *t+1* period continues to diversify 5 years later. Firms in all quintiles that performs technological diversification in the *t* to *t+1* period do not diversify additionally after 5 years (i.e., $\beta_4 \leq$

0). In particular, all of the firms in the top 30% of technological diversification rates in the *t* to *t+1* period did not carry out technological diversification 5 years later. However, the firms in the top 20% of technological diversification rates in the *t* to *t+1* period resumed further diversification after 6 years.

Combining the above results, the cycle of technological diversification can be estimated to be about 5 years. Firms with a high technological diversification rate in the *t* to *t+1* period carry out technological diversification until 2, 3, and 4 years later, and then stop additional technological diversification after 5 years, and resume technological diversification from the 6 years. Through this, it is confirmed that technological diversification of firms does not occur continuously and consecutively, but rather periodically. Firms in the bottom 30% of technological diversification rates in the *t* to *t+1* period do not diversify additionally even after 6 years. This is because long-term changes are not observed, although the rate of change after 2, 3, and 4 years is measured greatly even with small changes.

We checked how the technological specialization rate ($Tech\_Conc_{i,t}$) changes for the top 10% of firms that have performed technological diversification in the *t* to *t+1* period. If technological specialization does not occur during technological diversification and technological specialization occurs while technological diversification does not occur, then the firm can be said to be accumulating technological knowledge in a way of punctuated equilibrium. The result is shown in Figure 3-10.

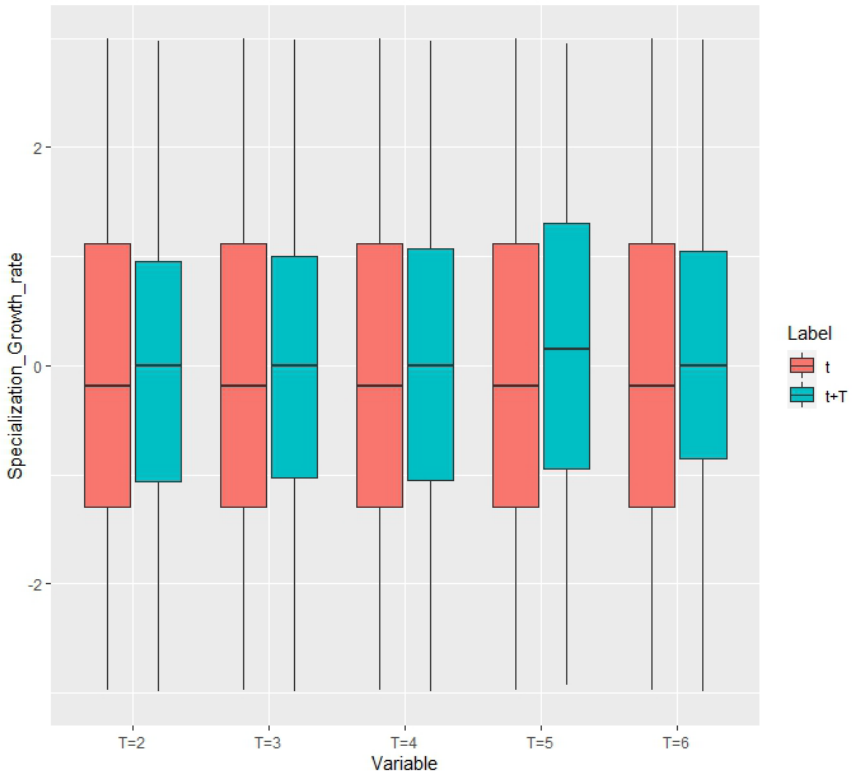

Figure 3-10. Specialization efforts in each T year for top 10% diversifying firms at period *t*

First, for the top 10% firms in the technological diversification rate in the *t* to *t+1* period, the technological specialization rate in the *t* to *t+1* period is examined (Label: t). The median of the technological specialization rate distribution of firms in the *t* to *t+1* period, confirmed through a box plot, records a negative value. In other words, firms that carry out technological diversification in the *t* to *t+1* period make less effort to specialize in core technology in the *t* to *t+1* period.

Next, we checked the technological specialization rate after year *T* of the top 10% firms in technological diversification rate in the t to $t+1$ period (Label: t+T). At $T = 2, 3, 4$, and 6, the rate of specialization of firms increases comparing with the result of the period t to $t + 1$, but the median value of the distribution recorded 0%. In other words, firms that have undergone technological diversification in the t to $t+1$ period and for $T = 2, 3, 4$, and 6, where technological diversification continues to occur, do not make efforts to specialize in core technology after period T.

$T = 5$ shows the result supporting Hypothesis 3-1. Unlike other years, when $T = 5$, the median value of the technological specialization rate distribution records 0.8%, which is greater than 0%. As we see at Figure 3-9, the firm's efforts to diversify their technology pause at the fifth year. In other words, when technological diversification is temporarily slowed down at T=5, firms that had technological diversification in the t to $t+1$ period make efforts for technological specialization in the T=5 period. The fact that the rate of technological specialization increases with the opposite cycle as the rate of technological diversification decreases supports punctuated equilibrium way of technological knowledge accumulation within firms.

3.5 Sub-conclusion

We looked at the process of accumulating technological knowledge within a firm from three dimensions at the same time. First of all, it was found that as a firm gets older, the entire technological knowledge of the firm gradually migrates. First, when the related density between a new technology and a firm's existing technologies increases by 1 unit, the odds of developing the new technology increases by 36%. Next, the firm's core technology does not change considerably as the firm grow, and even if it does change, it is changed to a related technology. In other words, it is found that the firm's technological portfolio gradually changes both at the periphery and at the center.

Second, we found that the entire boundary of a firm's technological portfolio expands as its business tenure increases. As the firm's tenure increases by one year, the boundary of technological portfolio is expanded by 0.1% on average. In particular, as the tenure of the firm exceeds 45 years, the technological portfolio expands more rapidly by 0.7% per a year. It is confirmed that as the firm's business tenure increases, the composition of the technology knowledge possessed by the firm becomes more diversified and the difference between each proportion becomes smaller.

Finally, we found that a firm's technological knowledge is accumulated in a punctuated equilibrium manner. Firms do not consistently pursue technological diversification in succession following the previous period. Technological diversification stops for a while after 5 years of first technological diversification efforts, and then the firm starts making efforts for technological diversification again after 6 years. In particular, the top 10% of firms with a high technological diversification rate make less effort for technological specialization during technological diversification, while focus again on technological specialization at the period when technology diversification does not occur.

In this study, after confirming the firm's technological portfolio from three different angles, the three perspectives were finally integrated into one. It is found that the process of firms accumulating technological knowledge is carried out in the form of 'gradual migration with punctuated equilibrial expansion'.

The implication of this study is to find the 'generalized' nature of the accumulation process of technological knowledge within a firm by simultaneously examining how the accumulation process of a firm varies according to business tenure from multifaceted windows. We tried to understand the technological portfolio in various ways, such as a simultaneous approach through three different concepts, a dynamics analysis of average values according to firm's tenure, and a statistical analysis through an econometric model. The results of this chapter are expected to be helpful in understanding the process of accumulating technological knowledge within a firm.

The results of this study will provide information to R&D managers in firms who are interested in dynamic changes in technological knowledge according to their business tenure, and will also help policy makers who want to understand the characteristics of technological knowledge. First, an understanding of the nature of technological knowledge and its accumulation is expected to help R&D managers enable efficient reallocation of resources. A firm's resources are limited. Therefore, the problem of deciding how to reallocate resources is directly related to the efficient use of limited resources, such as the use and reduction of R&D costs and the efficiency improvement of the R&D process. The gradual migration of firm's technological knowledge to related technologies can be a criterion when deciding to invest in new technologies.

Second, it becomes possible to establish a long-term plan related to technology accumulation within the firm. An understanding of the nature of technological knowledge helps to predict the composition of a firm's future technological knowledge. The fact that the type of technological knowledge of a firm does not decrease but increases steadily as the firm's tenure increases means that firms must prepare for continuous R&D of new technologies for their future.

Third, R&D managers will find it easier to deal with and manage unknown changes. Recognition that the accumulation of technological knowledge takes place in a way of punctuated equilibrium helps to be more flexible in the face of rapid changes in R&D costs, strategies, and technological portfolios. If we understand that rapid change is a natural process, it will be possible to reduce unnecessary waste of resources due to insecurity and to cope with fluctuations by changing R&D personnel.

Policy makers also need to understand the nature of technological knowledge accumulation. The gradual migration of accumulated technological knowledge also aids in the education and development of the workforce in the region. Policy makers should focus on the technologies possessed by firms located in their region and provide training programs related to these technologies. Similar, but not identical, related skills training will enable firms to more efficiently develop new technologies.

Next, the fact that the boundary of firms' technological knowledge continues to expand requires policy makers to act as mediators among firms. The continuous expansion of technological knowledge along with the increase in firm's tenure eventually causes the formation of intersections between firms in the technology space. In a situation where overlapping technology areas are created between firms, excessive competition between firms can be occurred and detrimental to both sides. Therefore, a technology policy that can promote the accumulation of technological knowledge from both sides must be prepared through cross-pollination between technologies of each firm through collaboration and partnership.

Finally, awareness of the fact that technological knowledge is accumulated within firms in a punctuated equilibrium way allows policy makers to establish more effective innovation policies. During the stable period, when firms' strategies for accumulating technological knowledge are continuously maintained, policies should focus on helping firms build their technological capabilities. On the other hand, when a period of rapid transition comes after the stabilization period, policies for firms should focus on supporting swift adoption.

Chapter 4. A new measure of accumulated technological capability

4.1 Introduction

A firm's technological capability refers to the ability to develop new products or processes, efficiently use facilities, and related to any technical function within the firm (Teece et al., 1997; Makadok, 2001). In resource-based theory, which views a firm as a set of heterogeneous resources and capabilities acquired and learned in a heterogeneous way, technological capabilities are one of the resources within a firm and seen as one of a source of comparative advantage (Penrose, 2009; Amit and Schoemaker, 1993). The comparative advantage of a firm in an industry according to technological capabilities is directly related to the growth of the firm. This is because high technological capabilities increase financial performance through development and sales of more innovative products and increases efficiency through more innovative processes, which become a driving force for cost reduction (Camisón and Villar-López, 2014).

Despite its importance, measuring technological capability is extremely difficult (Tsai, 2004). First, it is difficult to evaluate and quantify technological capabilities because they can be judged by various intangible factors such as technological knowledge, expertise, and innovation performance possessed by a firm (Coombs and Bierly III, 2006). Next, it is impossible to measure objectively the qualitative aspects such as the quality of firm's R&D,

the ability to recognize and attract talented person, and the culture of dealing with innovation by firm.

Accordingly, various methods have been devised to measure a firm's technological capability. The most representative way to directly measure a firm's technological capability is to conduct a survey by firm. The items of the survey, which are selected through extensive literature review and whose validity is reviewed by experts, are evaluated by firm members who have the highest understanding of the firm (such as CEOs). For example, Ortega (2010) set economies of scale and technological experience, how efficient and effective the manufacturing department is, and technological equipment possessed by the firm as questions for a questionnaire to measure technological capabilities. The survey method has a clear purpose of measuring technological capabilities, can comprehensively consider various factors, and is the most direct method. However, there is a disadvantage that it is not possible to judge the capabilities in the case of firms that do not participate in the survey.

Accordingly, complementary methods that can indirectly (or conversely) estimate technological capabilities through unintentionally generated (during the firm is operating) information have been used simultaneously. Information such as i) technology-related resources that can be used, ii) strategies for accumulating technological knowledge that can be utilized, and iii) technology-related activities or outcomes of firms have been used to indirectly measure a firm's technology capabilities.

First, when technological capabilities are indirectly measured through the technological knowledge used by a firm, i) *total R&D expenditure or R&D intensity* (which measures total R&D expenditure against scale) (McCutchen and Swamidass, 1996; Helfat, 1997; Aw and Batra, 1998; Deeds et al., 1998; DeCarolis and Deeds, 1999); ii) *skill endowment* (Piva and Vivarelli, 2009) or iii) *on-the-job training* (Aw and Batra, 1998) have been used. However, as technological resources are input factors for technological innovation, it is difficult to view them as technological capability itself. Because, according to the previous definition of technological capability, it means 'the ability to use it efficiently' beyond simply inputting the resources. In order for firms to acquire new technologies, effort and investment are required, but the results are uncertain and the ability to assimilate the same inputs varies from firm to firm (Lall, 1992). The causal relationship is also unclear. According to Kang et al. (2017), when sales increase, firms with high technological capabilities tend to increase R&D investment, but firms with low technological capabilities try to maintain R&D investment. Conversely, when sales decrease, firms with high technology capabilities try to maintain R&D investment, but firms with low technology capabilities try to reduce R&D investment.

A firm's technological diversification strategy has also been used to indirectly judge technological capabilities (Kim and Kogut, 1996; Choo et al., 2009). Because there is a close correlation between a firm's technological capabilities and thier technological diversification strategy (Argyres, 1996). However, representative indices that measure the firm's technological capabilities, such as entropy or the Hershman-Herfindahl Index, are dependent on the relative ratio of technology within a firm and the type of technology, regardless of the amount of technology stock possessed by each firm. Since the value is determined relatively by firm, it is difficult to track the dynamic change. In addition, it does not reflect the absolute amount of technology stock possessed by a firm, and the value varies greatly depending on the classification criteria (Robins et al., 2003; Pan et al., 2017). Accordingly, the firm's technological diversification strategy is mainly used in studies that analyzed the causal relationship according to the cross-sectional technology composition and strategic choice rather than analyzing the time series change.

Next, a firm's technological capabilities are measured indirectly through its technology-related activities and outputs. Examples of technology-related activities and outcomes include publications and patents (DeCarolis and Deeds, 1999), number of patent citations (Deeds et al., 1997; Deeds et al., 1998; DeCarolis and Deeds, 1999), and number of types of new products launched. (Deeds et al., 1997; Deeds et al., 1998; DeCarolis and Deeds, 1999). However, measuring technological capability through simple counting, such as the number of patents or the number of citations per patent, has the disadvantage that it cannot simultaneously consider multifaceted aspects related to patent activity. This is because a firm's technological portfolio can be evaluated in various dimensions, such as how many different technologies the firm has, how much it focuses on a specific technology, and how much the technologies are related.

The limitations of the two direct and indirect methods introduced above emphasize the need for the developing a new variable that can measure technological capability of a firm. Therefore, in this study, a new method of measuring a firm's technological capability is presented through the aspect of the technological portfolio, which is the result of the firm's strategic choice. This is because the features that can be observed in the technological portfolio, which is the accumulated technological knowledge within the firm, are the result of reflecting both intangible and qualitative factors that are difficult to quantify. As a representative characteristic of technology knowledge accumulated within a firm, this study considered the breadth and depth of the technological portfolio and the coherence between the constituent technologies.

A firm's technological capability is the result of integrating the above three factors into a single index by applying different weights. The heterogeneous influence of each factor on the proxy of technological capability was first identified statistically, and then the weight for each factor was determined. The advantages of measuring technological capabilities as an integrated value are, first, that it can be easily expressed. Second, it is useful in that it is possible to identify which factors firms should focus more on through relative comparison. Since each factor independently affects technological capability through different weights, an increase in any one of the three factors results in an increase in technological capability. However, the relative position of each factor relative to all firms in the industry is different. Therefore, by identifying the factor with the largest marginal effect, it is possible to determine the factor that should be invested first for the increase in technological capacity.[25]

[25] For example, let's assume that there is a firm whose breadth of technological knowledge is large enough compared to the industry as a whole, but the depth of technological knowledge is small compared to the industry as a whole. In this case, an increase in the breadth of technological knowledge by one unit also contributes to an increase in technological capacity. However, increasing the depth of technological knowledge by one unit can make a greater contribution to increasing technological capacity.

Based on the created technological capability measurement, two analyzes are performed. First of all, this chapter pays attention to the dynamic changes over time of the technology capability of firms. Technological capability is regarded as a resource that dynamically evolves over time due to learning, experiencing and technological change. Since the resources that a firm possesses to innovate and the ability to combine them (Prahalad and Hamel, 2009) change over time and characteristics of each resource, accumulated technological capabilities will also vary depending on the firm's tenure.

Next, the effect of the designed technology capability measurement on the innovation performance and financial performance of the firm is analyzed. As technological capabilities are the source of a firm's comparative advantage, various studies confirm the relationship between a firm's technological capabilities and innovation performance (Renko et al., 2009; Zhou and Wu, 2010; Haeussler et al., 2012) or technological capabilities and financial performance (Lee et al., 2001; Schoenecker and Swanson, 2002; Tsai, 2004; Sher and Yang, 2005; Coombs and Bierly III, 2006; Wang et al., 2006; Wang et al., 2006; Ortega, 2010; Kyläheiko et al., 2011). In particular, the effect of technological capability on financial performance or innovation performance has a higher impact than the effect on operational manufacturing performance, for manufacturing firms (Ahmad et al., 2014). Therefore, in this study, the explanatory power of the devised technological capability measure is examine through its impact on innovation performance and financial performance.

For analysis, a unique dataset matching the patent information and financial information of firms belonging to Korea's 'Electronic components, computer, radio, television and communication equipment and apparatuses' manufacturing sector (based on the 9th Korean Standard Industrial Classification (hereafter, KSIC) code)' was constructed. The 'Electronic components, computer, radio, television and communication equipment and apparatuses' manufacturing sector is a so-called high-tech industry, which represents Korea. According to the 'Survey of Research and Development in Korea, 2019' by the Science and Technology Policy Institute, this industry accounted for 49.2% of the total R&D expenditures of Korean firms and 10.14% of R&D expenditures to sales, which was the highest compared to other industries. By analyzing the high-tech industry, it is expected that the importance of the development, absorption and application of technological knowledge will become clear (Tsai, 2004).

The structure of this chapter is as follows. Section 4.2 first looked at various previous studies conducted to measure technological capabilities at the country and firm level. Next, after proposing a theoretical framework to indirectly measure technological capabilities through aspects of a firm's technological portfolio, the factors that make up aspects, such as breadth, depth, and coherence, were examined. Section 4.3 presented the data used to measure technological capability, the method of calculating heterogeneous weights for each factor, the method for measuring technological capability, and the model for empirical analysis. Section 4.4 shows the result of the analysis, and Section 4.5 tested the robustness of the main result. Finally, Section 4.6 draws the conclusions and implications of this study.

4.2 Literature review

4.2.1 Efforts for measuring technological capability

Various variables have been devised to measure technological capacity at the country or firm level, along with efforts to find out the factors influencing technological capacity. According to Ahmad et al. (2014) reviewing papers on firms' technological capabilities, among the 70 papers cited by the authors regarding technological capabilities, about 53% of theses investigate factors that affect to technological capability. In this c, technological capability measures, which are calculated as a single value by combining various factors, are introduced. Table 4-1 bellow summarizes the various technological capability measures and their factors at the country and firm level.

At the country level, Yeon et al. (2021) largely divided technological capability into implementation capability and design capability. Implementation competency is the ability to operate the know-how necessary to realize a design, and is developed through repeated action for adaptation and imitation (learning by doing). Design capability refers to the ability to differentiate the design of a new concept and the ability to apply new 'know why' knowledge to products or technologies. Design capability is learned through trials and error in the process of constructing and combining new technological knowledge striving for new designs (learning by building). A country's technological capacity is obtained as the sum of its implementation capacity and design capability, each calculated as an equal weighted sum of five normalized factors.

Table 4-1. Measures for Technological Capability (*TC*)

Level	Author	Factors	Equation	Interpretation	Main result
Country	Yeon et al. (2021)	● $Implementation\ Capability_{i,t}$(*IC*) - ISO 9001 certificates - Trademark applications - Manufacturing value added per capita - Employees in the total manufacturing sector - Gross fixed capital formation in the total manufacturing sector ● $Design\ Capability_{i,t}$ (*DC*) - Total patent applications by residents - Total industrial design applications by residents - High tech exports per capita - Researchers in R&D - Gross domestic expenditure on R&D by government	$NTC_{i,t} = Implementation\ Capability_{i,t} + Design\ Capability_{i,t}$	Total sum of *IC* and *DC* measuring different knowledge types (repetitive executions for *IC* and creative trials and error for *DC*) & learning modes (know-how for *IC* and know-why for *DC*)	Developing *IC* precedes development of *DC*. In other words, National Technological Capability (*NTC)* develops through technology conversion. *IC* has a greater impact on economic growth of low-income quantiles, while *DC* has a greater impact on economic growth of high-income quantiles.
Firm	Lee et al. (2010)	● The total number of patents (*TP*) ● The total number of utility model and design (*TUM&D*) ● The total number of quality assurance marks certified by foreign and domestic institution (*TQAM*)	$TC_{i,t} = TP + TUM\&D + TQAM$	Total sum of the number of patents shielded laws & quality control capability	Technological capability is positively associated with start-up's performance.

Firm	Tsai (2004)	● Internal technological learning & external technological learning - R&D efforts - in-house R&D - cooperative R&D - technology imports - technological alliance - technology licensing - technology instruction	$\mathrm{TC}_{i,t} = \sum_{j}(1-\delta_i)^j R_{i(t-1-j)}$ ● Where R is deflated measure of investment on technology learning ● δ is obsolescence rate of technological knowledge (varying across firm) (t-1-j) means lagged year	The firm's current internal technological learning & external technological learning will gradually, dynamically, and nonlinearly increase the firm's accumulated technological knowledge and its ability to use it (while simultaneously becoming obsolete by δ over time).	Technological capability has a significant, positive impact on firm performance (measured by labor productivity)

Next, at the firm level, Lee et al. (2010) perceived that a firm's technological capability is determined by the sum of two factors. One is the number of patents protected by patent law, and the other is the quality control capability, which is related to tacit knowledge and is difficult to duplicate and consequently enjoys high appropriability. Tsai (2004) found that firms' current internal technological learning and external technological learning gradually, dynamically, and nonlinearly affect their technological capabilities. At the same time, technological capabilities become obsolete by δ. A firm's current internal technological learning and external technological learning, including efforts for R&D and technology import, are used as factors to calculate one measurement.

4.2.2 Theoretical framework for measuring technological capability

Existing methods of measuring technological capability through technological activities and outcomes of firms, such as publications, patents, and new products launched, have limitations in that they do not provide an overall view of technological capability. This is because technological capability is comprehensively determined by various factors rather than a single factor, such as the variety of technology classifications or the absolute number of patents within a specific technology field. In addition, information on R&D differs from firm to firm (Coombs and Bierly III, 2006), and it is difficult to obtain information because it is not open to the public. The findings of Coombs and Bierly III (2006), which show that measuring technological capability with indicators such as the number of existing patents or R&D intensity, do not properly measure a firm's financial performance, support this claim.

The technological capability measure, which comprehensively considers various factors, has been developed and used mainly at the national level. On the other hand, firm-level studies that comprehensively considered factors influencing technological capabilities mainly use survey methods (Ortega, 2010; Zhou and Wu, 2010). However, it is also necessary to develop an indirect measure for technological capability by comprehensively considering the results of unconscious corporate behaviors. Because it is impossible to survey all firms due to various constraints.

Therefore, this study proposes a method of measuring a firm's technological capability through the multifaceted aspects of its technological knowledge. In this study, it is conceptualized that a firm's technological portfolio is composed of three dimensions: breadth, depth, and coherence. All three factors represent the characteristics of the technological portfolio that a firm has accumulated, and each represents the diversity of types of technologies possessed, the stock of core technologies possessed, and the average proximity between technologies that have comparative advantage compared to the entire industry. Several relevant literature studies with strong grounding support the fact that the three characteristics of a technological portfolio are related to a firm's technology capabilities and affect a firm's innovation performance and financial performance. The framework of this study is summarized in Figure 4-1.

