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Three Essays on Collaborative Innovation in the ICT Industry

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Abstract

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This paper consists of three essays on collaborative innovation in the Korean ICT industry. Firms compete with other firms to gain a competitive advantage in the market, but they also cooperate strategically with other firms for the same purpose. Collaborative innovation is a voluntary action resulting from firms' survival strategies, but the government has encouraged firms to participate in collaborative innovation to maximize the external effects of collaborative innovation on the economy. However, despite these government efforts, collaborative innovation has been limited in the industry. Despite the efforts of the government, the collaborative innovation ecosystem is not fully activated because it can be attributed to the inefficiency of policy instruments, or to the fundamental problems that policy has not been able to approach. Therefore, this study analyzes the form of three essays to better approach the answers to these questions. Specifically, the first essay explores the effects of industrial structure factors and government policies on cooperative behavior of firms from the angle of the interaction between agents and structure. The second essay investigates the impact of innovation and relationship factors on the

evolution of collaborative innovation networks from a structural perspective. The third essay analyzes the effect of firms' collaborative innovation on technology convergence from the agent's point of view. Through the diversified analysis, this study intends to expand the understanding of collaborative innovation among firms and come closer to its essence.

The first essay analyzes the effects of intra-industry heterogeneity and government policy on collaborative innovation. This study proposes to expand the existing debate on firm size and innovation from the firm level to the industrial level, focusing on the Firm Size Distribution (FSD) in the industry as a solution to the empirical limitations of the Schumpeterian hypothesis.

The purposes of this study are as follows. First, it investigates how collaborative innovation patterns are expressed differently according to the size heterogeneity in the industry. Second, it explores the effect of government incentives and regulatory policies on collaborative innovation patterns in industries with high heterogeneity. This study analyzes the changes in the collaborative innovation structure, firms' cooperation behavior, and collaborative innovation performance according to the SCP framework.

This study develops an agent-based model based on data from Korean ICT firms. The agent-based model constructed on a spatial NIPD game realizes collaborative innovation between 524 firms in the ICT industry in GIS-based virtual space. In this study, validation is performed using empirical data to enhance the explanatory power and robustness of the model, and then two simulations are performed according to the research questions.

The results suggest some stylized facts about intra-industry heterogeneity and innovation patterns. First, the decline in intra-industry heterogeneity positively

affects the collaborative innovation structure, behavior, and performance in the industry. Second, incentives are more effective than the same level of regulations, and certain levels of regulations can have adverse effects. There is also a positive interaction effect between incentives and regulations in the policy mix, and this interaction effect depends on the level of incentives and regulations. While incentives appear to be higher than both the main and interaction effects, regulation is also significant because it has an interaction effect that amplifies the effectiveness of incentives.

This study confirms that intra-industry heterogeneity, which has not been widely considered as an independent variable, is an important variable in the innovation ecosystem in the industry and suggests formal facts about the relationship between intra-industry heterogeneity and collaborative innovation. Finally, the results of this study reveal the effects of incentives and regulations on collaborative innovation in the industry and the positive interaction effect between incentives and regulations. These results suggest that the government needs to make efforts to mitigate intra-industry heterogeneity by recognizing that intra-industry heterogeneity is also an important factor as well as adjusting the payoff through incentives and regulations to create an open innovation ecosystem in the industry. The results also indicate that the government should implement these with appropriate incentives in the form of a policy mix rather than by implementing regulations alone to prevent the adverse effects of regulations.

The second essay analyzes the evolution of the collaborative innovation network in the Korean ICT industry. The purposes of this study are as follows. First, it aims to reveal the structural characteristics of the evolution of the inter-firm collaborative innovation network in the Korean ICT industry. Second, it analyzes the

effects of innovation and relational factors on inter-firm homophily and then attempts to identify the factors that exert a greater effect on homophily.