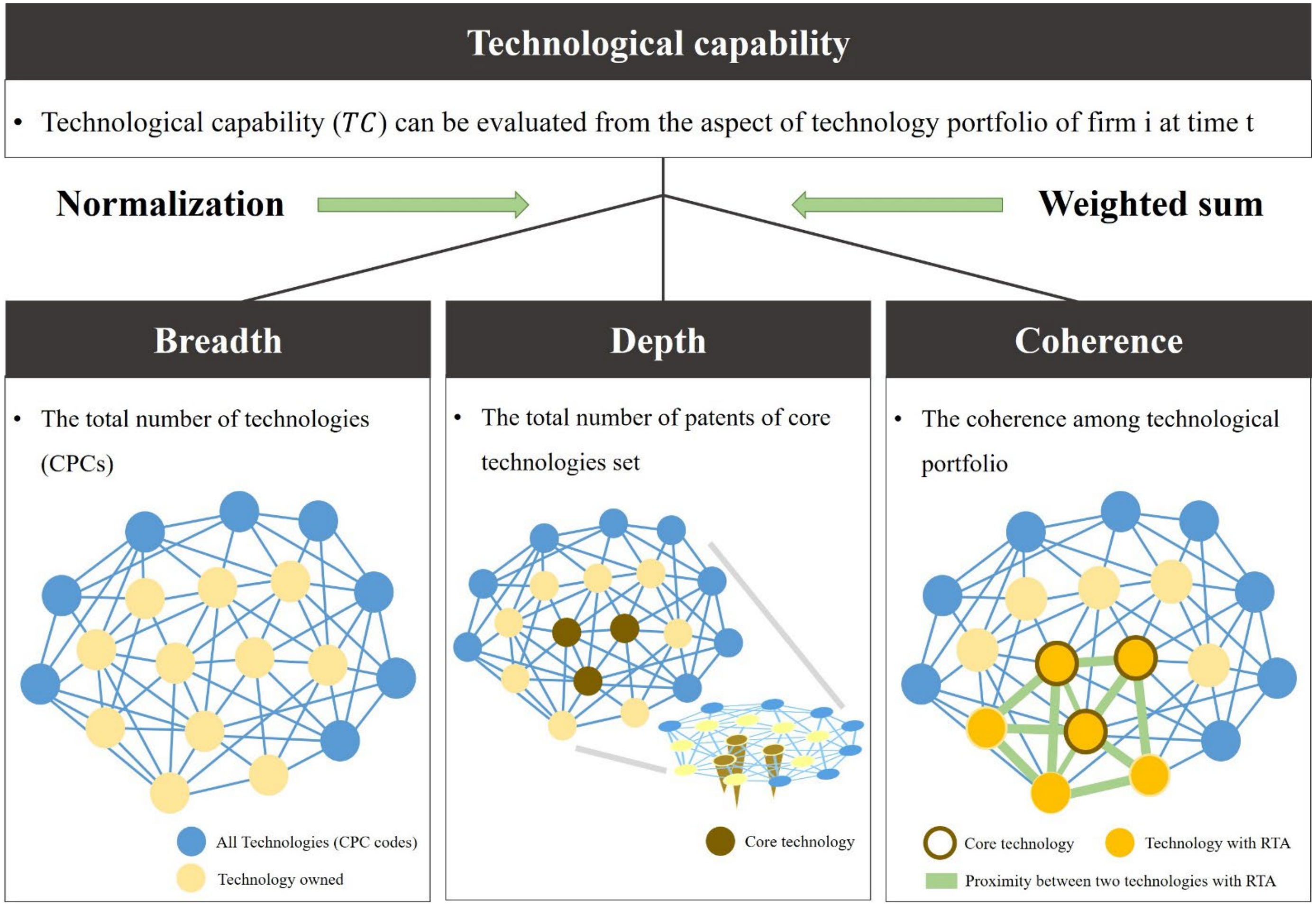

Figure 4-1. Framework for the research

4.2.2.1 Breadth of accumulated technological knowledge

The breadth of accumulated technological knowledge refers to the technological diversity in the horizontal dimension of a firm's technological portfolio (Zhou et al., 2012; Yao et al., 2021). Diversity of accumulated technological knowledge brings various benefits to a firm's innovation performance (George et al., 2008; Leiponen and Helfat, 2010; Zhou et al., 2012). As a result, most firms are investing in R&D to diversify their technological portfolios for the following reasons.

First, a firm's extensive accumulated technological knowledge provides the benefits of economies of scope. Panzar and Willing (1977; 1981) coined the term 'economies of scope' from the fact that combining two or more production lines in a firm is less expensive than producing them individually on each production line in a firm. This phenomenon is equally found at the level of technological knowledge possessed by firms. If the technological knowledge possessed by a firm is shared with other various technology and mutually complements each other, R&D costs can be reduced through mutual leverage (Miller, 2006). As a result, it enhances the synergy between various technologies (Granstrand, 1998; Kim et al., 2016).

Second, it helps firms increase absorb capacity. Diversity of knowledge increases absorptive capacity, allowing firms to make new combinations and connections (Cohen and Levinthal, 1990). This absorptive capacity provides firms with additional learning opportunities through partnerships (Zhang et al., 2007). Furthermore, high absorption capacity according to a firm's broad technological knowledge helps firms to achieve radical innovation by better sharing technology knowledge in various external and heterogeneous markets (Zhou et al. ., 2012).

Third, it reduces the risk of failure of additional R&D in new areas. Early stages of R&D are unlikely to lead to innovation. Thus, pursuing a larger number of goals increases the probability that at least one of them will result in a valuable innovation (Leiponen and Helfat, 2010). This is an interpretation consistent with Nelson's (1961) *parallelpath strategy*. In addition, firms judge alternatives 'heuristically' through their limited resources, which creates undue optimism (Tversky and Kahneman, 1974; Leiponen and Helfat, 2010). Since innovation is born through the recombination of knowledge, the risk of falling into the local optimum of undue optimism is reduced when more and more complementary technological knowledge is possessed (Kogut and Zander, 1992; Leiponen and Helfat, 1992). 2010). This gives firms the flexibility to adapt amid technological uncertainty (Pacheco-de-Almeida et al., 2008; Farazi et al., 2019; Yao et al., 2021).

4.2.2.2 Depth of accumulated technological knowledge

The depth of accumulated technological knowledge refers to the level of technological competence or complexity and sophistication of core technologies in the vertical dimension of a firm's technological portfolio (Bierly and Chakrabarti, 1996; Prahalad and Hamel, 2009; Zhou et al., 2012; Yao et al., 2021). Securing a deep understanding of specific technological knowledge brings various benefits to firms.

First, a firm's deep technological knowledge leads to a competitive advantage. This is because the deeper the technological depth, the more differentiated technological knowledge it may be difficult for other competitors to imitate. Expertise in a specific technology field contributes to securing firm professional specialty by activating the integration of related activities and helping to use them (Christensen, 2006).

Second, deep knowledge can improve efficiency. When firms have a thorough understanding of technology, they can use it more effectively and make their processes more efficient. A deep understanding of specific technological knowledge increases efficiency by helping firms to clearly understand how to optimize in the process of trials and error (Yao et al., 2021).

Third, depth of deep technological knowledge can promote innovation. A deep understanding of a technology can lead to significant innovation and progress, whereas a superficial understanding only enables incremental improvement (Christensen and Bower, 1996). Since the depth of technological knowledge is know-how accumulated through experience and trials and error through existing knowledge, the deeper the depth of expertise in core technologies, the more the acquisition of new related technology knowledge enables radical innovation beyond gradual improvement (Zhou et al., 2012).

4.2.2.3 Coherence of accumulated technological knowledge

Coherence between accumulated technological knowledge means the dimension of proximity between technologies within a technological portfolio. The average proximity between technologies with a comparative advantage brings various benefits to a firm as its value increases. First, high technology coherence generates innovation spillover. When innovation occurs in one technology field, technological coherence becomes a catalyst and promotes innovation in other related technology fields.

Second, high technology consistency increases the efficiency of R&D. The higher the proximity between technologies in which a firm has a comparative advantage, the easier it is to transfer and apply technological knowledge developed in one technology to other adjacent technology knowledge (Leten et al., 2007). This high degree of interconnectedness helps firms leverage the development of other technologies through specialization in one technology, which in turn allows firms to save on R&D costs.

Third, a firm with a coherent technological portfolio can more efficiently differentiate itself through comparative advantage within the market. If the technological knowledge possessed by a firm is inconsistently dispersed, the firm has difficulty in presenting a unique solution through the integration of technologies. Therefore, a consistent technological portfolio helps a firm secure its comparative advantage.

Fourth, a technological portfolio with high coherence between technologies reduces business risk. In an environment where the technology changes rapidly, it is difficult for firms to predict the rise and fall of a specific technology field. The management risk caused by a decline in one technology field can be mitigated by the consistency of the technological portfolio. This is because the decline of one technology classification can potentially be offset by the shift of resources to other technologies related to the declining technology field or the achievement and advances in the related technology classification.

4.3 Methodology

4.3.1 Data

Information about the applicant in the patent data is not uniquely identified. Even for the same applicant name, there are various variations. The reasons are come from i) different applicant names, ii) spelling mistakes, and iii) bewildering array of difficult-to-understand abbreviations, etc. In addition, for patent applications in the name of a firm, reasons such as iv) when a unified firm name is not used, v) when the firm name is changed due to restructuring such as M&A or spin off, vi) when the firm name is changed intentionally are added. For these various reasons, the process of matching patents owned by a firm with an owner cannot always be accurate. Accordingly, various efforts have been made since the early 2000s.

In addition to efforts of Hall et al. (2001), Bessen (2006), Arora et al. (2020, 2021) to match the PATSTAT (Worldwide Patent Statistical Database) with Compustat, the financial information of US firms (already mentioned at Section 3.3.1), there are numerous studies that match patents and financial information of firms in various countries. First, as an effort to match European firms, Thoma et al. (2007) matched patent applicants provided by PATSTAT with Amadeus accounting and financial information provided by Bureau van Dijk/Moody's Analytics for European listed firms. Later, Thomas et al. (2010) matches all applicant names of United States Patent and Trademark Office (hereafter, USPTO) patents, international patents under the Patent Cooperation Treaty, and European Patent Office (hereinafter referred to as EPO) patents from 1979 to 2008 with the firm name of Amadeus, which expands the scope of work done by Thoma et al. (2007). Alkemade et al. (2015) matched the 2,289 firm names provided by ORBIS with the applicants of 712,333 multinational patents (between 1993 and 2005) of the firms filed in at least two countries in PATSTAT to build a unique dataset called the Corporate Invention Board (CIB).

There are also attempts to match applicants using patent data other than PATSTAT. He et al. (2018) carried out matching of listed Chinese firms at the Shanghai Stock Exchange or Shenzhen Stock Exchange with the firm's applicant names for 191,325 patents filed between 1990 and 2010 provided by the State Intellectual Property Office (SIPO) in China. As a study of disambiguating Korean patent data, Kim et al. (2016) matched firm patent information provided by Korea Institute of Patent Information with firm financial information provided by Korea Information Service. As another Korean patent study, Lee et al. (2019) first collected all patents filed at the Korean Intellectual Property Office (hereafter, KIPO) during the period 1948-2016 and all patents filed and registered at the USPTO by applicants and inventors located in Korea during the period 1976-2016. Afterwards, i) Corporation number from DataGuide 5.0 provided by F&Guide, ii) Corporate registration number and applicant code provided by the KIPO, and iii) USPTO applicant information were matched through web crawling and string algorithms.

The OECD matches applicant names that exist in various forms in PATSTAT into unified one, then creates a matching dictionary and provides it twice a year under the name of HAN (Harmonized Applicants Names) database.[26]. In the HAN database, the applicant's name was first cleared through its own text-matching algorithms, and then a unique number, HAN-ID, was assigned to the standardized applicant's name. This HAN-ID works in conjunction with PATSTAT to save researchers the trouble of directly matching applicant names.

However, HAN-ID also has various kinds of mismatches and errors, and there is a problem that it cannot track when a firm's name is changed. To overcome these limitations, Kang et al. (2019) corrected errors in HAN database that did not recognize listed firms belonging to the Korean manufacturing sector as the same firm, and additionally performed a clarification process to track all changed firm name information and recognize them as the same firm. Referring to this work, Kim et al. (2022; 2023), Jun et al. (2023) also independently corrects and supplements the applicant's name of Korea manufacturing firms in the HAN database. And using the HAN database as a bridge, a unique unbalanced panel dataset was built by linking PATSTAT and KIS-value provided by National Information & Credit Evaluation Inc., which is the financial data of firms subject to external audit in all industries.

Following Kang et al. (2019), Kim et al. (2022; 2023) and Jun et al. (2023), this chapter combines financial information and patent information of firms belonging to the 'Manufacture of electronic components, computer, radio, television and communication

[26] Like PATSTAT, it is released twice a year. However, since the result of matching the applicant's name is provided, the HAN database can always be used 6 months after PATSTAT. For example, the HAN database linked with PATSTAT published in the spring of 2018 will be the version published in the fall of 2018.

equipment and apparatuses' industry (based on the 9th KSIC code)' in Korea. Thus, unique panel data was constructed. KIS-value data provides financial information (based on when the search was made) of external audited firms in Korea. As of 2022, a total of 1197 firms (286 listed firms and 911 unlisted firms)[27] subject to external audited were investigated within 'Manufacture of electronic components, computer, radio, television and communication equipment and apparatuses' industry.

We matched KIS-ID, a unique code assigned by KIS-value, with Han-ID provided by OECD HAN Database (Spring 2018 edition) for 1197 firms. Although the OECD HAN Database is the result of a disambiguation work through its own text matching algorithm, problems such as firm name changes, mismatches, and errors due to different nuances for each language still remain as mentioned earlier. In this chapter, HAN-ID, which still exists in various forms, is unified into one, and all firm name information changed after the firm enters the market is tracked so that it is recognized as the same firm. As a result, the number of matched KIS-value and HAN Database firms was 954.

Since HAN-ID is linked to the applicant ID of PATSTAT, we used the OECD HAN Database as a bridge and finally performed matching between PATSTAT and KIS-value. The PATSTAT database (Autumn 2017 edition), which provides information on filed

[27] There are three main types of listed markets in Korea. First, the Korea Composite Stock Price Index (KOSPI) is No. 1 stock market, where stocks centered on large corporations are traded in Korea. Next is the Korea Securities Dealers Automated Quotation (KOSDAQ), modeled after the NASDAQ market in the US, where transactions are conducted centering on promising small and medium-sized enterprises and venture companies based on cutting-edge technology. The last is Korea New Exchange (KONEX) market, which is located in the pre-KOSDAQ stage, and is a dedicated stock market for SMEs in the early stages of startups. Since the data in this chapter is for all firms included in each of the three types of stock markets, it can be seen as including all firms of various sizes among listed firms.

patents around the world, provides comprehensive bibliographical information such as applicants and filing dates for each patent, as well as Cooperative Patent Classification (hereafter, CPC) codes assigned to each patent, citation information, and abstracts. A total of 845 firms (of which 275 were listed and 670 were unlisted) matched by KIS-value and PATSTAT were investigated.

We analyzed the period from 1999 to 2015 in order to match the analysis target period of the constructed unbalanced panel data as closely as possible to the balanced panel data and to eliminate the effect of economic shocks experienced differently depending on business tenure. Korea has experienced a total of four economic shocks: Asian financial crisis that started in 1998, the IT bubble burst in 2004, the Global financial crisis that started in 2008, and the pandemic caused by Covid-19 that started in 2020. Firms that entered the market after 1999 shared and experienced the same economic shock of the Asian financial crisis that broke out in 1998. The collapse of the IT bubble in 2004 had a lesser impact on firms in manufacturing sector. Korea recovered relatively quickly from the Global financial crisis. The impact of the pandemic experienced from 2020 is irrelevant since it was before 2017 when patent information of our dataset was provided. Figure 4-2 is a graph comparing the patents of all manufacturing firms in Korea (red and green lines) and the unique patent dataset (blue line) used in this study. It can be seen that the fluctuation due to the economic shock is greatly smoothed by year compared to the patents of the entire manufacturing firm.

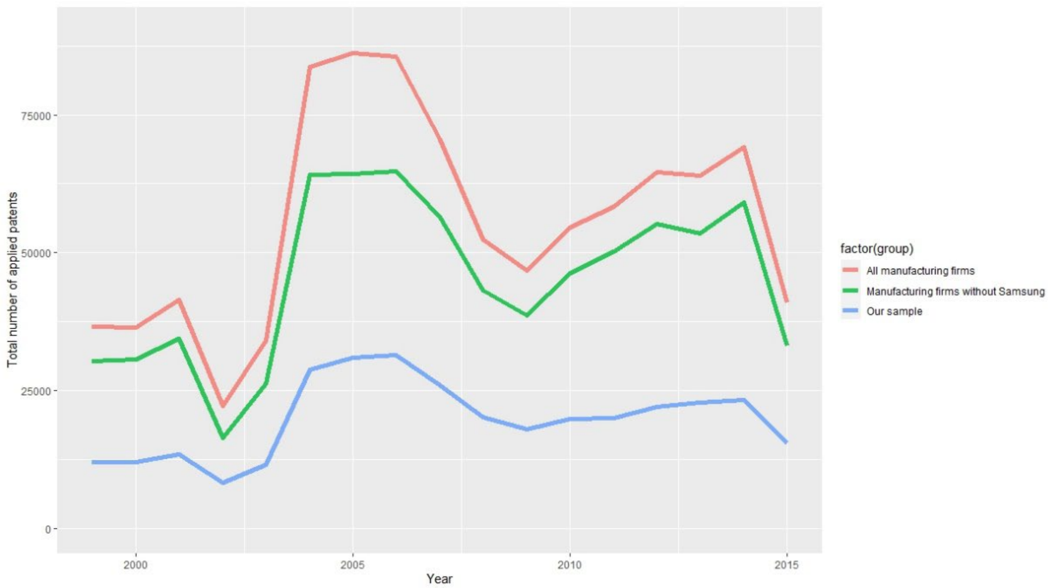

Figure 4-2. Total number of applied patents (Source: Unique dataset)

It was finally analyzed until 2015 according to the truncation of the patent. The date of establishment of the firm was calculated from the year it became subject to external audit, and among them, firms that had been operating for more than 10 years were selected. Among a total of 415 firms (125 listed firms, 290 unlisted firms) subject to external audit, LG Electronics, which was founded in 1958 under the name of 'Goldstar' and became independent and listed in 2002 (4 years of business as of 1998) was excluded. A total of 414 firms were the subject of analysis.

The technology stock held by the firm is 4 digit CPC code of patents filed in patent offices located at countries in Europe, the KIPO, the USPTO, and the EPO. The period during which the stock of technological knowledge accumulated within the firm exists was determined from the filing year t to t+10 years. This is based on a study by Hall et al. (2001) that 50% of the total number of citations in a patent is made in the 10 years after the application for a patent.

4.3.2 Measurement: Technological capability

As found in the literature review, aspects of a technological portfolio, including the breadth, depth, and coherence of technological knowledge, are closely related to a firm's technological capabilities. Therefore, we can indirectly measure a firm's technological capabilities by simultaneously considering the multifaceted aspects of its technological portfolio. The technology capability ($TC_{i,t}$) of firm *i* at time *t* is determined by the boundary including the breadth and depth of the technological portfolio and the coherence between the constituent technologies. This can be written as a following functional expression:

$$TC_{i,t} = f(breadth_{i,t}, depth_{i,t}, coherence_{i,t}) \quad \cdots\cdots\cdots\cdots\cdots \text{Eq. (4.1)}$$

However, the effects of breadth, depth, and coherence on a firm's technological capabilities could be different. Therefore, this study proposes the following equation.

$$TC_{i,t} = \sqrt{\alpha * breadth_{i,t}^2 + \beta * depth_{i,t}^2 + \gamma * coherence_{i,t}^2}$$

$$(\text{where,} \quad \alpha + \beta + \gamma = 1 \ )\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots \text{Eq. (4.2)}$$

The technology capability ($TC_{i,t}$) of firm i in time t proposed in this study is, after all, a scalar value (in other words, magnitude of vector) of the breadth, depth, and coherence of the technological portfolio. This value helps confirm the relative position of firms according to the factor value of $TC_{i,t}$ in the space where the breadth, depth, and coherence are the x, y, and z axes. In addition, it is easy to expand if other factors that can affect the technological capabilities of a firm are added, in addition to the three factors of accumulated technological knowledge considered in this study.

First, the breadth of the technological portfolio ($breadth_{i,t}$) means the degree of diversification of the technologies accumulated by firm i in time t. The breadth of technological knowledge is measured by the number of CPC codes to which a firm's patents belong in year t. It was standardized to [0, 10] for all firms in the industry by year.

Next, the depth of the technological portfolio ($depth_{i,t}$) means the degree of specialization of the core technology accumulated by firm i in time t. First, the core technology was selected as the top 3 technologies with the largest number of patents among technologies with a Revealed Technological Advantage (hereafter, RTA) greater than 0.5 for 3 consecutive years.[28] The formula for calculating RTA is shown at Equation 4.3.

[28] Even if it is 50% compared to the industry average, it is judged that there is a RTA in the technology if it has been consistently maintained this status for 3 consecutive years. Usually, studies are conducted with the RTA set to 1, but in this chapter, 0.5 was used as a criterion because the RTA value was not used as it is. Because the criterion of $RTA = 0.5$ used only means whether to judge as a core technology or not, and the capability of the core technology is finally judged by the number of patents. The fact that the RTA of a technology within a firm is greater than 0.5 for *t-1*, *t*, and *t+1* consecutive years means that the technology was not developed in a flash in one year, but was continuously secured and possessed by the firm.

$$RTA_{i,\alpha,t} = \frac{P_{i,\alpha,t}}{\sum_\alpha P_{i,\alpha,t}} \bigg/ \frac{\sum_i P_{i,\alpha,t}}{\sum_i \sum_\alpha P_{i,\alpha,t}} \qquad \text{Eq. (4.3)}$$

$P_{i,\alpha,t}$ is the number of technology α possessed by firm i in time t, and RTA_α is a binary variable that becomes 1 if it is greater than 0.5 and 0 if less than 0.5.

The reason for considering the number of patents for the technology, after selecting a core technology based on RTA, is as follows. In the case of simply adding the number of patents in the top three technologies possessed by each firm, the criterion for determining a firm's core technology is the result of the absolute value of each firm. In this case, it is difficult to determine how competitive the technologies judged as core technologies for each firm are compared to other firms. Therefore, in order to compare the technological capabilities of each firm, it is necessary to consider how much comparative advantage each technology classification has relative to the entire industry before considering the number of patents owned by the firm. If there is no technology with an RTA greater than 0.5, the depth ($depth_{i,t}$) is set to 0. After obtaining the combined number of patents for core technologies, it was standardized to [0,10] for all firms in the industry by year.

Lastly, the coherence of the technological portfolio ($coherence_{i,t}$) was calculated through *Coherent Technological Diversification (CTD)* developed by Pugliese et al., (2019). $coherence_{i,t}$ means the average of the sum of proximity connected by all technologies possessed by a firm. Expressed as an equation, it is:

$$coherence_{i,t}(\Gamma_{i,t}) = {\sum_{\alpha} M_{i,\alpha}\, \gamma_{i,\alpha}}\Big/{d_i} \quad \cdots\cdots\cdots\cdots\cdots\cdots\cdots \text{Eq. (4.4)}$$

Here, $M_{i,\alpha}$ is a binary matrix expressed as 1 if firm *i* has a comparative advantage in technology α and *0* if it does not. $\gamma_{i,\alpha}$ is $\sum_{\alpha} \phi_{\alpha,\beta}\, M_{i,\beta}$, which is the sum of proximity between technology α and other technologies (β) (in which firm i has a comparative advantage) connected to α. Proximity ($\phi_{\alpha,\beta}$) was calculated through the following equation (Hidalgo et al., 2007).

$$\varphi_{\alpha,\beta} = \min\{\Pr\left(RTA_{\alpha} \middle| RTA_{\beta}\right), \Pr(RTA_{\beta}|RTA_{\alpha})\} \quad \cdots\cdots\cdots\cdots\cdots \text{Eq. (4.5)}$$

d_i is $\sum_{\alpha} M_{i,\alpha}$, which means the number of technologies in which the firm has a comparative advantage. For $coherence_{i,t}$, a standardized value of [0,10] was also used. The method for calculating the $coherence_{i,t}$ of the technological portfolio can be checked with an example in Appendix 3.

First, it is identified whether breadth, depth, and coherence, which correspond to the aspects of technological knowledge, are factors that affect the technological capability of the firm, and the weights α, β and γ used in Equation (4.2) are calculated. The following regression model was set up to determine the weight value.

$$numPatent_{i,t+2}^{2} = \beta_0 + \beta_1 * Breadth^2{}_{it} + \beta_2 * Depth_{i,t}^{2} + \beta_3 Coherence^2{}_{it}$$
$$+\beta_4 * numPatents_{i,t} + \beta_5 Size_{i,t} + \beta_5 Profit\,ratio_{i,t} + \beta_6 Debt\,ratio_{i,t}$$
$$+year_t + \mu_i + \epsilon_{i,t} \quad \cdots\cdots \text{Eq. (4.6)}$$

The firm's stock of technological knowledge, represented by the number of patents ($numPatent_{i,t}$), was selected as a proxy indicator of technological capability. The number of patents is an indicator that has been mainly used to indirectly measure technological capabilities (DeCarolis and Deeds, 1999; Tsai, 2004). In order to control for potential endogeneity between the aspects of the technological portfolio and the technological knowledge stock, and to confirm causality, the number of patents two years later was investigated. $Patents_{i,t}$, a control variable, means the number of patents filed by firm i in year *t*. $Size_{i,t}$ is the size of firm *i* in year *t*, measured through the number of employees. $Profit\,ratio_{i,t}$ and $Debt\,ratio_{i,t}$ are values that measure the soundness of a firm's financial structure, and mean the sales ratio and debt ratio, respectively. The $Profit\,ratio_{i,t}$ was calculated as net profit/sales, and the $Debt\,ratio_{i,t}$ was calculated as total liability/total asset. $year_t$ is the year fixed effect (since the data is in a form close to the balanced panel data, it can be regarded as the firm's tenure), μ_i is the firm fixed effect, and $\epsilon_{i,t}$ is the error term. The basic statistics of the variables used in the regression and the correlation between variables are as follows.

Table 4-2. Descriptive statistics and correlations

Statistic	N	Mean	St. Dev.	1	2	3	4	5	6	7
1. $normalized\_Breadth_{i,t}$	2,311	0.558	2.144	1						
2. $normalized\_Depth_{i,t}$	2,311	0.060	0.467	0.296	1					
3. $normalized\_Coherence_{i,t}$	2,311	28.154	18.069	0.150	0.100	1				
4. $num\_Patent_{i,t}$	2,311	−0.000	4.075	0.218	0.136	-0.032	1			
5. $Labor_{i,t}$	2,311	0.000	1.039	0.164	0.119	0.138	0.148	1		
6. $Profit\_ratio_{i,t}$	2,311	0.000	127.110	-0.058	-0.054	-0.030	0.013	-0.007	1	
7. $Debt\_ratio_{i,t}$	2,311	−0.000	24.564	0.044	-0.046	-0.057	-0.074	-0.021	-0.390	1

Table 4-3. The effects of breadth, depth and coherence on technological capability

	Dependent variable: $num\_Patent^2_{i,t+2}$				
	(1)	(2)	(3)	(4)	(5)
$normalized\_Breadth^2_{i,t}$	0.129***			0.117***	0.089***
	(0.011)			(0.011)	(0.011)
$normalized\_Depth^2_{i,t}$		0.215***		0.102**	0.086**
		(0.044)		(0.044)	(0.042)
$normalized\_Coherence^2_{i,t}$			0.009***	0.007***	0.011***
			(0.002)	(0.002)	(0.001)
$num\_Patent_{i,t}$					0.068***
					(0.005)
$Labor_{i,t}$					0.271***
					(0.043)
$Profit\_ratio_{i,t}$					0.0001
					(0.0002)
$Debt\_ratio_{i,t}$					0.003**
					(0.001)
Firm fixed effect	*YES*	*YES*	*YES*	*YES*	*YES*
Observations	2,311	2,311	2,311	2,311	2,311
R^2	0.897	0.891	0.891	0.898	0.908
Adjusted R^2	0.880	0.873	0.874	0.882	0.893
Residual Std. Error	0.830 (df = 1996)	0.854 (df = 1996)	0.852 (df = 1996)	0.825 (df = 1994)	0.786 (df = 1990)
Note:					*p<0.1; **p<0.05; ***p<0.01

The results of the OLS regression analysis are shown in Table 4-3. It was confirmed that the breadth, depth, and coherence of technological knowledge within a firm had a positive and significant effect on a firm's technological capability. The high R^2 value in Table 4-3 means that each factor has a high explanatory power for technological capability, which is the basis for the argument that all three factors related to the aspect of technological knowledge should be considered when measuring technological capability. The weight was set to (α, β, γ) = (0.48, 0.46, 0.06) proportional to normalized regression coefficients (β_1, β_2, β_3) = (0.089, 0.086, 0.011) in Table 4-3. Equation 4.2 finally becomes:

$$TC_{i,t} = \sqrt{0.48 * breadth_{i,t}^2 + 0.46 * depth_{i,t}^2 + 0.06 * coherence_{i,t}^2} \quad \cdots\cdots \text{Eq. (4.7)}$$

4.3.3 Empirical Model

In order to confirm the explanatory power of the firm's technological capabilities ($TC_{i,t}$), regression analyzes were performed on two different types of dependent variables.

$$SalesGrowth_{i,t+2} = \beta_0 + \beta_1 TC_{it} + \beta_2 TC_{it}^2 + \beta_3 numPatents_{i,t} + \beta_4 Size_{i,t} + \beta_5 Profit\,ratio_{i,t} + \beta_6 Debt\,ratio_{i,t} + \beta_7 year_t + \mu_i + \epsilon_{i,t} \quad \cdots\cdots \text{Eq. (4.8)}$$

$$PatentGrowth_{i,t+2} = \beta_0 + \beta_1 TC_{it} + \beta_2 TC_{it}^2 + \beta_3 numPatents_{i,t} + \beta_4 Size_{i,t} + \beta_5 Profit\,ratio_{i,t} + \beta_6 Debt\,ratio_{i,t} + \beta_7 year_t + \mu_i + \epsilon_{i,t} \quad \cdots\cdots \text{Eq. (4.9)}$$

TC_{it} denotes the technological capability of firm i, in time t, obtained through Equation (4.7) above. The firm's financial performance ($SalesGrowth_{i,t+2}$) is the log difference of firm's sales between period t and $t+2$, and the firm's innovation performance ($PatentGrowth_{i,t+2}$) was obtained through the log difference of the number of patents between period t and period $t+2$. Each independent variable was calculated as follows according to the methodology suggested by Kang et al, (2019).

$$Growth\ \ of\ \ x_{i,t} = (\ln x_{i,t} - \ln \overline{x_{i,t-2}}) \quad \cdots\cdots \text{Eq. (4.10)}$$

where ($\overline{x_{i,t-2}}$) is the average of the x values (sales or number of patents) of firm i for 3 years of t-1, t-2, and t-3 ($(x_{i,t-1} + x_{i,t-2} + x_{i,t-3})/3$). Sales tend to be overestimated, and there is a disadvantage in that the value changes rapidly due to M&A, etc. (Kang et al., 2019). Therefore, we tried to minimize volatility by taking the average of the three years. There is no room for the number of patents to be overestimated, but since it is difficult to observe steadily and has a sparse data structure, variability was also minimized through a 3-year average.

The dataset of this study is targeted at firms that started operation after 1999 and continued their business for more than 10 years until 2015, and thus constitutes a structure of unbalanced panel data close to balance. As a result, a high correlation was observed between firm tenure (age_t) and year ($year_t$), The year ($year_t$), a categorical variable, was controlled except for the firm's tenure (age_t). Other control variables are the same as those used in Section 4.3.2 above. All variables were adjusted for distribution skewness through Box-Cox transformation (Box and Cox, 1964) after Min-Max normalization.

First, the basic statistics of the independent variables used in Equation (4.8) and Equation (4.9) and the correlation between variables are shown in Table 4-4. Although the correlation between $Debt\,ratio_{i,t}$ and $size_{i,t}$ was measured high, the VIF test result recorded a low value close to 1. Therefore, all variables were considered together in this regression model.

Table 4-4. Descriptive statistics and correlations for the main analysis

Statistic	N	Mean	St. Dev.	$TC_{i,t}$	$num\_Patents_{i,t}$	$Size_{i,t}$	$Profit\_ratio_{i,t}$	$Debt\_ratio_{i,t}$
$TC_{i,t}$	3,051	0.817	0.402	1				
$num\_Patents_{i,t}$	3,051	0.000	2.874	0.095	1			
$Size_{i,t}$	3,051	0.000	1.356	0.031	0.072	1		
$Profit\_ratio_{i,t}$	3,051	0.000	0.136	0.022	0.038	0.194	1	
$Debt\_ratio_{i,t}$	3,051	0.000	1.275	0.009	0.023	0.890	0.116	1

4.4 Empirical Results

4.4.1 Dynamic changes of technological capability

4.4.1.1 Comparison with other measurement

First, the validity of the devised technological capability (TC_{it}) measurement was verified by statistically checking how related with the other proxy used to measure technological capability. A representative value used as a proxy for technological capability

(TC_{it}) is the number of applied patents owned by a firm ($numPatent_{i,t}$) (DeCarolis and Deeds, 1999; Tsai, 2004), and this was also set up as a comparison in this study. Figure 4-3 shows the time-series graph of the average technology capability (TC_{it}) and the time-series graph of the average number of patent applications per firms ($numPatent_{i,t}$) by year.

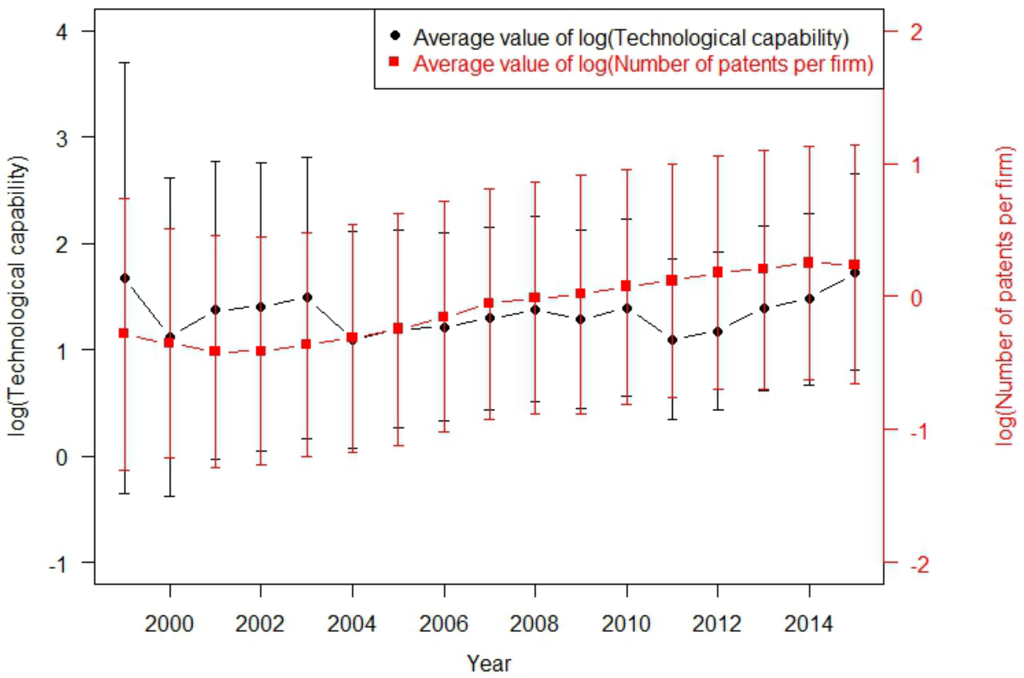

Figure 4-3. Time series of average technological capability (black) and the number of patents per firm (red) (Source: Unique dataset)

To confirm whether the two time series data were statistically stationary, a unit-root test was first performed. This is because, in the case of non-stationary time series data, a spurious regression problem arises in which a very strong relationship appears even though there is no correlation between the two data. After log processing, an Augmented Dickey-Fuller (ADF) test was performed on the level of each of the two time series that did not take the difference. The time series graph of technological capability (TC_{it}) did not show a clear trend of increasing over time, so the constant and trend were not included in the unit root test. On the other hand, in the time series graph of the average number of patents filed by firms ($numPatent_{i,t}$), a clear trend of increasing over time was observed, so a unit root test including the trend was performed. As a result of the test, both the t-value of the technological capability (TC_{it}) and the average number of applied patents held by the firm ($numPatent_{i,t}$) were smaller than the critical value of 5%, and as a result, It rejects the null hypothesis that the unit root exists.

After confirming that both time series are stationary, I(0) in which the unit root does not exist, the correlation between the two different time series was investigated through the cross correlation coefficient and leads and lags correlation. The cross correlation (if $k = 0$) and the lag correlation coefficient (if $k \neq 0$) indicates the degree of correlation between the time series data observed at time t (x_t) and the other time series data observed at time $t + k$ (y_{t+k}). With x_t as the average value of technological capability (TC_{it}) and y_{t+k} as the average number of patents owned by the firm ($numPatent_{i,t+k}$). As shown in Figure 4-4 below, A significant positive correlation of 0.496 and 0.501 was observed only in $k = 0$ or $k = 1$ in [-9,9], respectively. In other words, technological capability (TC_{it}) is covariant with the average number of patents owned by a firm in the same year

($numPatent_{i,t}$) and the average number of patents owned by a firm one year later ($numPatent_{i,t+1}$). Through the previous analysis, it was confirmed that the technological capability (TC_{it}) measurement is a valid indicator that is not significantly different from the average number of patents owned by firm ($numPatent_{i,t}$), which is a proxy indicator of technological capability that was previously used.

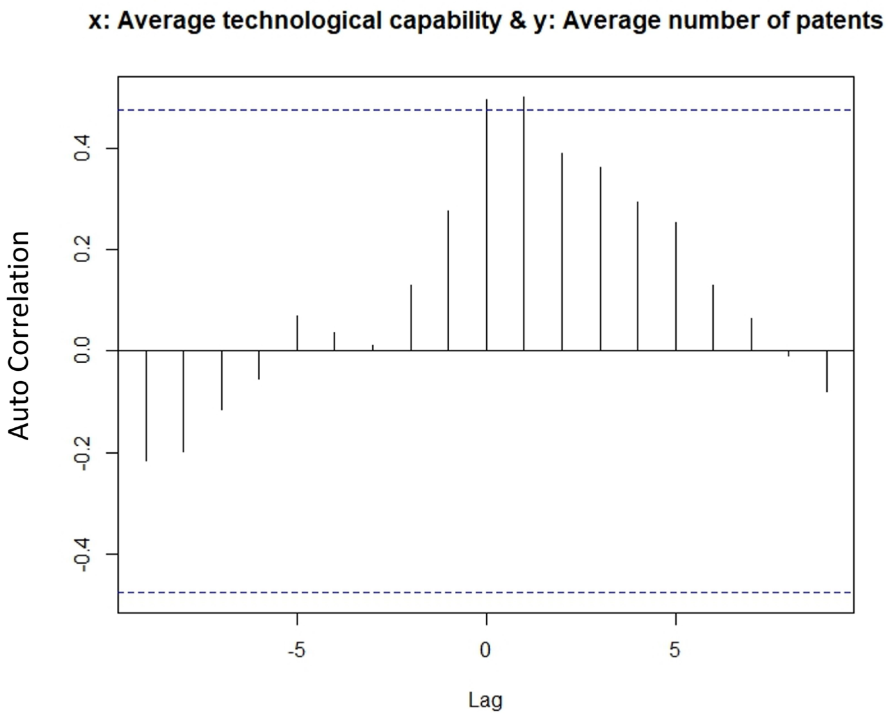

Figure 4-4. Result of Auto Correlation Function (ACF) between Average technological capability & Average number of patents per firm with various time lag, [-9,9]

4.4.1.2 Components of technological capability

Next, after drawing a scatter plot of all firms in the space composed of $(x, y, z) =$

$(breadth_{i,t}, depth_{i,t}, coherence_{i,t})$, We checked how the distribution of the scatterplot changes according to time. The advantage of displaying firms in space is that we can see the relative position of a particular firm. In particular, by identifying which factors ($breadth$, $depth$, $coherence$) are relatively lacking compared to the entire industry, firms can establish the following strategies for accumulating technological knowledge.

In this section, it was confirmed how the distribution of values ($breadth$, $depth$, $coherence$) across the industry changes over time. The values of each element were log-processed after standardization, and are values before weights $(\alpha, \beta, \gamma) = (0.48, 0.46, 0.06)$ were reflected.

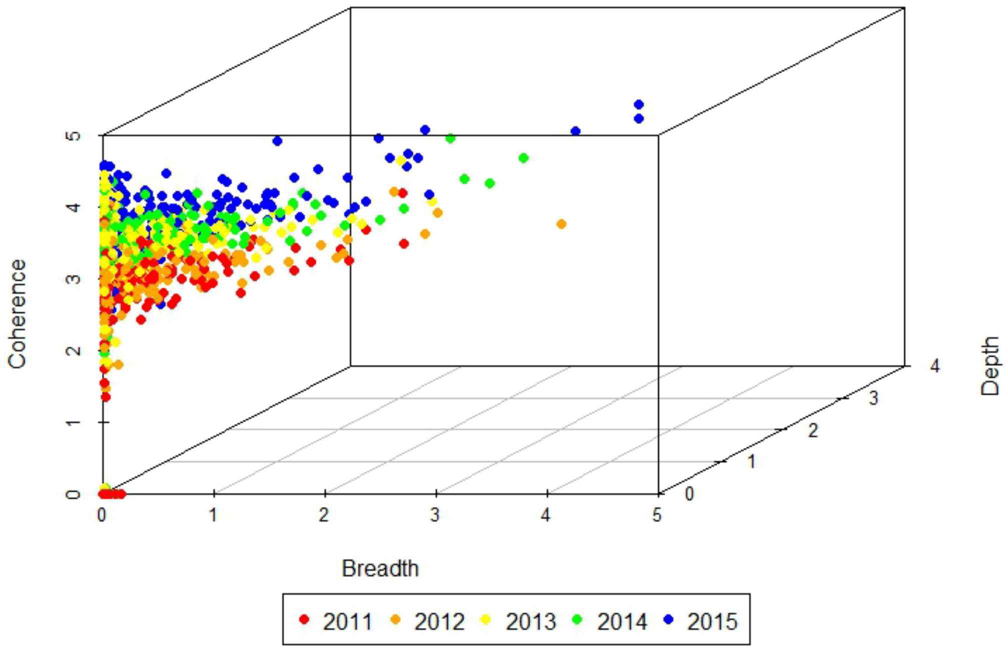

Figure 4-5. The Scatter plot of (breadth, depth, coherence) value of the firm (2011-2015)

The results in Figure 4-5 show the overall trend of how the ($breadth_{i,t}, depth_{i,t}, coherence_{i,t}$) values of firms' technological portfolios have changed over the past five years (representatively, the changes of the last five years from 2011 to 2015 are shown in Figure 4-5). Over time, the technological portfolios of all firms tended to increase in their breadth, depth, and coherence.

Table 4-5. The industrial average of (breadth, depth, coherence) value (2011-2015)

Year	Number of Samples	Mean log(breadth)	Mean log(depth)	Mean log(coherence)
2007	150	0.1924 (0.3660)	0.0105 (0.0316)	2.8788 (1.3676)
2008	175	0.2045 (0.3702)	0.0156 (0.0499)	3.0491 (1.3597)
2009	196	0.2305 (0.4001)	0.0346 (0.2180)	2.9758 (1.2686)
2010	205	0.2607 (0.4398)	0.0368 (0.2020)	3.0711 (1.3024)
2011	206	0.2841 (0.4492)	0.0401 (0.1769)	2.5057 (1.1735)
2012	219	0.3338 (0.5351)	0.0467 (0.1833)	2.7721 (0.9969)
2013	231	0.2993 (0.4548)	0.0395 (0.1685)	3.1316 (1.0554)
2014	236	0.3538 (0.5363)	0.0714 (0.2767)	3.2024 (1.1271)
2015	238	0.4410 (0.6106)	0.1692 (0.4866)	3.5117 (1.0411)

Table 4-5 shows the average values of breadth, depth, and coherence by year. The standard deviation is indicated in parentheses. Since each element is a normalized value through Min-Max Scaling, a large average value means that there are many firms that are similar to the firm that recorded the largest value for each breadth, depth, and coherence.

The average breadth, average depth, and average coherence of technological portfolios of firms in Korea's 'electronic components, computer, radio, television and communication equipment and apparatuses' industries continued to increase. In 2013, a period of decrease in both average breadth and average depth is found, but the average coherence increases the second largest (after 2010-2011). In particular, it is interesting to note that firms in Korea's 'electronic components, computer, radio, television and communication equipment and apparatuses' industries have developed in the direction of increasing the depth of core technologies of technological knowledge. The average depth of core technologies of firms in 2015 increased by about 16 times compared to 2007.

4.4.2 Technological capability and financial performance

In this section, we investigate the effect of the technology capability (TC_{it}) on a firm's financial performance. Two types of performance were identified: short-term performance ($SalesGrowth_{i,t+2}$), which calculated the rate of increase in sales after 2 years, and long-term performance ($SalesGrowth_{i,t+5}$) with sales after 5 years. The sample used to investigate long-term performance was limited to the period from 1999 to 2011, taking into account the period provided by the patent data (exists until 2017) and the truncation problem (analyzable until 2015).

The results of the OLS regression analysis of Equation (4.8) are shown in Table 4-6 below. Models (1) and (5) are the results of only examining the effect of TC_{it} and the square term of TC_{it} (TC_{it}^2), which are the key independent variables of this study, and Models (2) and (6) control the firm fixed effect (μ_i) from Models (1) and (5). In Models (3) and (7), control variables were added without firm fixed effects, and in Models (4) and (8), all control variables including firm fixed effects were also examined.

No statistically significant effect of a firm's technological capability (TC_{it}) on its short-term financial performance ($SalesGrowth_{i,t+2}$) was observed. On the other hand, a statistically significant effect of technology capability (TC_{it}) on long-term financial performance ($SalesGrowth_{i,t+5}$) was observed in models (6) and (8), which reflects firm fixed effects. This means that a period of two years is short for the technological capability (TC_{it}) accumulated by a firm to affect the firm's sales increase.

Table 4-6. The effects of technological capability on the financial performance of the firm

	Dependent variable:							
	$Sales\_Growth_{i,t+2}$				$Sales\_Growth_{i,t+5}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$TC_{i,t}$	6.549	−0.588	1.854	−2.187	−5.391	13.377*	5.010	14.989*
	(4.787)	(6.866)	(4.660)	(6.609)	(5.924)	(7.994)	(5.688)	(7.744)
$TC^2_{i,t}$	−6.690**	−1.504	−3.628	−0.636	1.033	−5.915**	−1.948	−6.070**
	(2.993)	(4.430)	(2.922)	(4.228)	(1.813)	(2.646)	(1.740)	(2.536)
$num\_Patents_{i,t}$			0.841***	0.294			1.452***	0.455
			(0.246)	(0.305)			(0.511)	(0.517)
$Size_{i,t}$			−1.717*	−6.993***			−6.678***	−8.371***
			(0.930)	(1.447)			(0.877)	(1.238)
$Profit\_ratio_{i,t}$			34.123***	10.621			0.001	−0.079***
			(7.251)	(8.029)			(0.025)	(0.023)
$Debt\_ratio_{i,t}$			24.684***	42.606***			1.065	3.354***
			(2.392)	(3.350)			(0.731)	(0.917)
Constant	7.735		28.354***		191.885***		158.180***	
	(7.816)		(7.827)		(28.317)		(26.918)	
Firm fixed effect	*No*	*Yes*	*No*	*Yes*	*No*	*Yes*	*No*	*Yes*
Observations	3,051	3,051	3,051	3,051	1,434	1,434	1,434	1,434
R^2	0.080	0.238	0.153	0.311	0.143	0.597	0.235	0.634
Adjusted R^2	0.074	0.145	0.146	0.226	0.135	0.505	0.226	0.548

Note: *p<0.1; **p<0.05; ***p<0.01

In the model (6) that observed only the effect of technology capability (TC_{it}) by applying firm fixed effects and the model (8) that added a control variable, we found that a statistically significant inverted U-shaped relationship between technology capability (TC_{it}) and long-term financial performance ($SalesGrowth_{i,t+5}$) was confirmed. In particular, compared to the models (5) and (7) where statistical significance was not observed, the R^2 values of the statistically significant models (6) and (8) were more than twice as high. This means that the explanatory power of technology capability (TC_{it}) varies greatly depending on the idiosyncratic features of firms that do not change over time, and as a result, must be controlled.