This study transforms the constructed panel data set into a firm-level adjacency matrix and performs QAP regression, which is network regression analysis. This study analyzes both the whole network and the connected network to reduce the potential large-network problem. Descriptive network analysis is also performed to explore the characteristics of network evolution in a more diverse way. Also, the results of the network regression analysis suggest that if a firm establishes a sufficient technology portfolio, the firm will participate in collaborative innovation according to the partner search mechanism in the market, based on the resources of the technology portfolio held by the firm. This is consistent with the argument presented by the resource-based theory for collaborative innovation. Therefore, the results of this study show that resource-based theory is more explanatory in the debate between resource-based theory and transaction cost theory about collaborative innovation. However, this study suggests that there is a preference for similarity among affiliates within the same group, which makes it possible to infer that group-level decision-making is also taking place in the collaborative innovation ecosystem. The results of this study show that, to participate in collaborative innovation networks, SMEs need to develop technologies in areas similar to the technology portfolios of large corporations in a central position in collaborative innovation networks. To this end, it may be more effective to extend the scope of business support to collaborative innovation among SMEs, as well as collaborative innovation between SMEs and large firms.

The third essay analyzes the effect of collaborative innovation on technological convergence. However, previous discussions on the relationship between

collaborative innovation and technological convergence have remained at the level of correlation, and previous studies have shown that the possibility of bias due to endogeneity has not been controlled adequately. This study analyzes the effect of collaborative innovation on the technological convergence of ICT firms. It also investigates which type of collaborative innovation best facilitates technological convergence.

This study builds a firm-level panel data set by merging 36 years of patent data and firm data and performs a regression analysis. To overcome the limitations of the previous studies, various variables that affect innovation are appropriately controlled in the research design, and the possibility of endogeneity due to simultaneity in the independent variables is tested.

The results of this study represent some new findings. First, collaborative innovation has a causal relationship that positively affects technological convergence. Second, simultaneity exists in which technological convergence affects inter-ICT firm collaborative innovation. Third, inter-ICT firm collaborative innovation among various types of collaborative innovation has the largest effect on technological convergence.

This study is significant in that it discusses the relationship between collaborative innovation and technological convergence to the level of causality. These results show that the existing policy, grounded on the resource-based approach, is reasonable. The existence of simultaneity between inter-ICT firm collaborative innovation and technological convergence indicates that ICT firms use collaborative innovation strategically to achieve technological convergence. Finally, the results of this study show that innovation mechanisms can be changed according to the partner type in collaborative innovation. These results imply that the current incentive system, which does not differentiate the budget allocation or the amount of support

depending on the type of innovation partner at the stage of application, is inefficient. Therefore, this study suggests the need to allocate incentives differentially to different partner types in policy design to promote technological convergence.

The results from these three studies extend the understanding of collaborative innovation by drawing out some simple mechanisms inherent in the complex interactions of collaborative innovation. The results of this study suggest various sources of support for resource-based theory in the debate between resource-based theory and transaction cost theory in relation to collaborative innovation. It also provides the theoretical underpinnings of the effects and interactions of incentives and regulations in the policy mix, which are considered significant in the collaborative innovation policy. Furthermore, the results of this study suggest that innovation-related theories such as resource-based theory should consider collaborative innovation type more thoroughly. Finally, this study suggests focusing on the structural characteristics of the industry as an alternative to the empirical limitations of the Schumpeterian hypothesis, which has been regarded as a premise in the field of innovation. In particular, the results of this study on the relationship between intra-industry heterogeneity and collaborative innovation have further elaborated on the relationship between firm size distribution and innovation, which has been discussed only conceptually in the past. It can contribute to knowledge growth.

The results of this study may also ultimately lead to an answer to what approach governments should take to promote collaborative innovation. The existing collaborative innovation policies are mainly directed toward direct interventions such as subsidies or regulation of firms. However, the results of this study suggest

that the collaborative innovation of firms responds sensitively to the factors of the industrial structure such as intra-industry heterogeneity, suggesting a paradigm shift of collaborative innovation policy by expanding the scope of government intervention. Therefore, the government needs to consider not only direct intervention in the firm but also environmental factors, including structural factors of the industry, to create an open innovation ecosystem. In conclusion, this study suggests that the collaborative innovation policy needs to be designed more effectively and the paradigm of the collaborative innovation policy should be changed by recognizing the importance of structural factors in addition to these direct interventions.