As the firm's technological capability (TC_{it}) increases, the firm's long-term financial performance increases (Based on model (8), it reaches a maximum when TC_{it} is 1.2347). But when the technological capability (TC_{it}) increases beyond a certain level (TC_{it} is 2.4694 or more) the firm's financial performance begins to decline rapidly again. This is a phenomenon that occurs because the cost becomes larger than the financial benefit due to the increase in firm technological capability (TC_{it}) from a certain point in time. The increase in technological capability (TC_{it}) is an act that entails costs. First, the additional increase in the breadth, depth, and coherence of technological knowledge within a firm requires hiring R&D labor force in new fields, providing more in-depth technological knowledge and skill training to existing R&D employees, and active exchange between R&D personnel. (Allen et al., 2007; Kim and Lee, 2022). Next, the further increase in a firm's technological capabilities (TC_{it}) requires the input and redeployment of additional managerial resources (Penrose, 2009). This is because a firm's R&D activities need to continuously invest additional resources and redeploy existing resources in order to expand the scope of R&D activities toward unknown areas in terms of breadth and depth, and to increase coherence between newly added technologies and existing technologies. As a result, excessive technological capabilities (TC_{it}^2) can act as a burden on the financial performance of firms.

4.4.3 Technological capability and innovation performance

The effect of the devised technology capability (TC_{it}) indicator on the innovation performance of firms was investigated. The innovation performance is classified by the short-term innovation performance ($PatentGrowth_{i,t+2}$), which calculates the increase rate by comparing the number of patent applications in year t+2 with year t, and the long-term innovation performance ($PatentGrowth_{i,t+5}$) by comparing with patents in year t+5.

The results of the OLS regression analysis of Equation (4.9) are shown in Table 4-7. Models (1) and (5) are the results of examining the only effect of TC_{it} and the square term of TC_{it} (TC_{it}^2), which are the key independent variables of this study, and Models (2) and (6) control the firm fixed effect (μ_i) based on Models (1) and (5). In Models (3) and (7), only control variables were reflected without firm fixed effects, and in Models (4) and (8), all control variables and firm fixed effects were also considered.

Table 4-7. The effects of technological capability on innovation performance of the firm

	Dependent variable:							
	$Patent\_Growth_{i,t+2}$				$Patent\_Growth_{i,t+5}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$TC_{i,t}$	-8.838^{**}	-32.292^{***}	-16.173^{***}	-31.814^{***}	-23.693^{**}	-53.218^{***}	-19.556^{*}	-60.562^{***}
	(4.404)	(5.554)	(4.025)	(5.275)	(10.252)	(9.920)	(10.250)	(9.935)
$TC^2_{i,t}$	-3.005	9.782^{***}	0.435	9.791^{***}	-4.898	11.518^{**}	-8.448	13.158^{**}
	(2.753)	(3.584)	(2.525)	(3.374)	(5.535)	(5.380)	(5.549)	(5.343)
$num\_Patents_{i,t}$			2.587^{***}	0.856^{***}			5.291^{***}	-3.320^{***}
			(0.213)	(0.244)			(0.751)	(0.633)
$Size_{i,t}$			-1.481	-6.165^{***}			0.217	-2.043
			(1.025)	(1.529)			(2.895)	(3.334)
$Profit\_ratio_{i,t}$			26.879^{***}	16.301^{***}			26.377^{*}	5.464
			(5.337)	(5.494)			(15.349)	(11.776)
$Debt\_ratio_{i,t}$			11.686^{***}	15.020^{***}			1.874	1.296
			(1.046)	(1.385)			(2.907)	(3.003)
Constant	13.392^{*}		40.880^{***}		138.085^{***}		150.439^{***}	
	(7.190)		(6.833)		(15.061)		(16.026)	
Firm fixed effect	*No*	*Yes*	*No*	*Yes*	*No*	*Yes*	*No*	*Yes*
Observations	3,051	3,051	3,051	3,051	1,658	1,658	1,658	1,658
R^2	0.102	0.425	0.270	0.494	0.118	0.706	0.149	0.712
Adjusted R^2	0.096	0.355	0.265	0.431	0.111	0.647	0.140	0.654

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Unlike the effect on financial performance, it was confirmed that technological capability (TC_{it}) had a statistically significant effect on short-term innovation performance and long-term innovation performance of the firm. Also, unlike the inverted U-shaped relationship with financial performance, a U-shaped relationship was observed between the technological capabilities (TC_{it}) and innovation performance.

First, looking at the effect of a firm's technological capability (TC_{it}) on short-term innovation performance, in models (1) and (3) that do not reflect the firm's fixed effect, the technological capability (TC_{it}) negatively affected innovation performance. However, a statistically significant U-shaped relationship was observed in models (2) and (4) with higher R^2 values in which the fixed effect of firms was reflected. In other words, as the firm's technological capability (TC_{it}) increased, the firm's short-term innovation performance decreased (based on Model (4), it reaches a minimum when TC_{it} is 1.6246), and when the technological capability (TC_{it}) increases beyond a certain level (TC_{it} is 3.2493 or higher), the firm's innovation performance increases rapidly again.

These results mean that it is difficult to obtain innovation performance, which is the increased growth rate of patents application of firms, by medium-level technological capabilities below TC_{it}=3.2493. In other words, in order for a firm to apply for an additional patent, the firm must possess a higher level of technological capability (TC_{it}=3.2493 or higher). In particular, a higher level of technological capability (TC_{it}) was required, with TC_{it}=4.6027 or higher to achieve long-term innovation performance.

The reason why a U-shaped relationship between technological capability and innovation performance is observed is that technological knowledge has a characteristic of cumulativeness. The process of technology accumulation follows a series of successive processes in which all steps cannot be performed simultaneously in a short period of time, and only after passing one step can move on to the next more complex step (Cool et al., 2016). Trials and error are essential in the process of increasing technological capabilities, and as a result, additional technological innovation cannot be expected immediately. This is the reason why innovation performance initially decreases as technological capability (TC_{it}) increases. On the other hand, if a firm achieves a certain level of technology accumulation through trials and error, experience is embodied and a learning effect occurs. As a result, firms experience increasing returns of scale for additional production factor inputs for technology (e.g. R&D expenditures) (Le Bas and Scellato, 2014). This is why innovation performance increases again when the technological capability (TC_{it}) exceeds a certain level.

4.5 Robustness check

The robustness of the main analysis results was confirmed through various types of dependent variables. First, as an indicator for measuring a firm's financial performance, the sales growth rate was used in the main analysis in Table 4-6. Next, as an index for measuring innovation performance, the increase rate of the number of patents was used in the main analysis in Table 4-7, and through this, the intensive margin was found. In order to confirm the robustness of the main analysis results, total assets and the number of employees were used as dependent variables in equation (4-8). The extensive margin determined as dependent variables in equation (4-9) used the rate of increase in the number of technology classification assigned to patents.

The results in Table 4-8 show that the influence of technological capabilities (TC_{it}) is not different from the results of the main analysis even when various dependent variables are used to measure the firm's performance. Through this, the robustness of the devised technological capability (TC_{it}) measurement was confirmed.

Table 4-8. The result of robustness check

	Dependent variable:					
	(1) $numEmployee\_Growth_{i,t+2}$	(2) $numEmployee\_Growth_{i,t+5}$	(3) $TotalAsset\_Growth_{i,t+2}$	(4) $TotalAsset\_Growth_{i,t+5}$	(5) $CPC\_Growth_{i,t+2}$	(6) $CPC\_Growth_{i,t+5}$
$TC_{i,t}$	0.712	34.982***	−2.791	45.054***	−33.584***	−70.750***
	(5.020)	(7.467)	(5.008)	(6.777)	(5.640)	(10.733)
$TC^2_{i,t}$	0.650	−14.156***	1.041	−18.158***	10.128***	16.855***
	(3.211)	(2.701)	(3.204)	(2.130)	(3.608)	(5.742)
$num\_Patents_{i,t}$	0.376	−0.389	0.165	−0.670	0.790***	−3.508***
	(0.232)	(0.482)	(0.231)	(0.503)	(0.260)	(0.677)
$Size_{i,t}$	−6.076***	−12.636***	−0.592	−9.460***	−6.127***	−5.378
	(1.099)	(0.765)	(1.096)	(1.216)	(1.635)	(3.576)
$Profit\_ratio_{i,t}$	67.917***	0.041***	83.604***	0.009	10.802*	−4.453
	(6.099)	(0.015)	(6.084)	(0.023)	(5.874)	(12.772)
$Debt\_ratio_{i,t}$	31.200***	2.178***	27.646***	2.308**	15.429***	4.850
	(2.545)	(0.400)	(2.539)	(0.902)	(1.481)	(3.217)
Firm fixed effect	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	3,051	1,136	3,051	1,469	3,051	1,654
R^2	0.321	0.759	0.415	0.668	0.478	0.694
Adjusted R^2	0.237	0.693	0.343	0.592	0.414	0.632
Residual Std. Error	27.001 (df = 2715)	41.458 (df = 891)	26.938 (df = 2715)	57.366 (df = 1196)	30.337 (df = 2715)	46.463 (df = 1376)

Note: *p<0.1; **p<0.05; ***p<0.01

4.6 Sub-conclusion

The significance of this study is that it proposes a new measure to estimate a firm's technological capability. In order to overcome the limitations of existing variables that measure technological capabilities, the following items were considered. First, a method for estimating technological capability based on the aspects of the technological portfolio was presented. Studies that measure firms' technological capability in an indirect way other than surveys use simple information such as input factors for technological knowledge (e.g. R&D expenditure) and outcomes of innovation (e.g. patents). However, the disparate learning capability of firms result in different outcomes even with the same input of resources. In addition, when the outcome of innovation is directly regarded as a firm's technological capability, ambiguity in the causal relationship arises. Therefore, it is necessary to determine the technological capability through the aspect of the technological portfolio of each firm that has changed through the heterogeneous learning process of input factors, and then confirm how much this technological capability affects the performance.

Next, the method of measuring technology capability presented in this study looks at the various characteristics of technological portfolio aspects at the same time. Unlike the one-dimensional approach used to measure technological capability in the past, this study considers three factors at the same time: breadth, depth, and coherence of a technological portfolio. In particular, it can be said to be a more realistic approach in that the weight for each factor is first calculated and then the heterogeneous weight is obtained and applied.

In addition, it is possible to display the technological capability of each firm in space through various dimensions, and through this, it is possible to know the relative position and understand which elements should be relatively focused.

Finally, the heterogeneous influence of each element on the overall technological capability was reflected. Breadth, depth, and coherence, which are aspects of a technological portfolio, are thought to have heterogeneous effects on technology capability. In this study, the size of each factor's influence on technology capability was measured through normalized regression coefficients. The result shows that breadth, depth and coherence affected the technological ability by magnitudes of 0.48, 0.46 and 0.06, respectively.

In order to verify the reliability of the devised technological capability measure, cross correlation coefficient and leads and lags correlation with other proxy indicators of technological capability were first checked. After confirming the validity of the indicators, changes of the average (*breadth, depth, and coherence*) value of technological portfolios of firms belonging to Korea's 'electronic components, computer, radio, television and communication equipment and apparatuses' industry were investigated. The technological portfolio's (breadth, depth, and coherence) of firms belonging to Korea's 'electronic components, computer, radio, television and communication equipment and apparatuses' industry has steadily increased over the past five years since 2011, and it was the depth of technological knowledge that has increased the most since 2007.

Finally, the effect of a firm's technological capability on its financial performance and innovation performance was investigated. First, no statistically significant relationship was observed between a firm's technological capability and its short-term financial performance. This means that two years is a short time for accumulated technological capability to affect product development and production, and lead to an increase in firm sales through selling them. On the other hand, a statistically significant inverted U-shaped relationship was observed between technological capability and long-term financial performance of firms. This means that the financial cost becomes greater than the financial benefit due to the increase in the firm's technological capability from a certain point in time. This is because the increase in (breadth, depth, coherence) of technological knowledge requires additional costs. Cost for active exchanges between departments are a representative example. When a firm's technological capability increases by more than 2.4694 units, the firm's long-term sales growth rate starts to become less than zero.

Next, a statistically significant U-shaped relationship was observed between a firm's technological capability and its innovation performance in both the short and long term. The firm's short-term innovation performance steadily decreased until the technological capability increased to 1.6246 units, then it started to increase again and recorded a value greater than 0 from 3.2493 units. This is because technological knowledge is characterized by its cumulative nature. The process of technology accumulation follows a series of procedures in which everything cannot be done at once in a short period of time, and one must pass previous stage before moving on to the next. Since it is impossible to do something new well from the beginning, trials and error are essential in this process, therewith, time for accumulation is required. This is why innovation performance initially decreases as technological capability increase. On the other hand, if a firm achieves a certain level of technology accumulation through trials and error, experience is embodied and a learning effect occurs. As a result, firms experience increasing returns of scale for additional inputs factor of innovation (e.g. R&D expenditures). This is why innovation performance increases rapidly from a certain point as technological capability increase. In particular, since the long-term innovation performance recorded a value greater than 0 from the point when the technological capability exceeded 4.6027 units, it can be seen that more technological capability need to be accumulated for long-term innovation performance.

When comparing the long-term financial performance of Model (8) in Table 4-6 with the long-term innovation performance of Model (8) in Table 4-7, firm fall into the dilemma of determining the appropriate technological capability (TC_{it}). Until the value of technological capability (TC_{it}) reaches 2.4694, the firm experiences positive financial growth, but experiences a decrease in innovation performance (A in Figure 4-6 below). On the other hand, when the value of technological capability (TC_{it}) is between 2.4694 and 4.6027, the firm experiences both negative innovation performance and financial performance (B in Figure 4-6). When the value of technological capability (TC_{it}) is 4.6027 or higher, the firm's innovation performance increases rapidly, but at the same time, it experiences a sharp decrease in financial performance (C in Figure 4-6). Therefore, between long-term financial performance and innovation performance (B), firms will have to choose between investing for a more distant future (high hanging fruit) and current easily achievable goals (low hanging fruit). Therefore, the selection and investion dilemma in technological capability can be described as the Stanford marshmallow experiment (De Posada and Singer, 2005) at the firm level.

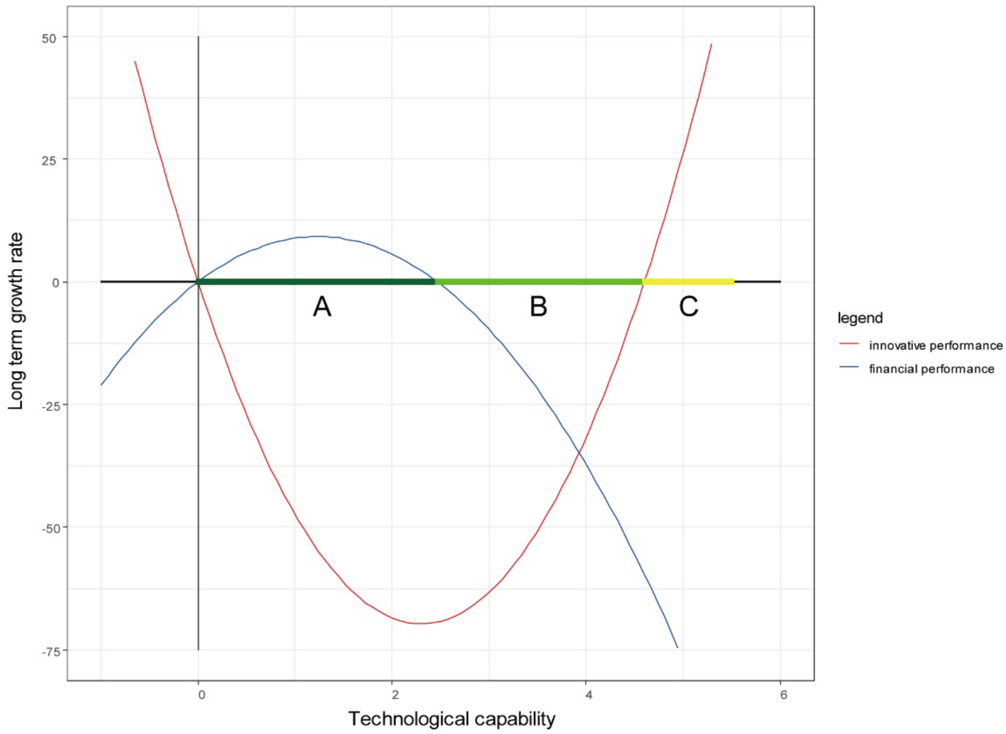

Figure 4-6. Three different sections of technological capability on long term growth rate

Careful interpretation is required in that this study focused on 'Manufacture of electronic components, computer, radio, television and communication equipment and apparatuses' of Korea. This is because it accounts for 49.2% of the total R&D expenditure of Korean firms and the ratio of R&D expenditure to sales is 10.14%, which is the highest compared to other industries (Science and Technology Policy Institute, 2021). Since it is an industry with a high proportion of R&D, the effect of technological capability could be greater than other industries, so additional efforts will be needed to expand and analyze the other industries in order to measure generalized technological capability.

Chapter 5. The optimal technological knowledge accumulation strategy for the firm's financial performance

5.1 Introduction

Technological knowledge accumulated in a wide area is the driving force for securing a comparative advantage and financial growth through it (Fai, 2003). Accordingly, various academic fields emphasize the importance of technological diversification within firms. According to the Resource based theory, firms diversify their technologies to exploit economic of the scope of R&D and technological knowledge, and secure synergy between technologies by efficiently deploying limited resources (Dosi, 1982; Miller, 2006). Evolutionary economics also emphasizes that securing various technologies is essential. Many novel approaches are designed to solve unrelated problems, and firms can secure more technological opportunities and technological possibilities through them (Nelson, 1959). In Complexity economics, since the complexity of products and production processes increases over time, firms need to secure a variety of technologies and even with outsourcing, it is argued that technology diversification is essential to secure absorptive capacity to fully understand the external technology (Rycroft and Kash, 1999; Patel and Pavitt, 1997). The results of various empirical analyzes revealing the impact of firms' technological diversification on their innovation performance (Garcia-Vega, 2006;

Quintana-García et al., 2008; Leten et al., 2007; Huang and Chen, 2010; Lee et al., 2012; Aktamov, 2014) and on their financial performance (Granstrand and Oskarsson, 1994; Gambardella and Torrisi, 1998; Miller, 2004; Watanabe et al., 2005; Watanabe et al., 2007; Kim et al. 2016), support this fact.

Previous empirical studies related to technological diversification mainly attribute differences in technological diversification strategies to changes in technology composition within technological portfolios. In particular, it is based on the premise that the greater the value in the types of technology (quantity aspect) or the balance between the proportions of technology (qualitative aspect) in the technological portfolio, the greater the degree of diversification of the firm's accumulated technology. A representative technological diversification index reflecting these two factors is the Herschman-Herfindahl Index (hereafter, HHI) or entropy index, which is used in most studies. According to Ceipek et al. (2019), 15 out of 23 financial performance studies and 13 out of 21 innovation performance studies (more than half, conducted up to 2018) used these two indices to analyze the impact of technological diversification.

However, in our reality, contrary to the theory, firms with low technology stock and a narrow variety of technologies continue to operate and even grow. This claim is supported by the fact that small hidden champions, despite possessing a small number of technologies, are recording stable sales and growing steadily. According to Hermann Simon (2014), the majority of Small hidden champion in German are highly specialized in a narrow market. In order to explain the gap between theory and our reality, the growth of firms with a small number of technology stocks, the need to consider the heterogeneous characteristics of each technology is raised.

In particular, when both the quantitative aspect of technology types and the qualitative aspect of technology balance within a firm's technological portfolio are considered, distortion occurs in understanding the technology accumulation strategy. This is an inherent limitation of scaled ratio-based measures, including HHI or entropy indices, because the value converges to zero if a firm owns an even proportion of a small number of technologies. As a result, in previous studies, firms specialized in a small number of technologies were regarded as having low growth rates regardless of the type of technology they have. This is the reason we can find cases where there is no effect of technological diversification or a negative interpretation, when a firm's technological diversification strategy is measured through the number of technology classification or content analysis by broadening the methodology for measuring technological diversification (Wilbon, 1999; Wilbon, 2002; Nasta, 2008).

In addition, when judging the impact of technological diversification in terms of the quantitative aspect of the type of technology within a firm, the result is predominantly influenced by large-scale or mature firms. Due to the advantages of technological diversification mentioned above, having a variety of technologies will improve a firm's financial performance to a certain level, but this is only true for large firms that can afford to have a variety of technologies. There is a limit to the ability of small firms to possess various types of technologies through in-house R&D or M&A. This is the reason why the effects of technological diversification do not converge to a single result, but vary by context (Wilbon, 1999; Wilbon, 2002; Lin et al., 2006; Nesta, 2008; Kim et al., 2009; Bergek et al., 2009; Chen et al., 2013; Lee et al., 2017; Pan et al., 2017).

In summary, the existing studies that analyzed the effect of a firm's technological diversification on its financial performance have room for improvement in the following aspects. First, since even firms with a small number of technology stock achieve financial performance, a firm's technology accumulation strategy should be analyzed differently depending on the level of technology stock. Second, since firms with various types of technologies are likely to be large-scale firms that can invest sufficient resources in (in-house) R&D or M&A, the firm's technology accumulation strategy should be analyzed differently according to their size. Third, to explain the financial performance of firms with a small number of technologies, a technology accumulation strategy that considers the complexity of technologies should be included. Fourth, the technological diversification indices used in previous studies postulate only one type of technologies, proximity between technologies should be additionally considered.

Therefore, in this study, first, the heterogeneity among the technologies constituting the technological portfolio was additionally considered. This effort was made by reflecting the distance between technologies, that is, proximity, which is not considered in the HHI or entropy index. The addition of more disparate technologies that are farther from those in a firm's existing technological portfolio is expected to force firms to strive more for technological diversification. This is because there is little in common between the background knowledge required for the technology development.

Next, the firm's technology accumulation strategy is divided into two types: i) technological diversification (reflecting heterogeneity) and ii) technological complexity. In this study, among the various characteristics that can judge the heterogeneity between technologies, the complexity of the technologies that make up a firm's technological portfolio was additionally considered. The relative scarcity, non-ubiquity, sophistication, or complexity of the technologies possessed by a firm can be said to be an important factor influencing a firm's technological comparative advantage (apart from the influence of technological diversification strategy). This is because the relative scarcity of a particular technology (i.e., if there are only a few firm that have that technology) means that it is difficult to develop that technology (Hidalgo et al., 2009; Balland et al., 2019; Hidalgo, 2021). As a result, even if the same number of types of technological knowledge is possessed, if the complexity of the technologies possessed increases, it is possible to secure a large technological comparative advantage, and as a result, the firm's financial performance is expected to increase.

Therefore, a firm's technology knowledge accumulation strategy, i) technological diversification and ii) technological complexity, should be analyzed differently depending on the firm's technology stock and their size. In this study, 2,731 firms in the US manufacturing industry, for which patents and financial information were identified, were first classified into the following four groups; i) large firms with high technology stocks; ii) small firms with high technology stocks; iii) large firms with low technology stocks; iv)

Small firms with low technology stocks. Then, how each group's technological diversification or technological complexity strategy for the accumulation of technological knowledge changes was investigated.

According to the results of the analysis, the strategy of accumulating technological knowledge for optimal financial performance should be different for each group. i) For large firms with high technology stocks, technological diversification was the only effective technology accumulating strategy for financial performance. ii) For small firms with high technology stocks, improving their financial structure was more effective in improving their financial performance than efforts to accumulate technological knowledge. iii & iv) For firms with low technology stocks, strategies that increase the level of complexity of technology knowledge or the amount of technology stock are most effective regardless of the size of the firm.

The structure of this chapter is as follows. In Section 5.2, we first look at previous studies on the effect of a firm's technological diversification strategy on its financial performance by context, and then discuss the need to additionally consider the technological complexity strategy. Section 5.3 examines data, variables, and models for empirical analysis. Section 5.4 summarizes the results of the empirical analysis, and Section 5.5 describes the conclusion of this study.