Keywords: Collaborative Innovation, Intra-industry Heterogeneity, Innovation Policy, Agent-based Modeling, Collaborative Innovation Network, Technological Convergence

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Table of Contents

List of Tables

List of Figures

Chapter 1. Introduction

Firms compete with other firms in the industry to survive and gain a competitive advantage in the market, but they also cooperate strategically with other firms for the same purpose. Innovation is the most important growth engine for firms in the modern industry, where technology demand is rapidly diversifying. Innovation competition among firms in the industry is often compared to a prisoner's dilemma game: firms may cooperate, betray, and sometimes be betrayed by other firms as needed. Recently, the interactions between firms have become more complicated due to rapid technological change, including ICT-based convergence. Firms test each other's limits with strategically symbiotic and sometimes endless chicken games. However, it has long been known that the optimal solution in the iterated prisoner's dilemma game is mutual cooperation. This phenomenon, called the emergence of cooperation, is not just a textbook or a well-controlled laboratory exercise. Numerous cases of cooperation—which can be observed not only in technological innovation but also in international politics, intergovernmental relations, and ecosystems—show that cooperation can actually be created in competition. Exploring the causes and consequences of cooperation in competition can bring us closer to its essence. Through this approach, this study can find valuable evidences for the creation of the so-called ‘collaborative innovation ecosystem’ that the government is ultimately pursuing.

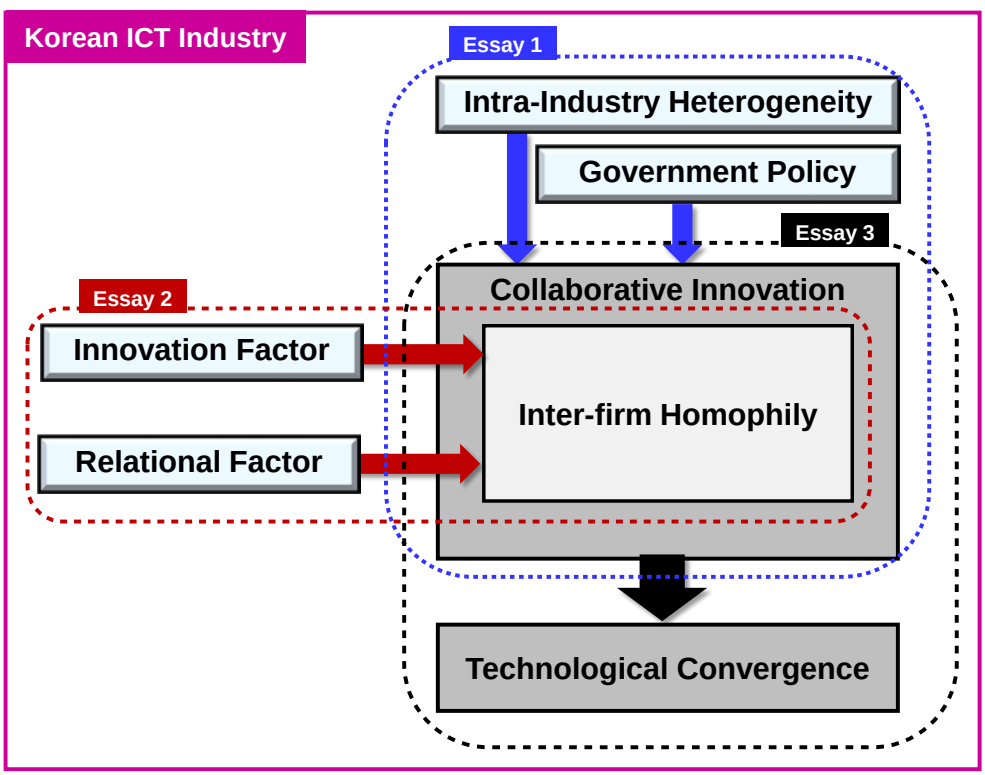
Many scholars have provided their grounds for asserting that governments should encourage collaborative innovation. Collaborative innovation can combine the unique innovation resources held by various firms to respond rapidly to market demand or create new technology demand that did not exist before. In particular, through the characteristic of general purpose technology, collaborative innovation based on ICT is