5.2 Literature review

5.2.1 Technological diversification and financial performance: mixed results

Technological diversification provides firms with multiple benefits. First, securing various technologies provides firms with flexibility. This flexibility makes firms possible to quickly shift and adapt in an uncertain and rapidly changing technological environment, resulting in greater options (Farazi et al., 2019; Toh and Kim, 2013; Yao et al., 2021). Second, as the base of technological knowledge expands, firms enjoy economies of scope for R&D activities (Panzar & Willing, 1977; 1981). As a result, R&D costs are reduced (Miller, 2006) and synergies between technologies are generated (Granstrand, 1998; Kim et al., 2016). Third, it enhances the absorption capacity of firms. When a firm has a broad range of knowledge, it is better able to identify, assimilate the value of new technological knowledge and then apply it better (Cohen and Levinthal, 1990). This helps to increase a firm's technological competence (Kim et al., 2016) and enables partnerships with other firms (Zhang et al., 2007). Fourth, technological diversification reduces R&D risk. Since R&D at an early stage has a high probability of failure, firms can increase the probability of R&D success by diversifying investments into various technologies (Garcia-Vega, 2006; Leiponen and Helfat, 2010). In addition, when a firm faces a new problem, they try to solve it in a 'heuristic' way according to the existing 'routine' (Nelson and Winter, 1982/2014), therewith, the result is highly dependent on the existing resources of the firm. Therefore, the more diverse technological knowledge a firm possesses, the more diverse solutions it can find through knowledge recombination (Kogut and Zander, 1992), and as a result, the probability of R&D failure can be reduced.

Nevertheless, if the degree of technological diversification is excessive, it will have a negative impact on the firm's financial growth. This is because the more diversified the types of technologies, the more the coordination costs outweigh the profits from diversification (Penrose, 1959; Argyres, 1996). In addition, as disparate technologies with small proximity are added from the core technology owned by the firm, the proximity between technologies is lowered, resulting in a decrease in R&D productivity (Seru, 2014). Lastly, the addition of R&D personnel to utilize new technologies also causes cost increases due to excessive diversification of technologies.

Most studies have found that a firm's technological diversification has a positive effect on its financial performance (Granstrand and Oskarsson, 1994; Gambardella and Torrisi, 1998; Miller, 2004; Miller, 2006; Watanabe et al., 2007), and it is argued that negative effects are observed only when the degree is excessive (Kim et al., 2016). However, the results of empirical studies analyzing the effect of a firm's technological diversification on a firm's financial performance are not uniform, but mixed. There are also studies that claim to have negative or no relevance (Wilbon, 1999; Wilbon, 2002; Lin et al., 2006; Nesta, 2008; Kim et al., 2009; Bergek et al., 2009; Chen et al., 2013; Lee et al., 2017; Pan et al., 2017).

Despite the many advantages of technological diversification, there are two main reasons for such mixed results. First, it is that entropy and HHI, which are representative variables that measure the degree of technological diversification of a firm used previously, are incomplete (Pan et al., 2017). In particular, there is room for improvement in that differences between technologies are not reflected in the entropy index or the HHI.

Next, the fact that the effect of technological diversification varies depending on the context of the study also contributes to the mixed results. The results of various empirical analyzes have revealed that the effect of technological diversification on financial performance varies depending on the level of technology stocks or organizational slacks held by the firm (Lin et al., 2006; Kim et al., 2009; Chen et al., 2013; Lee et al., 2017; Pan et al., 2017). Accordingly, the heterogeneous effect of technological diversification according to context was confirmed through the effect of various types of moderating variables on technological diversification.

5.2.1.1 Technological diversification by size

Previous studies related to technological diversification have mainly focused on presenting technology accumulation strategies for large firms. Conversely, research related to technological diversification in small firms has received relatively little attention (Corradini et al., 2016). This is due to the relative disadvantages of small firms compared to large firms. First, it is difficult for small firms to enjoy the economies of scale through R&D (Vossen, 1998). This is because firms need costs to carry out R&D projects, and a certain amount of scale is required to finance them (Vossen, 1998). In addition, even if successful R&D leads to product development and production, the larger the size, the better it is for sales to recover fixed costs. (Vossen, 1998).

Next, the limited resources relative to large firms have a severely negative impact on the choice of technological diversification strategies by small firms. This is because the size of a firm means how much access to resources (Kim and Wang, 2014). The fact that access to various types of resources is limited presents significant challenges to the innovative activities small firms can undertake (Ortega-Argilés et al., 2009; Corradini et al., 2016). Thus, resource-constrained situations force small firms to choose other strategies than technological diversification (Antonelli and Scellato, 2015).

Various empirical analyzes also reveal that a firm's strategy should be different depending on the size of the firm (or the amount of resources it has). First, Lin et al. (2007) argued that the alliance strategy should be different depending on the size of the firm. It is advantageous for large firms to do exploration and exploration at the same time, but it is more advantageous for small firms to focus their resources on either exploration or exploration. Next, Chen et al. (2013) surveyed smartphone manufacturers in Taiwan, and found that for all samples, technological diversification had a negative effect on financial performance (Tobin's q & Market Value Added). However, the increase in absorbed organizational slack, such as major repair funds, inventory funds and accounts payable, has positively changed the impact of technological diversification on financial performance. . The foregoing results emphasize how significant the impact of resources is on technological diversification.

In particular, the study by Lee et al. (2017) proves that resources are equally important even for large firms that already have sufficient resources. An analysis of 168 firms in the 2008 Standard & Poor's (S&P) 500 found that technological diversification had a significant and positive impact on financial growth. However, the greater the financial slack, the greater the positive impact of technological diversification on financial performance. The research result of Lee et al. (2017) emphasizes once again that the size (i.e. resources) of a firm is an essential prerequisite for selecting a technological diversification strategy.

5.2.1.2 Technological diversification by technology stock

A firm's technological resources play an important role in its diversification strategy. First, the higher the level of a firm's technology stock, the higher the probability of successful technological diversification. According to the principle of relatedness, the more related technological knowledge that a firm has in common with existing technological knowledge, principles or backgrounds, the higher the probability of acquiring that technology (Kim et al., 2022; Kim et al., 2023; Jun et al., 2023). Therefore, the more technology stocks a firm possesses, the higher the relevance of new technologies, thus increasing the probability of successful technological diversification. Next, the higher the level of a firm's technology stock, the easier the technological integration between the newly acquired technology and the existing technology stock (Lin et al., 2006). This is also related to absorption capacity. A firm's experience can also be said to be a stock of technology owned by a firm, because the more a firm 's experience accumulates, the better it is to recognize, acquire new technologies and be able to assimilate and transform them well (Cohen and Levinthal 1990; Zahra and George, 2002). As a result, even if the same technological diversification strategy is selected, different financial performance is expected depending on the technology stock held by the firm.

Lin et al. (2006) and Kim et al. (2009) conducted an empirical analysis about the effect of technology stock on technological diversification of firms. First, Lin et al. (2006) surveyed 94 US firms from 1985 to 1999 and investigated the effect of broad technology diversity (as diversification strategy) and core field diversity (as specialization strategy) on the firm's financial performance. As a result of the analysis, diversification strategy had a significant negative effect on the firm's financial performance, but the effect of technological specialization was not statistically significant. Only for firms with a very high technology stocks (measured by a percentage of the number of patents to total assets), technological diversification was an optimal strategy for financial performance (profitability). On the other hand, the firm's technological specialization strategy was a strategy that had a significant effect on the financial performance (shareholder value) of firms with a technology stocks above average. The authors suggested that, when the amount of technology stock held by a firm is not large, a firm should choose a technological specialization strategy that focuses on a narrow technology area rather than technological diversification.

Kim et al. (2009) investigated Korean firms, obtained similar results with Lin et al. (2006). Kim et al. (2009) first confirmed that diversification strategy (broad technology diversity) has a statistically insignificant effect on financial performance. The variable that played a role in changing the relationship between diversification strategy and financial performance with a statistically significant positive relationship was the increase in technology stock.

5.2.2 Technological complexity and financial performance

The understanding of phenomena through interaction or relationship made it possible to realize many things that could not be expressed through the existing discrete method of interpretation. In particular, by considering the interaction between economic agents or the relationship between economic activities, we have been able to classify the unique characteristics of each economic agents and economic activity into a spectrum. This feature indicates the level of complexity of an object, and its origins are in Hidalgo et al. (2009).

Hidalgo et al. (2009) believed that a country's productivity lies in the diversity of non-tradable capabilities, and interpreted the reason for differences in income among countries as the level of heterogeneous capabilities, that is, differences in the complexity inherent in the economy. Consideration of complexity explains the fundamental cause of the division of labor (Smith, 2002), which Adam Smith explained as the source of national wealth. The heterogeneous level of complexity among the economic agents that make up the global economy suggests that it is best for everyone to perform economic activities that are best suited to their capabilities and trade with them by interaction in the market.

The accumulation of technological knowledge within firms and firms can also be interpreted through complexity. The difference in the diversity of capabilities of each firm determines the heterogeneity of the complexity of the technological knowledge possessed by the firm. To borrow the expression of Hidalgo et al. (2009), let the firm be a bucket containing Lego pieces, and the technology the firm is trying to develop a Lego model. If a Lego basket contains enough Lego pieces to build a Lego model, the firm will be able to mobilize all necessary capabilities to develop the targeted technology. Hidalgo et al. (2009, 2021) realize and visualized this description through a bipartite network that connects countries and products they export.

The high complexity of technologies at the firm level means that the technologies possessed are sophisticated and difficult to develop, rather than ubiquitous to other firms. This is because the greater the variety of capabilities needed to develop a given technology, the fewer firms can satisfy and equip all of these capabilities. As a result, when a firm increases the complexity level of their technological portfolio, it means that the complexity level of the technologies they own increases. Therefore, for firms, efforts to increase the complexity of their technological portfolio will be a technology accumulation strategy that helps them secure a technological comparative advantage.

Indeed, various empirical analyzes have proven that the complexity of various economic activities at the level of various economic agents affects the growth of economic agents. national complexity through export goods (Hidalgo et al., 2009; Hausmann et al., 2014; Zhu et al., 2017; Domini, 2022), national complexity through export goods and service goods (Stojkoski et al., 2016), national complexity through patents (Sweet and Eterovic, 2019), and regional or city-specific complexity through industry (Chávez et al., 2017; Gao et al., 2018; Fritz et al., 2021) states that the higher the complexity, the more positively affected the financial growth of each economic agent.

It is expected to be self-evident that the level of complexity of a technological portfolio will affect the financial performance of an economic agent. However, there has been no study to date using firm-level patent data to determine how increasing complexity of a firm's technological portfolio affects a firm's financial performance. As a result, there is also no research that analyzes how the effect of technological complexity varies depending on the firm's conditions (e.g. size or technology stock, in this study). The effort in this chapter to analyze the complexity of a firm's technological portfolio is expected to open a new horizon for understanding Economic complexity.

5.3 Methodology

5.3.1 Data

In order to obtain an answer to the above research questions, first of all, a disambiguation between the firm's patent and the firm's financial data must be performed. It is very difficult to identify the owner of the patent at the firm level due to i) different applicant names, ii) spelling mistakes, and iii) a bewildering array of abbreviations. At the same time, even in the case of firm financial data, it is very difficult to track a specific firm's financial information due to reasons such as i) mergers and acquisitions, ii) name change, and iii) change in governance structure. Therefore, in order to use patent data and financial data together, first, various applicant information on a single firm in the patent data must be linked to financial information of the firm that exists independently.

Attempts to comprehensively match a firm's patent information and financial information have been made before Hall et al.'s (2001) study, which laid the foundation for the rapid development of innovation-related research. Schmookler (1966), who counted the number of patents after concordance between industry classification and patent classification, followed by Griliches (1984), who included information on the filing date of each firm's patents. However, research on innovation in the early days was merely counting the number of patents. Scherer (1982) classified 15,000 patents into the industry of origin and the industry where the use is anticipated through contextual inspection, but innovation was also expressed in terms of the number of patents, rather than understanding innovation through various information in patents.

Starting with this critical mind, Hall et al. (2001, 2005) developed a patent database standardized by applicant names through the National Bureau of Economic Research (hereafter, NBER) Patent Data Project (PDP), and provided 'The NBER patent citation data file'. NBER PDP firstly compared 3 million granted US patents from 1963 to 1999 and 16 million citations of those patents from 1975 to 1999, and matched with Compustat, which is financial information of US firms. It shows a success rate of about 50-65% (depending on the year). Afterwards, the range of data is secondarily extended to 2006 by Bessen

(2006). Based on Trajtenberg's (1990) research that the value of innovation and the number of patent citations are correlated, the NBER PDP provides values for originality and generality of patents calculated through citation information. This can be said to be a remarkable achievement that made it possible to interpret innovation more three-dimensionally.

Kogan et al. (2017) standardized the applicants of all patents in Google Patents as firm names searched in the CRSP (The Center for Research in Security Prices) database, and then added patents not included in NBER PDP. The traditional method performed by NBER-PDP is expensive to build in that it requires extensive manual inspection. To overcome the disadvantage, Autor et al. (2020) improved accuracy by performing USPTO-Compustat matching until 2014 with an independent algorithm. In addition, Feldman et al. (2015) collected information on 4200 technology-intensive firms located in and near North Carolina’s Research Triangle Park from 30 different data sources. Feldman et al. (2015) included all known information career changes and education levels, interview articles of CEO through firm's SNS, websites, annual reports, publications, newspaper articles, university library or laboratory data, and CEO's personal SNS, along with firm financial data and patent data. Various studies conducted so far to match applicants by firm names are summarized in the following Table 5-1.[29]

[29] In addition, Li et al. (2014) carried out the disambiguation of the names of unique inventors of patents provided by the USPTO between 1975 and 2010. In this study, since the main field of interest is 'the work of disambiguating the applicant's name of a firm', a literature review was conducted focusing on studies related to the matching of applicants of firm names.

Table 5-1. Efforts for patent disambiguation

Countries where firms are located	Periods	Source of patent information	Source of financial information	Author
US	1975-1999	PATSTAT	Compustat	Hall et al. (2001)
	1980-2005	PATSTAT	Compustat	Bessen (2006)
	1926-2010	Google Patents	CRSP	Kogan et al.(2017)
	1975-2013	US Patent and Inventor Database (Li et al, 2014)	Compustat	Autor et al.(2020)
	1980-2015	PATSTAT	Compustat	Arora et al. (2020, 2021)
Europe	1997-2005	PATSTAT	Amadeus	Thoma et al. (2007)
	1979-2008	Online databases & offline databases including PATSTAT	Amadeus	Thoma et al. (2010)
Multinational firms (largest R&D investments only)	1993-2005	PATSTAT	ORBIS	Alkemade et al.(2015)
Korea	1991-2005 (Manufacturing Industry only)	KIPI (Korea Institute of Patent Information)	KIS (Korea Information Service)	Kim et al.(2016)

Korea (Continued)	1948-2016	KIPO (Korea Intellectual Property Office);	DataGuide 5.0	Lee et al. (2019)
	1976-2017	USPTO		
	1985-2015 (Manufacturing Industry only)	PATSTAT	KIS (Korea Information Service)	Kang et al. (2019)
	1984-2014 (Manufacturing Industry only)	PATSTAT	KIS (Korea Information Service)	Kim et al. (2023)
	2007-2018 (Manufacturing Industry only)	PATSTAT	KIS (Korea Information Service)	Kim et al. (2022)
	1990-2021 (Manufacturing & IT Industry only)	PATSTAT	KIS (Korea Information Service)	Jun et al. (2023)
China	1990-2010	State Intellectual Property Office (SIPO)	Shanghai Stock Exchange & Shenzhen Stock Exchange	He et al. (2018)

In this study, the same data set used in Chapter 2 was used for analysis. Patent information and financial information of firms in the US manufacturing industry over a period of 30 years (1986-2015) were analyzed. We matched two different dataset based on the DISCERN dataset by Arora et al. (2020, 2021). First, by combining the DISCERN dataset with PATSTAT, we analyzed patents filed by firms located in the United States over a period of 30 years (1986-2015).

The 4-digit CPC codes for each patent corresponding to a total of 653 technology classifications were considered as firm's technologies. In particular, when multiple CPCs were assigned to a single patent, each of the multiple CPCs was considered as one technology. In other words, if a patent applied by firm i in time t belongs to two technology classifications j and k, then the combination (i, j, t) and (i, k, t) are technologies owned by firm, respectively.

Technologies filed in year t were averaged over a 5-year time window. That is, the technological knowledge filed in year t is the stock accumulated in the firm until t+5. This is based on the previous study that the rate of depreciation of knowledge capital is very fast and usually loses its value within 5 years (Griliches, 1979). Among manufacturing firms whose financial information used for all control variables was included without omission in Compustat, 2162 firms with two or more technology classifications were finally analyzed in this study.

5.3.2 Variables

5.3.2.1 Diversification level of technological portfolio

In reality, all technologies are developed from different theories and principles, through different coincidences and experimental processes. The technology classification codes of patents, which are considered as technologies in this study, are also the result of being divided into mutually exclusive technologies (WIPO, 2023). However, most studies only consider the fact that technologies are different, that is, differences in types, and do not consider the degree of heterogeneity, how and to what extent each technology is different. For example, in the case of the entropy index or HHI, only variety (how many different types of technology a firm has) and balance (what is the proportion of each technology) are considered, and it does not matter what characteristics they have and how they differ.

Considering heterogeneity between technologies is the same as considering proximity between technologies. This is because the difference in heterogeneous characteristics between technologies is the same as the distance (or disparity) between technologies. Going beyond the judgment that two different technologies are simply different, considering how different they, that is, considering disparity can be said to reflect reality better. When technology diversity increases by one unit, the degree of disorder of the technological portfolio will be higher when more disparate technologies with low similarity are added, rather than when technologies with high similarity to the existing constituent technologies are added.

Therefore, in this study, considering the technological proximity ($\phi_{\alpha,\beta,t}$) among the constituent technologies, the Rao-stirling index, which is additionally weighted and averaged so that the diversification index becomes larger as the technological similarity is smaller, was used (Rao, 1982; Stirling, 2007). The method for obtaining the Rao-stirling index is as follows.

$$Tech\_Div_{it} = \sum_{\alpha,\beta}(1 - \phi_{\alpha,\beta})\left(\frac{P_{i,\alpha,t}}{P_{i,t}}\right)\left(\frac{P_{i,\beta,t}}{P_{i,t}}\right) \quad \cdots\cdots\cdots\cdots\cdots\cdots\cdots \text{Eq. (5.1)}$$

Here, $P_{i,\alpha,t}$ means the number of patents held by firm i for technology classification α in year t. In addition to diversity and unbalance, the Rao-stirling index also considers 1-technological proximity ($\phi_{\alpha,\beta}$), that is, as the disparity value between technologies increases (i.e. as technological proximity decreases) its value increases. The technological proximity ($\phi_{\alpha,\beta}$) proposed by Hidalgo et al. (2007) was calculated through the following equation.

$$\phi_{\alpha\beta,t} = \min\{Pr(RTA_\alpha | RTA_\beta), Pr(RTA_\beta | RTA_\alpha)\} \quad \cdots\cdots\cdots\cdots\cdots\cdots \text{Eq. (5.2)}$$

RTA_α is the number of firms that have a comparative advantage (Revealed Technological Advantage, hereafter, RTA) in technology α, and $\phi_{\alpha,\beta}$ is the probability that firms have two different technologies α and β at the same time. Firm i's RTA in technology α is calculated using the following formula (Balassa, 1965).

$$RTA_{i,\alpha,t} = \frac{P_{i,\alpha,t}}{\sum_\alpha P_{i,\alpha,t}} \Big/ \frac{\sum_i P_{i,\alpha,t}}{\sum_i \sum_\alpha P_{i,\alpha,t}} \quad \cdots\cdots \text{Eq. (5.3)}$$

5.3.2.2 Complexity level of technological portfolio

In a firm-technology bipartite data structure, information about a particular technology is classified according to how many firms own that technology. At the same time, information about a particular firm is differentiated according to how diverse the technology that firm possesses. Combining these two information, 'how many technologies firms have' and 'what firms developed each technology' can be expressed in a state while information is preserved.

The information on the firm and the information on the technology are expressed in the following formulas.

$$Complexity\ of\ firm:\quad K_{i,N} = \frac{1}{K_{i,0}} \sum_\alpha M_{i,\alpha} K_{\alpha,N-1} \quad \cdots\cdots \text{Eq. (5.4)}$$

$$Complexity\ of\ technology:\quad K_{\alpha,N} = \frac{1}{K_{\alpha,0}} \sum_i M_{i,\alpha} K_{i,N-1} \quad \cdots\cdots \text{Eq. (5.5)}$$

Equation (5.4) measures the level of complexity of a firm's technological portfolio, and Equation (5.5) measures the level of complexity of a technology. N is the number of iterations greater than or equal to 1. As *N* increases, the average value of the previous level characteristics of neighboring points is repeatedly calculated *N* times, alternating between the dimension of firm *i* and the dimension of technology α in the bipartite network. In other words, *N* means how many times the 'node of the other dimension located on the opposite side' is weighted by iteratively reciprocating like a mirror image. Given the structure of bipartite data, the dimension of a firm can be expressed as a vector from, $\overrightarrow{k_\iota} = (k_{i,0}, k_{i,1}, k_{i,2}, \dots, k_{i,20})$ The dimension of the technology also can be expressed as a vector $\overrightarrow{k_\alpha} = (k_{\alpha,0}, k_{\alpha,1}, k_{\alpha,2}, \dots, k_{\alpha,20})$.

Depending on whether the value of N is an even number or an odd number, the meaning of each dimension is different. For firm information $\overrightarrow{k_\iota}$, if *N* is an even number, $\overrightarrow{k_\iota} = (k_{i,0}, k_{i,2}, k_{i,4}, \dots)$ is a generalized measure of technological diversification, when *N* is odd $\overrightarrow{k_\iota} = (k_{i,1}, k_{i,3}, k_{i,5}, \dots)$ is the ubiquity of the possessed technology. Symmetrically, for information on technology $\overrightarrow{k_\alpha}$, if *N* is an even number $\overrightarrow{k_\alpha} = (k_{\alpha,0}, k_{\alpha,2}, k_{\alpha,4}, \dots)$ is a generalized measure of ubiquity, and if *N* is odd, $\overrightarrow{k_\alpha} = (k_{\alpha,1}, k_{\alpha,3}, k_{\alpha,5}, \dots)$ is the degree of diversification of a firm that has corresponding technology, α.

Also, depending on the value of *N*, the implied meaning also changes. The values of *N* mainly used for analysis are 0, 1, and 20. $K_{i,0}$ and $K_{\alpha,0}$ are the initial conditions when *N* is 0, and mean the degree or number of links of firm *i* or technology α. Interpreted on a bipartite network, $K_{i,0}$ is the observed number of diversification of the firm (the number of technologies the firm possesses and has a comparative advantage in), and symmetrically

$K_{\alpha,0}$ is the observed number to which it is held by a number of firms. It refers to the degree of ubiquity (the number of firms that have *RTA* in a given technology). This is the same as degree centrality in network theory. Expressed as a mathematical formula, it is:

$$Diversification\ \ of\ \ firm\text{:}\ K_{i,0} = \sum_{\alpha} M_{i,\alpha} \cdots\cdots \text{Eq. (5.6)}$$

$$Ubiquity\ \ of\ \ technology\text{:}\ \ K_{\alpha,0} = \sum_{i} M_{i,\alpha} \cdots\cdots \text{Eq. (5.7)}$$

If *N* is 1, it is the average nearest neighbor degree value of the links connected to neighboring nodes. $K_{i,1}$ is the average ubiquity of technologies developed by firm *i*. In other words, it indicates how many firms on average have the technologies developed by firm *i,* as common. Symmetrically, $K_{\alpha,1}$ represents the average diversification of firms who develops technology, α. In other words, it indicates how diversified, on average, the firms that developed technology α are.

According to the rule of thumb, when *N* is 20 for firm information ($\overrightarrow{k_\iota}$) and when N is 19 for technology information ($\overrightarrow{k_\alpha}$), the iteration for weighted average considered to have been sufficiently performed. This study uses the result of iteration 20 times ($\overrightarrow{k_{\iota,20}}$) because the complexity of a firm's technological portfolio is a variable of our interest. The sufficiently converged result ($\overrightarrow{k_{\iota,20}}$) is called the Technological Complexity Index (hereafter referred to as *Complexity*) of firm *i*.

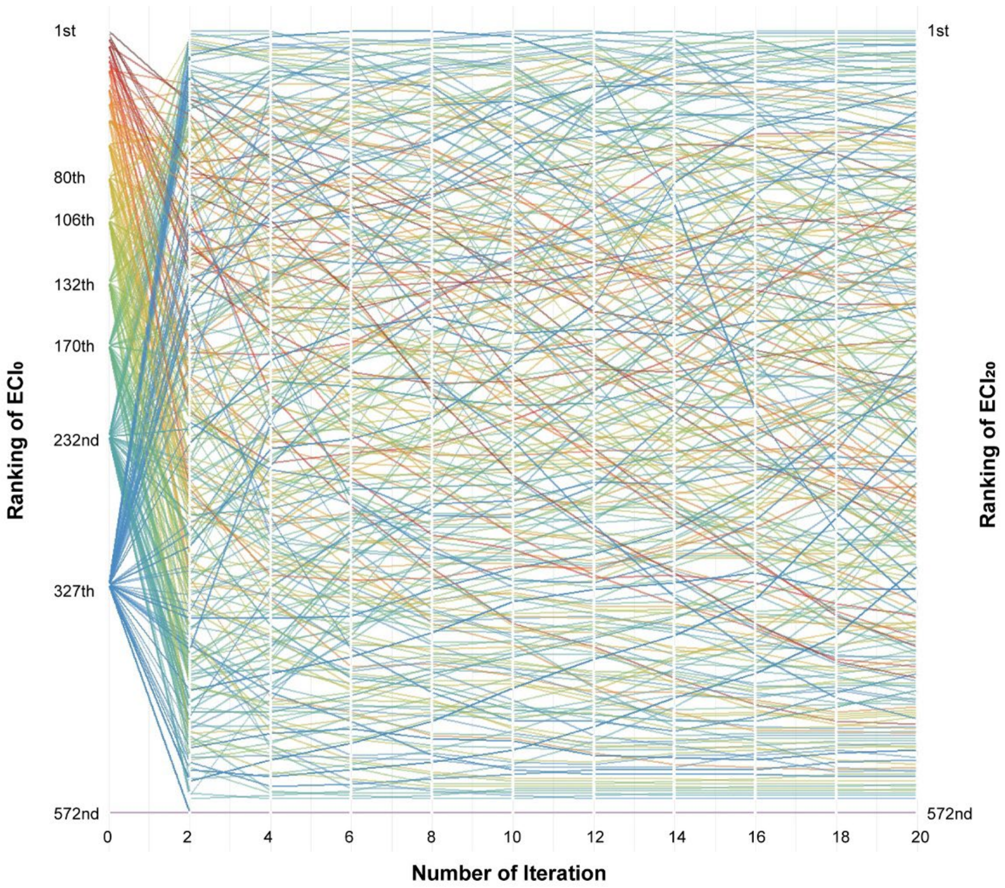

Figure 5-1. Ranking of Economic Complexity Index ($\overrightarrow{k_{i,N}}$) of the firm based on the iteration number, N

Complexity, also called technological complexity, is a value that reflects information obtained by averaging the diversification of firms and the ubiquity of technology over 20 repetitions. As can be seen in Figure 5-1, as the number of iterations increases, the ranking of the complexity ($K_{i,20}$) value of each firm's technological portfolio converges to single value. In particular, it is interesting to note that even if a firm's observed degree of diversification ($K_{i,0}$) is low, it can have a value of *Complexity* ($K_{i,20}$) for a broad spectrum. The ranks of $K_{i,20}$ of the 327th firms with only one technology (blue) varied greatly depending on the complexity of the technologies they possessed. These findings suggest that a technological portfolio should not be judged simply by the number of technology classification a firm has. Even if there is only one type of technology that holds *RTA,* if the technology is more rare (non-ubiquitous), the complexity ($K_{i,20}$) of the firm's technological portfolio can increase.

A detailed description of the *Complexity* is added to Appendix 2 along with examples.

5.3.3 Empirical Model

5.3.3.1 Model for the entire samples

The following regression model was established to confirm the overall effect of the two technology accumulation strategies, namely technological diversification and technological complexity, on the firm's financial performance.

$$
\begin{aligned}
SalesGrowth_{i,t+2} \\
&= \beta_0 + \beta_1 TD_{it} + \beta_2 TD_{it}^2 + \beta_3 TD_{it} \times Complexity_{it} + \beta_4 TD_{it}^2 \\
&\times Complexity_{it} + \beta_5 Complexity_{it} + \beta_6 Complexity_{it}^2 \\
&\quad + \boldsymbol{\beta_7 X_{i,t}} + \beta_8 Z_{mt} + \beta_9 Y_t + \mu_i + \epsilon_{i,t} \quad \cdots\cdots\cdots\cdots \text{Eq. (5.8)}
\end{aligned}
$$

$SalesGrowth_{i,t+2}$ on the left side represents the firm's financial performance as a log difference value of the firm's sales from time t to time $t+2$. Financial performance was calculated as $\ln Sales_{i,t} - \ln \overline{Sales_{\iota,t-2}}$ according to the methodology used by Kang et al, (2019) . Where $\overline{Sales_{\iota,t-2}}$ is the average value of sales of firm i over the three years t-1, t-2, and t-3 $((Sales_{i,t-1} + Sales_{i,t-2} + Sales_{i,t-3})/3)$. Sales tend to be overestimated, and since the value changes rapidly due to M&A, etc., we tried to minimize volatility by taking the average of the three years (Kang et al., 2019). To control for potential endogeneity issues between independent and dependent variables, lagged two years were set.

On the right-hand side, TD_{it} is the technological diversification index of firm i at time t, calculated through Equation (5.1). Next, $Complexity_{it}$ is the complexity value of the technological portfolio of firm i at time t, calculated through Equation (5.4). The interaction term of TD_{it} and $Complexity_{it}$ indicates that a firm diversifies its technology into technologies with high complexity. $\boldsymbol{X_{i,t}}$ represents the vector of firm-specific control variables known to affect the firm's financial performance. Size measured by the number of employees of firm i in time t ($num\_Employee_{i,t}$), technology stock measured by number of patents filed ($numPatents_{i,t}$), tenure of business ($age_{i,t}$), net profit to sales ($Profit\,ratio_{i,t}$) and total debt to total assets ($Debt\,ratio_{i,t}$) were included. Z_{mt} is an industry control variable proxied by the industry growth rate, which is the growth rate of total sales ($Sales$) in the industry (based on the two-digit level Standard Industrial Classification). Y_t is a year dummy variable, and μ_i is an independent variable related to the fixed effect of firm i, which is a firm-specific characteristic that does not change over time and is not observed. $\epsilon_{i,t}$ denotes the idiosyncratic error term of firm i at time t, unrelated to μ_i.

5.3.3.2 Model for the subsamples

Next, it is confirmed how the firm's technology accumulation strategy varies depending on the size of the firm and the stock of accumulated technological knowledge. To this end, first, the total sample firms were divided into two subsamples based on the number of patents ($numPatents_{i,t}$), which is a proxy for the amount of accumulated technology stock. In the case of 12,040 firms with the number of patents greater than or equal to the median value by year ($\widetilde{numPatents_{i,t}}$), they were judged to be firms with high technology stock. Conversely, 10,645 firms with the number of patents smaller than the median value per year ($\widetilde{numPatents_{i,t}}$) were judged to be firms with low technology stock. The regression analysis was performed by Equation (5.9) for each of the two subsamples.

Here, $Dummy\_Employee$ is a value obtained by converting the number of employees, which is a proxy for the size of the firm ($Size_{i,t}$), into binary numbers. It represents 1 if it is greater than or equal to the median value by year ($\widetilde{Size_{i,t}}$), and 0 if it is smaller. The $Size_{i,t}$ of firm i in time t was excluded from $\boldsymbol{X_{i,t}}$ as the size of the firm was controlled as a dummy variable. Other control variables used in Equation (5.9) are the same as those described in Equation (5.8).

$$
\begin{aligned}
SalesGrowth_{i,t+2} &= \beta_0 + \beta_1 TD_{it} + \beta_2 TD_{it} \times Dummy\_Employee \\
&+\beta_3 TD_{it}^2 + \beta_4 TD_{it}^2 \times Dummy\_Employee \\
&+\beta_5 TD_{it} \times Complexity_{it} + \beta_6 TD_{it} \times Complexity_{it} \times Dummy\_Employee \\
&+\beta_7 TD_{it}^2 \times Complexity_{it} + \beta_8 TD_{it}^2 \times Complexity_{it} \times Dummy\_Employee \\
&+\beta_9 Complexity_{it} + \beta_{10} Complexity_{it} \times Dummy\_Employee \\
&+\beta_{11} Complexity_{it}^2 + \beta_{12} Complexity_{it}^2 \times Dummy\_Employee \\
&+\boldsymbol{\beta_{13} X_{i,t}} + \boldsymbol{\beta_{14} X_{i,t}} \times Dummy\_Employee \\
&+\beta_{15} Z_{mt} + \beta_{15} Y_t + \mu_i + \epsilon_{i,t} \quad \cdots\cdots\cdots \text{Eq. (5.9)}
\end{aligned}
$$

As a result, the full sample of firms was classified into four types of subsamples based on the amount of technology stock and firm size. The classification criteria and definitions of each subsample are summarized in Table 5-2 above.

Table 5-2. Four subsamples categorized by tech stock and size of the firm

Tech stock \ Size	$Dummy\_Employee = 1$	$Dummy\_Employee = 0$
Firms with 1st & 2nd quartile value of $numPatents_{i,t}$	Firms of high tech stock with large size	Firms of high tech stock with small size
Firms with 3rd & 4th quartile value of $numPatents_{i,t}$	Firms of low tech stock with large size	Firms of low tech stock with small size

5.4 Empirical Results

5.4.1 Result for the entire samples

First, the basic statistics of the variables and the correlation between the variables used in Equation (5.8) were checked. Prior to regression analysis, all variables were normalized through Min-Max Scaling, and Box-Cox transformation (Box and Cox, 1964) was performed yearly to adjust the skewness of the distribution.

Table 5-3. Descriptive statistics and correlations

Statistic	N	Mean	St. Dev.	1.	2.	3.	4.	5.	6.	7.	8.
1. $Tech\_Diversification_{i,t}$	22,685	27.988	8.427	1							
2. $Complexity_{i,t}$	22,685	36.320	7.612	0.136	1						
3. $num\_Employee_{i,t}$	22,685	0.007	1.961	0.448	0.095	1					
4. $num\_Patent_{i,t}$	22,685	0.002	2.060	0.378	0.130	0.574	1				
5. $age_{i,t}$	22,685	0.002	1.617	0.305	0.031	0.550	0.238	1			
6. $Profit\_ratio_{i,t}$	22,685	−0.002	6.405	0.003	0.123	0.082	0.099	0.027	1		
7. $Debt\_ratio_{i,t}$	22,685	0.00001	0.817	0.209	-0.045	0.381	0.110	0.255	-0.112	1	
8. $IND\_Grow_{m,t}$	22,685	−0.002	2.728	-0.074	-0.021	-0.093	-0.006	-0.048	0.072	-0.089	1

Through the results of Table 5-3, the following facts were confirmed. First, a relatively high correlation was observed between firm's tenure (age_{it}), size ($num\_Employee_{i,t}$), and technology stock ($numPatents_{i,t}$). This means that the older the firm, the larger the size and the greater the amount of accumulated technology stock, which can be seen as a result consistent with common sense. Second, a relatively high correlation was observed between a firm's business tenure (age_{it}), size ($num\_Employee_{i,t}$), and technology stock ($numPatents_{i,t}$) and technological diversification (TD_{it}). The fact that the larger a firm's business tenure, the greater the amount of accumulated technology stock, and the larger the size of the firm, the greater the degree of diversification of the firm's technological portfolio can be interpreted in the same context as our starting point of this study. So, the effect of technology diversification should be confirmed differently depending on the firm's accumulated technology stock and firm's size. Third, there was no correlation between the degree of diversification (TD_{it}) and complexity ($Complexity_{it}$) within a firm's technological portfolio. This partially supports the fact shown in Figure 5-1 that the diversity of a firm's technology classification does not correlate with the complexity of its technological portfolio as a whole.

A variance inflation factor (VIF) test was conducted between Technological diversification (TD_{it}) and size ($num\_Employee_{i,t}$), technology stock ($numPatents_{i,t}$) and size ($num\_Employee_{i,t}$), tenure (age_{it}) and size ($num\_Employee_{i,t}$) of firms with a correlation coefficient exceeding 0.4. After confirming that the results of the VIF test were sufficiently lower than 10, all variables were included in the regression model.

Next, we investigated how the strategy of technology accumulation through technological diversification and increase in technological complexity affects the firm's financial performance for the entire sample. The regression analysis results of Equation (5.8) are summarized in Table 5-4. Models (1), (3), and (5) are results that do not reflect the firm's fixed effect, while Models (2), (4), and (6) add the firm's fixed effect to control time-invariant, unobserved firm-specific factors that affect the firm's financial performance.

Table 5-4. Technology accumulation strategies and financial performance for the entire sample

	Dependent variable: $Growth\_Sales_{i,t+2}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$Tech\_Diversification_{i,t}$	0.009 (0.036)	−0.038 (0.049)	0.588*** (0.163)	0.249 (0.199)	1.937*** (0.631)	0.680 (0.700)
$Tech\_Diversification^2_{i,t}$			−0.011*** (0.003)	−0.006 (0.004)	−0.042*** (0.014)	−0.010 (0.015)
$Tech\_Diversification_{i,t} \times Complexity_{i,t}$					−0.037** (0.017)	−0.013 (0.019)
$Tech\_Diversification^2_{i,t} \times Complexity_{i,t}$					0.001** (0.0004)	0.0001 (0.0004)
$Complexity_{i,t}$	1.167*** (0.162)	0.503** (0.229)	1.191*** (0.162)	0.505** (0.229)	1.564*** (0.235)	0.636** (0.290)
$Complexity^2_{i,t}$	−0.023*** (0.003)	−0.010*** (0.004)	−0.023*** (0.003)	−0.010*** (0.004)	−0.024*** (0.003)	−0.008** (0.004)
$num\_Employee_{i,t}$	0.229 (0.207)	−13.344*** (0.527)	0.298 (0.208)	−13.319*** (0.527)	0.306 (0.208)	−13.324*** (0.527)
$num\_Patent_{i,t}$	1.666*** (0.162)	1.241*** (0.205)	1.678*** (0.162)	1.246*** (0.205)	1.672*** (0.162)	1.251*** (0.205)
$age_{i,t}$	−4.061*** (0.197)	−5.126*** (0.394)	−4.023*** (0.197)	−5.166*** (0.395)	−4.024*** (0.197)	−5.163*** (0.395)
$Profit\_ratio_{i,t}$	0.256*** (0.042)	−0.059 (0.065)	0.248*** (0.042)	−0.059 (0.065)	0.251*** (0.042)	−0.060 (0.065)
$Debt\_ratio_{i,t}$	−4.907*** (0.356)	−2.962*** (0.491)	−4.844*** (0.357)	−2.952*** (0.491)	−4.844*** (0.357)	−2.935*** (0.491)
$IND\_Grow_{m,t}$	0.891*** (0.097)	1.069*** (0.092)	0.878*** (0.097)	1.066*** (0.092)	0.882*** (0.097)	1.064*** (0.092)
Constant	8.522*** (2.936)		0.874 (3.608)		−12.103* (7.271)	
Firm fixed effect	No	Yes	No	Yes	No	Yes
Observations	22,685	22,685	22,685	22,685	22,685	22,685
R^2	0.080	0.385	0.081	0.385	0.081	0.385
Adjusted R^2	0.079	0.319	0.079	0.319	0.079	0.319
Note:						*p<0.1; **p<0.05; ***p<0.01

As a result of analyzing all samples, in Model (5), which does not include fixed effects, it was confirmed that a firm's technological diversification affects its financial performance with an inverted-U shape. On the other hand, technological diversification into complex technologies affected the firm's financial performance in a U-shape. However, the higher

R^2 values of models (2), (4), and (6) than those of models (1), (3), and (5) mean that firm-specific effects must be controlled when analyzing a firm's technological diversification strategy.

The results of Model (6) for the entire sample show that, rather than technological diversification, technology accumulation only in the direction of increasing the complexity of a technological portfolio is more conducive to a firm's financial performance. This is because no statistically significant effect was observed on technological diversification of firms, and no statistically significant effect was observed on technological diversification into complex technologies. However, when the complexity of the technological portfolio becomes too large ($Complexity_{it} \geq 79.5$), the complexity of the technological portfolio within the firm starts to have a negative impact on financial performance again.

As examined in the literature review in Section 5.2, the influence of a firm's technological diversification strategy is expected to vary depending on the level of technology stock accumulated by the firm and the size of the firm. This is because economies of scale are determined by the firm's size, and the power to access resources is different. In addition, the probability of success in technological diversification varies depending on the firm's technology stock, this is because the ability of integration with new technologies and absorptive capability of firm is varied by technology stock. Therefore, it was investigated how the strategy of technology accumulation should vary according to the level of technology stock accumulated by firms and the size of the firm.

5.4.2 Result for the subsamples with high technology stock

Table 5-5. Technology accumulation strategies and financial performance for the subsample: high technology stock

	Dependent variable: $Growth\_Sales_{i,t+2}$		
	High technology stock		
	(1)	(2)	(3)
$Tech\_Diversification_{i,t}$	−0.330***	−0.905**	−4.486**
	(0.116)	(0.450)	(1.757)
$Tech\_Diversification_{i,t} \times Dummy\_Employee$	0.079	1.337**	8.769***
	(0.135)	(0.572)	(2.543)
$Tech\_Diversification^2_{i,t}$		0.012	0.103**
		(0.009)	(0.041)
$Tech\_Diversification^2_{i,t} \times Dummy\_Employee$		−0.023**	−0.172***
		(0.010)	(0.052)
$Tech\_Diversification_{i,t} \times Complexity_{i,t}$			0.094**
			(0.045)
$Tech\_Diversification_{i,t} \times Complexity_{i,t} \times Dummy\_Employee$			−0.197***
			(0.065)
$Tech\_Diversification^2_{i,t} \times Complexity_{i,t}$			−0.002**
			(0.001)
$Tech\_Diversification^2_{i,t} \times Complexity_{i,t} \times Dummy\_Employee$			0.004***
			(0.001)
$Complexity_{i,t}$	1.288***	1.316***	0.346
	(0.386)	(0.386)	(0.600)
$Complexity_{i,t} \times Dummy\_Employee$	−1.016**	−1.086**	1.033
	(0.516)	(0.517)	(0.885)
$Complexity^2_{i,t}$	−0.018***	−0.019***	−0.015**
	(0.006)	(0.006)	(0.006)
$Complexity^2_{i,t} \times Dummy\_Employee$	0.014*	0.015*	0.018**
	(0.008)	(0.008)	(0.009)
$Dummy\_Employee$	2.755	−12.188	−96.024***
	(9.372)	(11.435)	(30.982)
$num\_Patent_{i,t}$	0.611	0.541	0.646
	(1.072)	(1.073)	(1.073)
$num\_Patent_{i,t} \times Dummy\_Employee$	−1.355	−1.294	−1.441
	(1.142)	(1.142)	(1.142)

$age_{i,t}$	-9.052^{***}	-9.259^{***}	-9.300^{***}
	(0.599)	(0.606)	(0.607)
$age_{i,t} \times Dummy\_Employee$	3.490^{***}	3.579^{***}	3.621^{***}
	(0.735)	(0.736)	(0.737)
$Profit\_ratio_{i,t}$	-0.179^{*}	-0.178^{*}	-0.168
	(0.105)	(0.105)	(0.105)
$Profit\_ratio_{i,t} \times Dummy\_Employee$	0.649^{***}	0.646^{***}	0.623^{***}
	(0.228)	(0.228)	(0.228)
$Debt\_ratio_{i,t}$	-2.903^{***}	-2.934^{***}	-2.897^{***}
	(0.912)	(0.912)	(0.914)
$Debt\_ratio_{i,t} \times Dummy\_Employee$	0.173	0.213	0.150
	(1.226)	(1.226)	(1.227)
$IND\_Grow_{m,t}$	1.421^{***}	1.412^{***}	1.408^{***}
	(0.108)	(0.108)	(0.109)
Firm fixed effect	*Yes*	*Yes*	*Yes*
Observations	12,040	12,040	12,040
R^2	0.427	0.428	0.428
Adjusted R^2	0.344	0.344	0.345
Note:			$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

First, the technology accumulation strategy of the subsample with a high technology stock, in which the technology stock is larger than the median, was checked. The result is shown in the table 5-5.

Based on model (3), among firms with large technology stocks (Firms with 1st & 2nd quartile value of $numPatents_{i,t}$), in the case of large firms ($Dummy\_Employee = 1$), it was confirmed that the optimal strategy is to carry out technological diversification for financial performance. When a firm purely performed technological diversification ($Complexity_{it} = 0$), an inverted-U-shaped relationship was observed between the firm's technological diversification and financial performance. The increase in technological diversification had a positive and significant effect on financial performance, but after a certain point ($Tech\_Diversification_{i,t} = 31.036$), the marginal effect began to decrease. In particular, after the value of technological diversification became greater than 62.0725, financial performance began to decrease rather negatively. This is in line with the previous study by Kim et al. (2016), which found an inverted U-shaped relationship between a firm's technological diversification and financial performance.

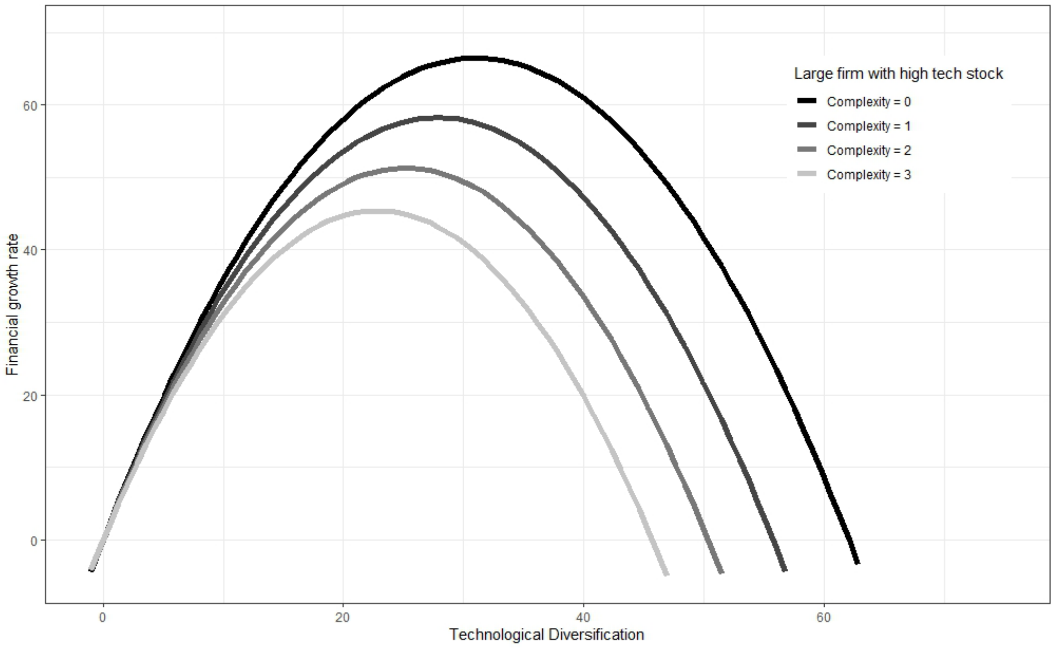

Figure 5-2. The relationship between diversification toward complex technologies and financial growth of the large firm with high tech stock

Efforts to diversify into high-complexity technologies also had a significant effect of the inverted-U-shaped relationship on firms' financial performance. However, as shown in

Figure 5-2, when a firm simultaneously performed efforts to increase the complexity of its technological portfolio and technological diversification, the maximum value of the firm's financial performance decreased as the value of complexity increased. In addition, the local maximum by technological diversification also came earlier. This means that if a firm pursues both technology accumulation strategies at the same time, it will lead to inferior results. This is because simultaneously increasing the depth (complexity) and breadth (diversification) of technological knowledge creates tension from a learning perspective (Ricciardi et al, 2016), and are mutually exclusive due to limited resources (Gupta et al., 2006).

On the other hand, the strategy of increasing the technological complexity of a large firm with a high accumulated technology stock did not have a statistically significant effect on financial performance, but a positively significant effect was observed as the value increased. However, when complexity increased by 1 unit, financial performance increased by 0.3%, which was modest. In summary, the best technology accumulation strategy for financial performance for large firms with a high stock of accumulated technology was to diversify as much technology as possible without increasing technological complexity. This means that firms with sufficient accumulated technologies and resources are more likely to develop new technologies when they expand the scope of technological knowledge across multiple technology classifications, and the synergy effect that occurs as a result of integration with existing technologies is greater. (Yang et al., 2017).

Next, among firms with high technology stock (Firms with 1st & 2nd quartile value of

$numPatents_{i,t}$), the technology accumulation strategy of small firms ($Dummy\_Employee = 0$) was investigated. In this case, a pure technological diversification strategy ($Complexity_{it} = 0$) has a U-shaped relationship with the firm's growth, which initially had a negative impact. The firm's financial performance continued to decrease as the firm diversified its technology, started to increase again from TD_{it}=21.7767, and recorded an increase rate greater than 0 after TD_{it}=43.5534. As shown in Figure 5-3 below, strategies in which firms diversify into complex technologies also have a negative impact to a certain degree, with a U-shaped relationship with the firm's growth, regardless of the level of complexity.

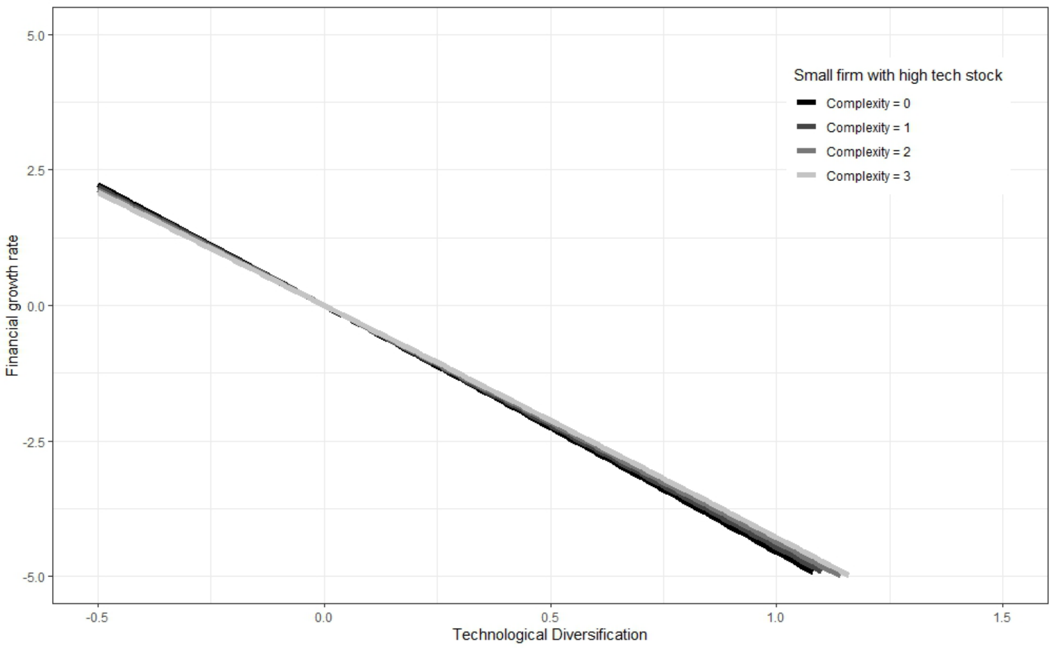

Figure 5-3. The relationship between diversification toward complex technologies and financial growth of the small firm with high tech stock

On the other hand, strategies that increase the complexity of the technology did not have a statistically significant effect on financial performance when the degree was small, but had a significant negative effect when the degree was excessive. This result is probably due to the fact that the level of technological complexity ($Complexity_{it}$) of small-sized firms with high technology stock is already high enough, therewith, the surplus resources to further increase the technological complexity ($Complexity_{it}$) are insufficient (due to their small size). As a result of the t-test, although the p-value is weak evidence corresponding to a 90% confidence interval, the average $Complexity_{it}$ value of small-sized firms with high technology stock is higher than that of large-sized firms with high technology stock. It was 0.22434 greater than the average technological complexity value. These results support the fact that no statistically significant effect of technological complexity ($Complexity_{it}$) was observed.

To sum up, efforts to accumulate technology for financial performance were not a priority for small size firms with a high level of technology stock. Even if new technologies are acquired through technological diversification, costs are higher in terms of economies of scale due to lack of resources caused by small size. In addition, the increase in technological complexity was also negative for performance, as technological complexity was already high enough compared to larger firms due to high technology stock relative to their size. This well explains the situation in our reality where highly specialized hidden champions in a narrow market are securing a stable market share with narrow technologies and products they already possess. Therefore, small size firms with a high level of technology stock should prioritize efforts to improve their firm financial structure or soundness in the short term.

The results of the control variables are as follows. First, the size ($Dummy\_Employee$) of high technology stock firms had a negative effect on the firm's financial performance when the value was larger than the median ($Dummy\_Employee = 1$). This is also consistent with the results in Table 5-4 for the entire sample. Capkun et al. (2009) who found that the size of US firms has a negative effect on their financial performance (measured by the rate of change in Earnings Before Interest and Taxes) supports the results of our study. For firms with already high technology stocks, an increase in technology stock did not have a statistically significant effect on an increase in the firm's financial performance. Firm tenure had a negative effect on the financial growth of firms with high technology stocks, but the negative effect slightly decreased when the size of the firm was large. Following the analogy of Coad et al. (2013), for firms with high technology stocks, tenure served as a 'deterioration' like milk rather than wine. The firm's profitability ratio ($Profit\,ratio_{i,t}$) had a significant positive effect only when the size of the firm was large. This is because the market selection mechanism played a role in reallocating firms' resources from small-size firms to large-size firms (Coad, 2009). An increase in a firm's $Debt\,ratio_{i,t}$ had a significant negative impact on the firm's financial performance, regardless of firm size. This can be attributed to the fact that a high debt ratio makes stable business activities difficult and delays investment for growth opportunities (Kang et al., 2019).

5.4.3 Result for the subsamples with low technology stock

Table 5-6. Technology accumulation strategies and financial performance for the subsample: low technology stock

	Dependent variable: $Growth\_Sales_{i,t+2}$		
	Low technology stock		
	(1)	(2)	(3)
$Tech\_Diversification_{i,t}$	0.159*	0.370	0.515
	(0.088)	(0.380)	(1.235)
$Tech\_Diversification_{i,t} \times Dummy\_Employee$	−0.231	−0.062	−0.107
	(0.151)	(0.668)	(3.040)
$Tech\_Diversification^2_{i,t}$		−0.005	0.008
		(0.008)	(0.030)
$Tech\_Diversification^2_{i,t} \times Dummy\_Employee$		−0.003	−0.022
		(0.013)	(0.066)
$Tech\_Diversification_{i,t} \times Complexity_{i,t}$			−0.007
			(0.034)
$Tech\_Diversification_{i,t} \times Complexity_{i,t} \times Dummy\_Employee$			0.004
			(0.083)
$Tech\_Diversification^2_{i,t} \times Complexity_{i,t}$			−0.0003
			(0.001)
$Tech\_Diversification^2_{i,t} \times Complexity_{i,t} \times Dummy\_Employee$			0.0004
			(0.002)
$Complexity_{i,t}$	0.861**	0.866**	0.997**
	(0.392)	(0.392)	(0.491)
$Complexity_{i,t} \times Dummy\_Employee$	0.380	0.386	0.228
	(0.978)	(0.978)	(1.357)
$Complexity^2_{i,t}$	−0.016**	−0.016**	−0.013**
	(0.007)	(0.007)	(0.007)
$Complexity^2_{i,t} \times Dummy\_Employee$	−0.002	−0.002	−0.005
	(0.015)	(0.015)	(0.015)
$Dummy\_Employee$	−18.766	−20.986	−12.124
	(16.773)	(18.145)	(37.565)
$num\_Patent_{i,t}$	1.147***	1.152***	1.169***
	(0.393)	(0.393)	(0.393)
$num\_Patent_{i,t} \times Dummy\_Employee$	−0.676	−0.668	−0.673
	(0.723)	(0.723)	(0.724)

$age_{i,t}$	-8.264^{***}	-8.279^{***}	-8.277^{***}
	(0.790)	(0.794)	(0.794)
$age_{i,t} \times Dummy\_Employee$	4.031^{***}	4.055^{***}	4.040^{***}
	(1.218)	(1.221)	(1.221)
$Profit\_ratio_{i,t}$	-0.217^{**}	-0.217^{**}	-0.217^{**}
	(0.103)	(0.103)	(0.103)
$Profit\_ratio_{i,t} \times Dummy\_Employee$	0.704	0.719	0.715
	(0.507)	(0.508)	(0.508)
$Debt\_ratio_{i,t}$	-3.598^{***}	-3.590^{***}	-3.563^{***}
	(0.828)	(0.828)	(0.828)
$Debt\_ratio_{i,t} \times Dummy\_Employee$	−0.458	−0.423	−0.469
	(2.037)	(2.038)	(2.039)
$IND\_Grow_{m,t}$	0.835^{***}	0.833^{***}	0.829^{***}
	(0.159)	(0.159)	(0.159)
Firm fixed effect	*Yes*	*Yes*	*Yes*
Observations	10,645	10,645	10,645
R^2	0.433	0.433	0.434
Adjusted R^2	0.315	0.314	0.314
Note:			$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Next, the technology accumulation strategies of sub-sample firms with low technology stocks, which are smaller than the median, were checked. The result is shown in the table 5-6.

For firms with low technology stocks, no statistically significant effect of technological diversification on financial performance was observed. This means that in order for technological diversification to have an impact on a firm's financial performance, sufficient technology stock must precede it. Technological experience can be judged through an accumulated technology stock, it also serves as an absorptive capability to recognize, acquire, assimilate and transform more know-how from outside the firm (Cohen and

Levinthal 1990; Zahra and George, 2002). From the above results, it can be inferred that firms with low technology stocks have difficulty connecting the results of technological diversification to financial performance due to their low absorption capacity.

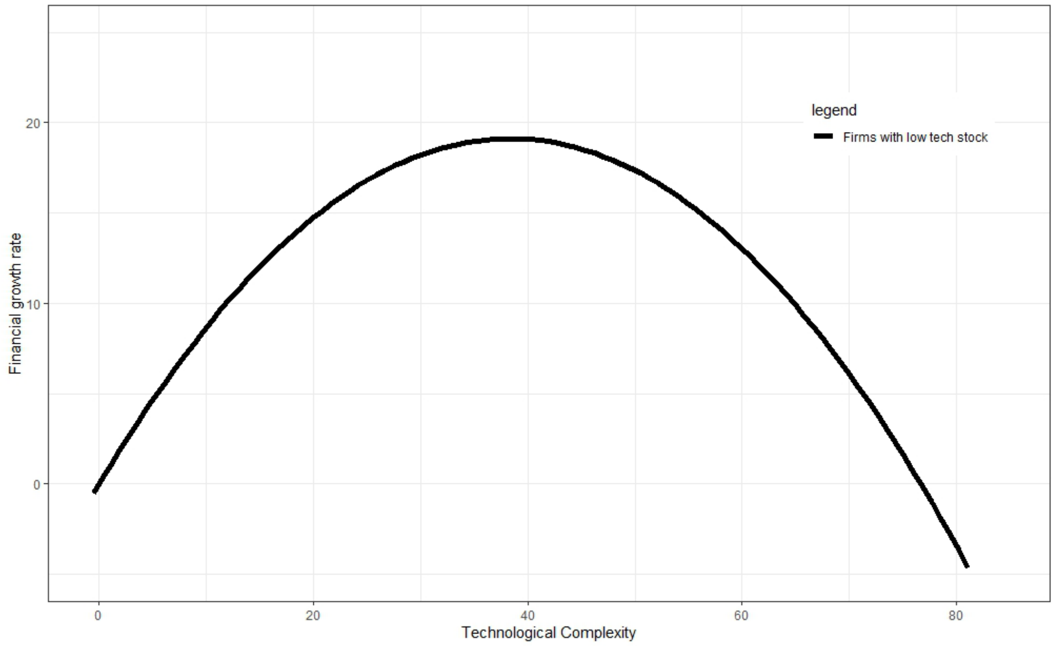

Figure 5-4. The relationship between technological complexity and financial growth of the firms with low tech stock

Firms with low technology stocks, regardless of size, needed to increase the complexity of the technology they possess. In other words, the most optimal strategy to increase a firm's comparative advantage in a situation where technology stock is low is to increase the non-ubiquity of the technologies it possesses. As we can be seen in Figure 5-4, the firm's financial performance increased when the firm's complexity ($Complexity_{it}$) increased to

38.39615. However, if it increases beyond that point, the marginal effect starts to decrease, and the financial performance starts to become less than zero from the point when the complexity value becomes 76.6923 or more.

In the case of firms with low technology stocks, above all, accumulating technology stock has a significant impact on the firm's financial performance, regardless of firm's size. In summary, regardless of size, firms with low technology stock will have to increase the complexity of their technologies or increasing the amount of technology stock. This is because an increase in the complexity of the technology possessed has a positive effect on a firm to secure a comparative advantage, and an increase in technology stock helps to increase absorption capacity. Firms with low absorption capacity due to low technology stock find it difficult to recognize, acquire, and assimilate new technologies, and even if they secure new technologies through technological diversification, it is difficult to digest and transform them internally.

The results of the control variables are as follows. First, for firms with low technology stock, size ($Dummy\_Employee$) did not have a significant effect on their financial performance. Even for firms with low technology stocks, their tenure played a role of 'deterioration' like milk rather than wine (Coad et al., 2013). The firm's profitability ratio ($Profit\ ratio_{i,t}$) had a significant negative effect regardless of the size of the firm, which, again, can be explained through the market selection mechanism (Coad, 2009). This is because market selection mechanisms have played a role in reallocating firms' resources from firms with low technology stock to firms with high technology stock. An increase in a firm's $Debt\,ratio_{i,t}$ has a negative significant effect on a firm's financial performance because it makes stable business activities difficult and delays investment for growth opportunities regardless of the size of the firm. (Kang et al., 2019).

5.5 Sub-conclusion

In this study, we investigated the optimal technology accumulation strategy that affects the financial performance of US manufacturing firms. Unlike previous studies on technological diversification, this study first added the concept of inter-technology heterogeneity to a firm's technology accumulation strategy. Technological diversification of firms was measured through the Rao-Stirling index to which the concept of proximity between technologies was added. Moreover, a technological complexity strategy considering the level of difference by technology was additionally considered. Next, in this study, based on the size of the firm and the firm's technology stock, the heterogeneous technology accumulation strategy for each group according to the state of the firm was examined. The results of this study emphasize that the firm's technology accumulation strategy should be different depending on the size of the firm and the level of the firm's technology stock.

Table 5-7. Four different technology accumulation strategies categorized by tech stock and size of the firm

Tech stock \ Size	Large	Small
High	● Diversifying into new technologies ● Not increasing technological complexity	● Improving financial structure rather than investing on technological knowledge
Low	● Increasing technological complexity ● Increasing technology stock	

The optimal technology accumulation strategies for each group are summarized in Table 5-7. First, it was found that technological diversification is the optimal technology accumulation strategy for firms with high technology stock and large firms. This is because the benefits from the synergies generated by rearranging and combining new technologies outweigh the costs if the firm has sufficient resources and sufficient absorption capacity. On the other hand, diversification into complex technologies had a positive effect on financial performance, but it was difficult to say that it was an optimal strategy because the magnitude of expected financial performance decreased as complexity increased. Efforts to simultaneously increase the breadth (technological diversification) and depth (technological complexity) of technological knowledge create tension in terms of learning, as they are mutually exclusive choices due to the limited resources of firms. Strategies that independently increase technological complexity are possible, but only begin to have a small impact on financial performance when the value is significantly higher.

Next, in the case of firms with sufficient technology stock but small firms, efforts to improve the firm's financial soundness should be prioritized rather than additional technology accumulation. Technological diversification has a negative impact on financial performance, and diversification into complex technologies also has a negative impact on financial performance. If the degree of technological diversification increases, the impact on financial performance will recover positively, but firms will have to endure short-term losses incurred in the process of technological diversification. This is because the small size of the firm lacks sufficient resources to utilize the newly developed technology. Also, since high technology stock already raises the average level of technological complexity, it only had a negative impact if it was excessive. Therefore, it can be said that the best growth strategy for small-sized firms with sufficiently high technology stocks is to maintain the current technology and invest in non-technological factors. This strategy can be confirmed in the case of small hidden champion that record stable sales based on highly specialized technology or products in a specific field.

Lastly, for firms with insufficient technology stock, regardless of the size of the firm, it is necessary to maintain a strategy of possessing a small number of technologies, but strive to increase the complexity of the technologies possessed. Alternatively, strategies that increase the level of a firm's technology stock were primarily useful. This means that the top priority should be given to securing technological comparative advantage and absorption capacity for firms with insufficient technology stock.

As we can see from the previous empirical evidence, a firm's technological diversification strategy should vary depending on its size and accumulated technology stock. Although many previous studies emphasize the positive role of firm technological diversification on financial performance, it was found that the results were limited to large-scale firms with high technology stocks. Therefore, it can be said that the effect of technological diversification on financial performance is somewhat exaggerated. Technological diversification is not the only strategy for technology accumulation, and firms will have to use a variety of heterogeneous technology accumulation strategies to suit their current state of affairs.

Chapter 6. Conclusion

6.1 Summary

A firm's technological knowledge is the driving force behind its growth. In particular, since it becomes the source of product development and a firm grows financially through product production and sales, the technological knowledge of a firm, located at the bottommost layer, can be said to be the fundamental force of growth. However, technological knowledge is accumulated within the firm based on 'accumulation time' through sufficient trials and error, so it requires a lot of time. In addition, the uncertainty of technology development and the limited resources and rationality of firms force firms to be careful in the accumulation of technological knowledge. For the efficient accumulation of technological knowledge, efforts to understand technological knowledge more elaborately are needed.

In this study, the technological knowledge and its accumulation of firms were examined in three aspects: the process of technological knowledge, measurement, and strategy. In particular, the viewpoints of multifacetedness, dynamics, and heterogeneity among technologies were additionally considered based on the existing understanding and perspectives on each. To this end, a panel dataset matching patent-financial information was established targeting manufacturing firms in the US and Korea, and the following three empirical analyses were conducted.

In Chapter 3, we tried to understand the nature of technological knowledge and its accumulation pattern by taking a multi-faceted view of the process of technological knowledge accumulation in firms. According to the results of the analysis, first, as the firm's tenure increases, the entire technological knowledge of the firm gradually migrates. Neither the firm's peripheral nor core technologies change considerably, and even if they do change, they are changed to related technologies. Next, as the firm's tenure grows, it is found that the entire boundary of the firm's technological portfolio expands. Lastly, we found that a firm's technological knowledge is accumulated in a punctuated equilibrium manner. In the process of technology accumulation, three multifaceted aspects are identified at the same time. Finally, by integrating all three perspectives into one, a new concept, the technology accumulation of firms is identified through the pattern of 'gradual migration with punctuated equilibrial expansion' is presented.

In Chapter 4, a new measurement was devised to estimate a firm's accumulated technological capability. Unlike existing indices to measure technology capability, the devised measurement estimates a firm's technological capability through aspects of its accumulated technological portfolio. In particular, the method of measuring technological capability presented in this chapter is an attempt considering the multifaceted characteristics of technological knowledge in that it simultaneously considers the three factors that affect technological capability: breadth, depth, and coherence. An inverted U-shaped relationship is observed between a firm's technological capability and financial performance, and a U-shaped relationship is observed between a firm's technological capability and its innovation performance. In particular, firms fall into a dilemma in which both financial performance and innovation performance of the firm decrease as technological capability increases. At that point, firms need to make strategic choices between short-term financial performance and greater innovation performance.

In the last chapter 5, it was clarified that the technology accumulation strategy should be different depending on the size of the firm and the level of technology stock. To this end, we analyzed how the effects of technological diversification strategies and strategies that increase the complexity of technological portfolios on financial performance vary depending on the firm's conditions. For large firms with high technology stocks, only technological diversification is the optimal strategy for financial performance. On the other hand, it was found that small-sized firms with high technology stock should prioritize improving their financial structure rather than strategies for technology accumulation. Finally, when a firm's technology stock is low, strategies to increase the amount of technology stock or increase the complexity of existing technology are important, regardless of their size.

This study identified the importance of a more sophisticated approach and interpretation that reflects multifacetedness, dynamics, and heterogeneity between technologies in the accumulation of technological knowledge within a firm. To consider the multifacetedness, dynamics, and heterogeneity of technological knowledge as a new perspective to understand the accumulation of technological knowledge in firms, we have come to understand our reality that cannot be systematically explained by previous studies.

6.2 Implications

6.2.1 Strategic implications

The method we have chosen so far to depict a firm's technological knowledge has been to draw croquis. Despite the loss of information, it was an unavoidable choice because it was prioritized to capture the characteristics of movements and shapes. This is also because it is so difficult to fully understand intangible technological knowledge. As a result, existing studies have explained the technology accumulation process of firms through a single concept or principle. We have understood and analyzed firms and the technological knowledge they acquire as static and passive objects, not as objects that change and evolve over time. And strategies for the accumulation of this knowledge have been established without considering the differences in the characteristics of each technology.

If the probability of failure of technology accumulation can be reduced and the efficiency of investment can be improved even a little, firms need to change their existing strategies. This is because the accumulation of technological knowledge is a vital issue for firms. Firms 'invest' in uncertain current technology knowledge for future growth. Therefore, a more sophisticated way and new window of understanding of technological knowledge were proposed in this study.

According to the results of this study, firms should establish an accumulation strategy that simultaneously considers the various characteristics of technological knowledge. When a concept is born, attempts to explain all phenomena in the firm with that concept spread like a trend. The results of empirical analysis, which increase like rain after rain, serve as evidence to support a theory until it is recognized as a stylized fact. However, the co-existence of various stylized facts about technological knowledge disproves that technological knowledge is a three-dimensional entity that cannot be explained with a single concept. Therefore, firms must establish an accumulation strategy by simultaneously considering various stylized facts. If a firm adheres to a technology accumulation strategy born simply through a single concept, the best outcome a firm will face is the local optimum of the technology accumulation process and financial performance.

Firms also need to pay attention to the changes over time. This is because everything changes with time: the state of the firm being analyzed, the technological knowledge that is the goal of the firm, and the various kinds of environments surrounding the firm. As a result of understanding technological knowledge, firms and the process of accumulating technological knowledge from a static point of view, if a firm sticks to one strategy even as its tenure increases, the firm may miss opportunities for potential technology accumulation and financial growth. A firm's strategy for accumulating technological knowledge must change rapidly from moment to moment. And the starting point is recognizing the fact that technology and firms are evolving beings.

Finally, firms should set up strategies for accumulating technological knowledge by considering the heterogeneous characteristics of each technology. What matters is not 'how diversified a firm is', but 'how much diversification is done with which technologies'. The premise that all technologies are different is essential in formulating a technological strategy. However, in the studies conducted so far, the difference in level between technologies based on the characteristics of each technology was not considered. In this study, the heterogeneous characteristics of each technology were additionally considered through a window called complexity economics, which considers all interactions between firms and technologies as the subject of analysis. Technological diversification is not a panacea for financial growth. When acquiring a new complex technology through technological diversification, a firm needs to first consider their internal situation (resources and technology stock, etc.), whether they can digest or absorb a newly acquired technology.

More sophisticated perspectives, approaches and thinking are required for firms seeking to accumulate technological knowledge. We need to go beyond the croquis that concisely contains only some features on a flat surface. When three-dimensional, time-changing technological knowledge and firms are accepted as they are, firms will be able to enjoy the greatest performance of global maximum.

6.2.2 Policy implications

The government's policy supporting i) revitalization of innovation activities and support for new industries through R&D subsidies and technology development projects; ii) exploration of new technological opportunities and future growth engines through industry development projects, is ultimately aimed at improving the competitiveness of firms. The government's policy to support the accumulation of technological knowledge of firms must also consider the multifacetedness, dynamics, and heterogeneity of technological knowledge.

First, the various characteristics of the technological knowledge possessed by firms should be evaluated from various angles at the same time in the process of selecting government-supported projects. Most of the government support projects have a specific subject and technological scope required, and firms are recruited through public announcements. In fact, many firms temporarily change their existing R&D strategies to participate in government-supported projects, or conduct R&D related to the project only while receiving support. However, due to resource constraints, the government cannot arbitrarily provide support to firms, and as a result, the process of identifying and selecting the right firms also costs money. Accordingly, in order to express their understanding of prior background related to technology development, firms emphasize information such as the current status of holding related patents and whether government-supported projects have been selected in the past. However, the information selected and limited by the firm in relation to the announced project is only helpful in determining the technological suitability of the applicant firm, and has limitations in grasping the firm's overall technological knowledge. Therefore, a firm's business plan must include items that can simultaneously evaluate various aspects (such as breadth, depth, coherence) of the firm's current technological knowledge in order to evaluate the overall technological knowledge. The goal of the government support is not to exploit firms for the development of specific technologies, but to create a virtuous cycle that contributes to the development of firms' technological capabilities and allows technological innovation created to again serves as a driving force for economic growth. Because of this, the technological suitability and commercialization potential of the firm are basically considered, but even if there are insufficient parts among the characteristics of the current technological capability, how the technology development through government support can strengthen the weakness should also be considered.[30]

Next, as firms and their technological knowledge change dynamically over time, government support should be provided in stages through multiple evaluations. If government support is all done at once, it is difficult to expect the maximum result from the support for firms. As we can see from the results drawn in Chapter 3, the process of accumulating technological knowledge within firms varies over time. It is difficult to expect that all firms will plan to use the large amount of support they have received until the distant future, taking into account the process of developing all-technological knowledge. Sometimes, short-term problems (other than technology development) can feel

[30] The purpose of government support for firm should not be limited to developing specific technologies. Government support should go beyond the goal of technology development and play a role in helping firms enhance their technological capabilities so that they can innovate on their own even after the support ends. Therefore, along with the development of the specific technology targeted by the project, it is necessary to examine whether the government's support is actually helpful in enhancing the technological capability of the firm concerned. For example, rather than just determining a firm 's technological fitness for a specific task, how that task can make the lack of a firm 's existing technological capability improve (for example, in one of the dimensions of breadth, depth, or coherence) should also be taken into consideration.

bigger. Therefore, it is desirable to provide step-by-step support so that firms can continue their innovation activities from a long-term perspective, rather than just providing temporary and collective support. If the degree of achievement of each step is confirmed through several interim evaluations, the government subsidy can be used only for the purpose of accumulating technological knowledge within the firm more efficiently.

6.3 Limitations and future research directions

This study has a unique academic meaning in that it analyzed the process, measurement, and strategy of technological knowledge and its accumulation within a firm, taking into account the multifaceted and dynamic characteristics of technological knowledge and the heterogeneity between technologies. Nonetheless, it does have some limitations. In this section, the limitations of the three previous studies are identified, and the direction of future research is suggested based on these limitations.

First, this study conducted an empirical analysis targeting firms belonging to the manufacturing sector. However, various characteristics related to technological knowledge and its accumulation may differ by industry. The manufacturing industry is the industry with the highest rate of patent applications, and prominent activities related to technology development of firms are observed. In particular, in Chapter 4, since the analysis was conducted on firms belonging to the 'electronic components, computer, radio, television and communication equipment and apparatuses' manufacturing industries, where technological changes are rapid and patent applications are the most active, the effect of technological capabilities remains unknown at the industries where technology development is less important. In addition, the influence of the breadth, depth, and coherence of technological portfolios on technology capabilities may vary by industry. In future studies, it will be necessary to additionally consider the multifacetedness, dynamics and heterogeneity of technology knowledge under the control of the unique characteristics of each industry. To do this, it is necessary to expand the dataset to include all firms in all industries other than the manufacturing industry. When there are differences by industry, it is anticipated that a new taxonomy for the accumulation of technological knowledge can be proposed by grouping industries with similar characteristics.

Second, this study conducted an empirical analysis targeting firms located in the US or Korea. In the case of Chapters 3 and 5, the analysis was conducted on listed firms in the US, and in the case of Chapter 4, firms subject to external audit in Korea. In particular, in the case of Chapter 4, patent disambiguation work was conducted targeting Korean firms in order to include all unlisted SMEs in the analysis. In future studies, it is necessary to analyze the process, measurement, and strategy of technological knowledge accumulation considering the multifaceted and dynamic characteristics of technological knowledge and the heterogeneity among technologies under the heterogeneous context of each country. In the future, if the data set is expanded to firms in manufacturing powerhouses such as the US, Germany, Japan, and China, and comparisons between countries become possible, it is expected that a more fundamental understanding of technological knowledge will be possible.

Third, in this study, analysis was conducted through the one-digit of technology classification code. Analysis was performed with 3 digits in Chapter 3 and 4 digits in Chapters 4 and 5. Chen et al. (2010) argued that based on a 4-digit technology classification, the number of technologies observed is too small to be appropriate at a lower digit when examining a single industry while, it spreads too widely causing distortion of the results when the number of technologies observed is too many. Based on this, in the case of Chapter 3, which identified the entire manufacturing industry, analysis was performed with 3-digit numbers, and in the case of Chapter 4, which investigated a single industry, analysis was conducted with 4-digit numbers. Although it studies the entire manufacturing industry, in Chapter 5, where technology diversification is the focus of the study, it was analyzed by 4-digit number. However, indices measuring a firm's technological portfolio may have different results depending on the number of digits in the technology classification code (Beaudry and Schiffauerova, 2009). Therefore, if additional cross checks are performed with 4-digits in Chapter 3 and 3-digits in Chapters 4 and 5, the robustness of the results can be more strictly verified.

Fourth, this study confirmed the average tendency of firms. Since it is the result of examining the average or trend of firms, it may not be reasonable to interpret all firms uniformly based on this. Special cases that cannot be explained through the average tendency can be found depending on the firm. Therefore, richer interpretation and implications can be obtained if the case analysis by firm is additionally performed.

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Appendix 1: The related density

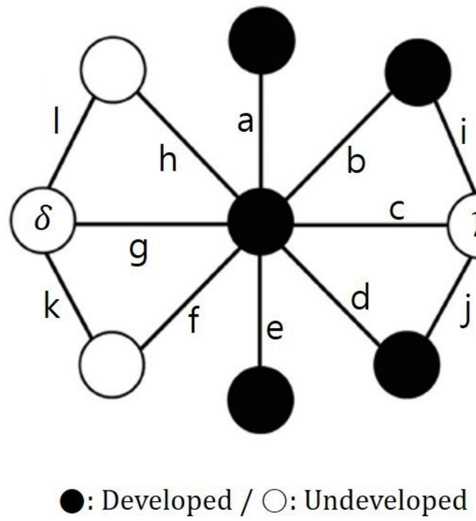

Figure A-1. A simple network as an example used to explain the related density (Source: Hidalgo et al., 2018)

Example 1) $\omega_{i,\delta} = \frac{g}{g+k+l}$

Example 2) $\omega_{i,\gamma} = \frac{c+i+j}{c+i+j}$

Appendix 2: The method of reflections

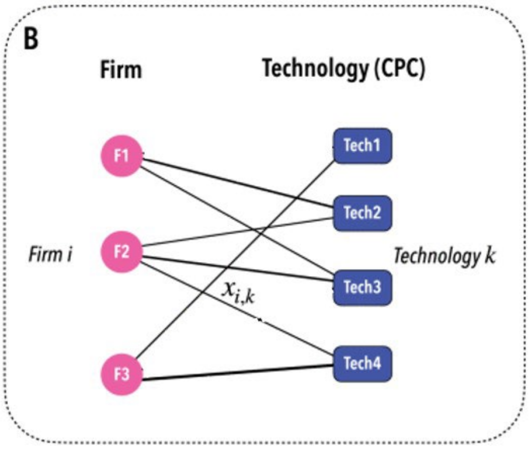

Figure A-2. A simple network as an example used to explain the method of reflections (Source: Jun et al., 2023)

Example 1) Diversification of firm

$$K_{firm_1,0} = 2$$

$$K_{firm_2,0} = 3$$

$$K_{firm_3,0} = 2$$

Example 2) Ubiquity of technology

$$K_{tech_1,0} = 1$$

$$K_{tech_2,0} = 2$$

$$K_{tech_3,0} = 2$$

$$K_{tech_4,0} = 2$$

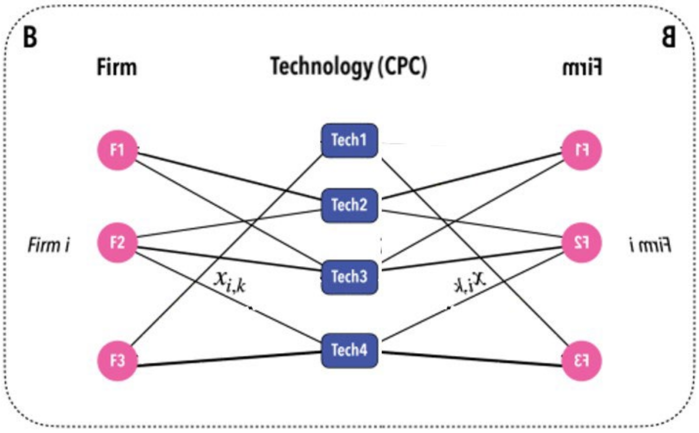

Figure A-3. An expanded network with the properties of the reflected nodes to show how the method of reflections is calculated (Source: Jun et al., 2023)

Example 1) Average ubiquity of the technology developed by firm (first reflection, n=1)

$$K_{firm_1,1} = (1/2)(2+2)$$

$$K_{firm_2,1} = (1/3)(2+2+2)$$

$$K_{firm_3,1} = (1/2)(1+2)$$

Example 2) Average diversification of the firm developing technology (first reflection, n=1)

$$K_{tech_1,1} = (1/1)(2)$$

$$K_{tech_2,1} = (1/2)(2+3)$$

$$K_{tech_3,1} = (1/2)(2+3)$$

$$K_{tech_3,1} = (1/2)(2+3)$$

Appendix 3: The coherence of technological portfolio

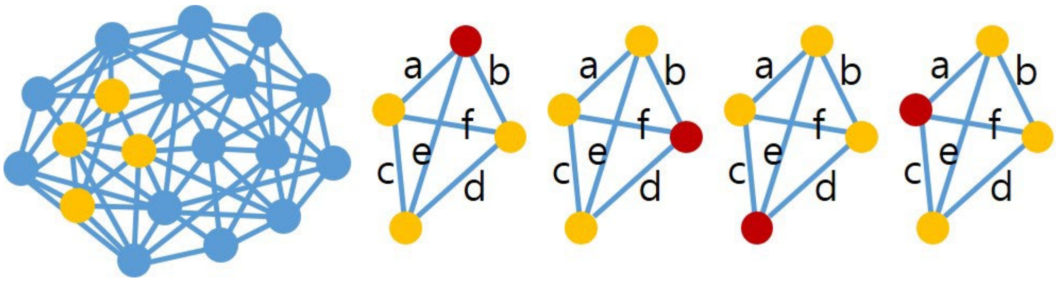

Figure A-4. A simple network as an example used to explain the coherence of technological portfolio

$$\Gamma_f = [(c+d+e) + (a+f+c) + (a+b+e) + (b+d+f)] / 4$$

Appendix 4: Gradual migration of core technology by industry

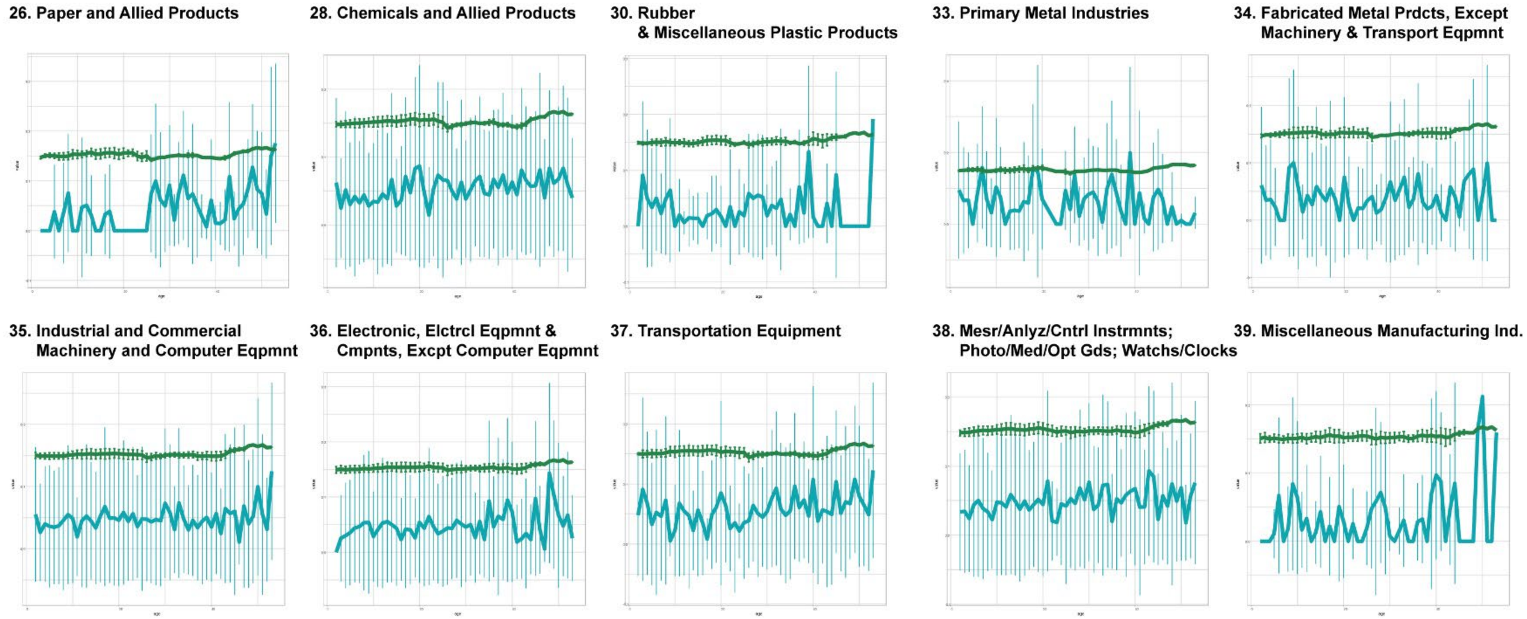

Figure A-5. Comparison average change of proximity between core technologies ($\overline{\phi_{J,p,t}}$, light blue) with average proximity ($\overline{\overline{\phi_{\alpha,\beta,t}}}$, green) according to firm's age by industry

- If the number of samples belonging to each industry was less than 30, the industry was excluded from the analysis.
- Based on SIC code with 2 digits, 10 out of a total of 20 industries were analyzed.

Appendix 5: Expansion of boundary by industry

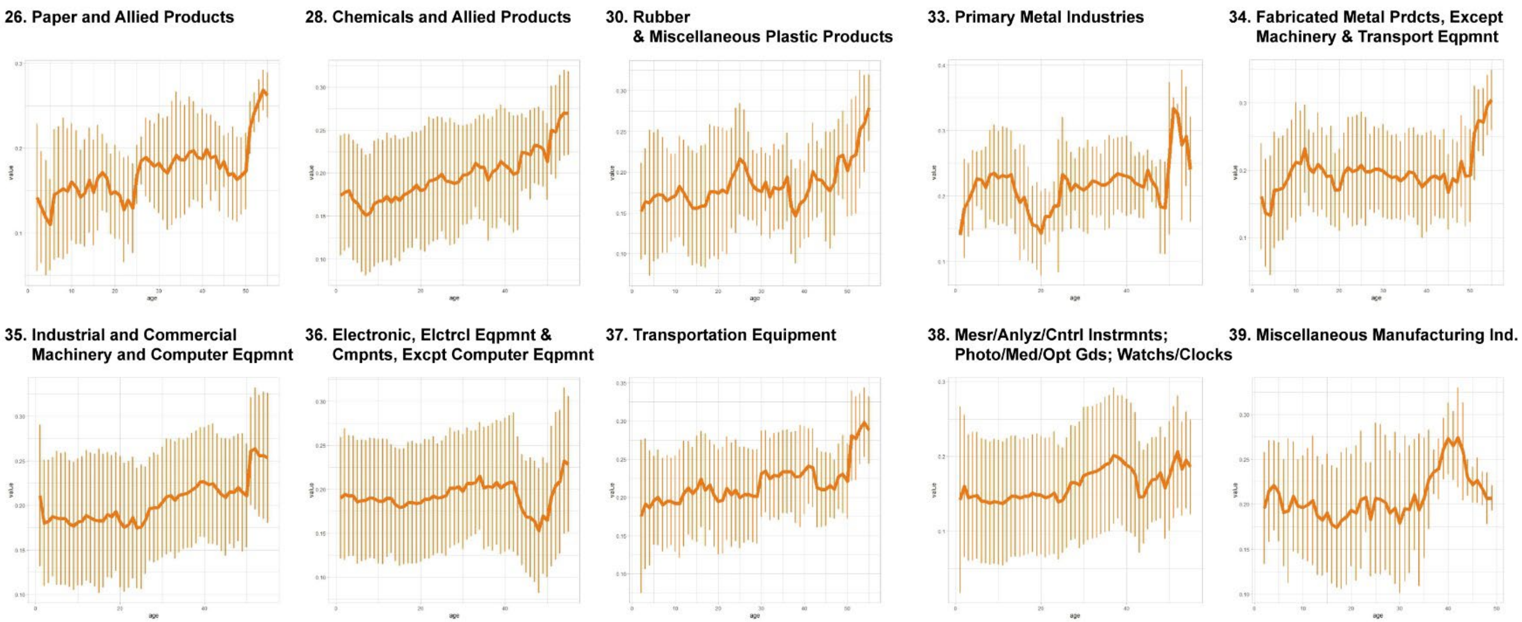

Figure A-6. Average degree of technological diversification ($\overline{Tech\_Div_{it}}$) according to firm's age by industry

- If the number of samples belonging to each industry was less than 30, the industry was excluded from the analysis.
- Based on SIC code with 2 digits, 10 out of a total of 20 industries were analyzed.

Abstract (Korean)

혁신하지 않는 기업은 생존할 수 없다. 기업의 혁신은 기업의 생존율을 높일뿐더러, 새로운 기술의 탄생으로 급변하는 환경 속 적응을 위한 필요조건이기 때문이다. 기업의 혁신은 이를 구성하고 있는 제품 혁신과 기술 혁신 간의 공진화를 통해 이루어지는데 특히, 기술 혁신은 제품 혁신보다 더 선행하여 나타나, 제품 혁신의 토대를 형성하게 된다. 기업은 축적된 기술을 바탕으로 새로운 혁신 제품을 개발할 수 있으며, 혁신 제품을 시장에 판매함으로써 재정적으로 성장할 수 있다. 따라서 기업의 성장을 이해하기 위해 개념적으로 가장 기저에 위치한 기술의 특성을 이해하는 것이 필수적이다.

그러나 기술 관련된 지식은 쉽게 획득할 수 있는 것이 아닌, 오랜 축적이 필요하다. 오직 시행착오를 경험하기 위한 충분한 축적의 시간을 통해 기술 지식은 기업 내에 축적될 수 있기 때문이다. 따라서 많은 자원이 요구되는 '기술 축적'의 본질을 이해하기 위해 다양한 개념들이 만들어져 왔다. 다양한 개념들은 크게 기술 축적을 어떻게 할 것인지와 관련된 축적의 방법, 기술 축적의 방법을 수행하기 위한 축적의 전략, 기술 축적의 전략에 따른 결과로 나타나는 현상인 축적의 양상으로 구분할 수 있다.

하지만 기존의 연구들은 다음의 3가지 측면에서 개선의 여지가 있다. 먼저 기술의 축적 양상은 입체적이기 때문에, 하나의 개념으로만 설명할 수 없다. 다음으로, 기술의 축적의 방법은 역동적인 변화를 따르기 때문에 시간이

지남에 따라 달라진다. 마지막으로 기술 개발의 난이도는 기술마다 다르기에, 기술의 이질성은 기술 축적의 전략에도 영향을 미칠 것이다.

본 연구는 기업의 기술 축적과 관련된 논의들을 다양한 측면에서 분석하였다. 또한 동태적인 변화를 이해하기 위해 시간에 따른 시계열 변화를 확인하였다. 이를 위해 기업의 특허와 재무 정보를 연결한 불균형 패널 데이터 셋을 사용하여 실증분석을 진행하였다. 최종적으로, 본 연구에서는 기술 축적에 관한 기존의 논의가 보다 더 정교하게 이해되어야 함을 규명하였다.

구체적으로, 3장에서는 기업 내 기술 지식이 축적되는 동태적인 과정을 다면적인(multifaceted) 측면에서 알아보았다. 먼저 기업의 업력이 증가함에 따라, 기업의 기술 지식 전체(중심과 주변부를 포함하는)는 점진적으로 이동(gradual migration) 하였다. 다음으로, 기업의 업력이 증가함에 따라, 기업의 기술 지식의 외연(boundary)은 확장(expansion) 하였다. 마지막으로, 기업의 기술 지식은 단속 평형(punctuated equlibrium) 식으로 축적되었다. 세 가지 관점을 통합하여, 기업내 기술 지식의 축적이 '단속 평형식으로 확장하며 점진적으로 이동(gradual migration with punctuated equilibrial expansion)'의 과정을 따름을 밝혔다.

4장에서는 축적된 기술 지식의 양상(aspect)을 통해 기술 역량을 측정하는 새로운 방법을 제시하였다. 기업이 보유한 기술 포트폴리오의 너비(breadth), 깊이(depth) 그리고 정합성(coherence)을 통해 기업의 기술역량은 간접적으로 측정되었다. 고안된 기술 역량 지수를 통해, 대한민국의 '전자부품, 컴퓨터,

영상, 음향 및 통신장비 제조' 산업 내 기업들은 핵심기술의 깊이가 깊어지는 방향으로 발전해 왔음을 알 수 있었다. 기업의 기술 역량과 기업의 장기적 재무적 성과 사이에는 역-U자 형의 관계가 관찰되었고, 기업의 기술 역량과 기업의 혁신 성과 사이에는 U자 형의 관계가 관찰되었다. 혁신 성과와 장기적 재무적 성과 사이 딜레마 속에서, 기업은 미래를 위한 기술역량에 투자할 것인지 결정해야 할 것이다.

5장에서는, 기업의 규모 및 기술 재고의 수준에 따라 기술 축적의 전략(기술 다각화 및 기술 복잡성)이 어떻게 달라져야 하는지 규명하였다. 먼저 기업의 기술 재고가 높고, 기업의 규모가 큰 기업은 기술 다각화가 재무적 성과를 위한 최적의 기술 축적 전략이다. 다음으로 기업의 기술 재고가 높지만 기업의 규모가 작은 기업의 경우, 추가적인 기술 축적의 전략보다는 재무적 건전성을 높이는 것이 최적의 기술 축적 전략이다. 마지막으로 기술 재고가 낮은 기업들의 경우, 규모와는 상관없이 보유한 기술의 복잡성을 높이거나 또는 기술 재고를 높이려는 노력을 해야만 한다. 이를 통해, 기술 다각화가 재무적 성과에 미치는 영향은 기업이 처한 상황(즉, 맥락)에 따라 다르게 해석되어야 함을 알 수 있었다.

연구의 결과를 종합하면, 기업 내 기술 지식의 축적을 이해하고 해석하는 데 있어서 기술 지식의 다면성 (multifacetedness), 동태성 (dynamics) 그리고 기술 간 이질성 (heterogeneity)을 고려한, 보다 정교한 접근이 중요하다. 기술 지식의 축적과 관련된 기존 연구들의 1) 수렴되지 않은 결과 및 2) 현실을 이해하고 설명하는데 발생하는 한계는, 기술 지식을 크로키(croquis)와 같이

최대한 단순화하여 이해하려는 시도에서 기인한 것이다. 이는 동세나 형태의 특징을 잡아내는 것이 우선시 되었기 때문에, 정보의 손실이 있음에도 불구하고 어쩔 수 없는 선택이었다. 입체적인 모습의, 시간에 따라 변화하는, 이질적인 기술 지식과 기업을 있는 그대로 받아들일 때, 우리는 기술 혁신과 기업의 성장을 오롯이 이해하고 설명할 수 있을 것이다.

주요어 : 기술 지식의 본질, 기술 축적 과정, 기술 역량 측정, 기술 축적 전략, 특허 명료화, 실증 분석

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