transformed widely by innovation in the industry, and externally positively affects the national economy. Therefore, many developed countries have implemented various policies to promote the participation of firms in collaborative innovation. The government has encouraged firms to engage in collaborative innovation by holding both incentives, or carrots, and regulations, or sticks. However, many governments are struggling to create a collaborative innovation ecosystem. There are two reasons for this difficulty: the government's policy instruments may not be appropriate, or government policy instruments may not have access to the fundamental barriers to collaborative innovation.

Given the complexity and uncertainty associated with interactions between heterogeneous agents, the piecemeal approach can only provide an incomplete understanding of the phenomenon. Therefore, this study seeks to contribute to the evidence-based policy by approaching the nature of collaborative innovation through a diversified analysis of causes, consequences, and ripple effects of collaborative innovation. This study consists of three essays, all with different views on collaborative innovation. This study approaches collaborative innovation from three perspectives: agents, structure, and interaction between agents and structure. Specifically, the first essay explores the effects of industrial structure factors and government policies on cooperative behavior of firms from the angle of the interaction between agents and structure. The second essay investigates the impact of innovation and relationship factors on the evolution of collaborative innovation networks from a structural perspective. The third essay analyzes the effect of firms' collaborative innovation on technology convergence from the agent's point of view. This study shows that different approaches to collaborative innovation provide different insights on collaborative innovation. These different insights emphasize the need for a multidisciplinary

approach by showing that contributions from existing empirical studies, which have mainly focused on agents, and contributions from the remaining approaches are different. In conclusion, this study suggests that an approach from a diversified perspective may be more effective than a piecemeal approach when analyzing collaborative innovation. The integrated conceptual framework of this study is presented in Figure 1.1 below.

Figure 1.1 The Conceptual Framework of the Study



The first essay explores the effect of intra-industry heterogeneity and government policy on collaborative innovation. This study explores the effect of intra-industry heterogeneity on firms' collaborative behavior and industry collaborative innovation

patterns. This approach can improve the understanding of how government policy instruments in high intra-industry heterogeneity situations interact and how they interact.

The second essay explores the determinants of the macroscopic pattern of homophily in the collaborative innovation network. This study extends the overall understanding of the collaborative innovation network, identifies the openness of the collaborative innovation ecosystem, and explores the optimal intervention strategy of the government from the network point of view.

The third essay analyzes the effect of collaborative innovation on technological convergence and explores which types of collaborative innovation have the most significant effect on technological convergence. This study can contribute to the effective implementation of government finances by evaluating the argument of government policy to promote technological convergence through collaborative innovation from the perspective of causality and enabling more effective policy design.

This study is also related to the question about the argument of the nature of the collaborative innovation that the resource-based theory assumes. Resource-based theory suggests that firms perform collaborative innovation to complement technology. Most technologically advanced countries have designed and implemented collaborative innovation policies based on these resource-based theories. However, transaction cost theory argues that firms participate in collaborative innovation to reduce the costs associated with internal innovation rather than participating in collaborative innovation for complimentary use of technology. This study starts from the premise of resource-based theory, but it is also meaningful as another chapter to examine the old debate between resource-based theory and transaction cost theory. The government's incentives and regulations in the first essay each determine the net utility by affecting the benefits and costs of participating in the firm's collaborative innovation. The profits

can be explained in terms of resource-based theory, and the costs can be explained in terms of transaction cost theory. Firms are more sensitive to their profits and costs, so they can get closer to firms' motivation to participate in collaborative innovation. Also, among the determinants of the inter-firm homophily in the second essay, the innovation factors can be explained from the viewpoint of resource-based theory and the relationship factor from the viewpoint of transaction cost theory. Finally, a discussion of the effect of collaborative innovation on technological convergence in the third essay confirms whether the description of the resource-based theory of collaborative innovation is validated through the results of a collaborative innovation called technological convergence.

This study also raises a question on the Schumpeterian hypothesis, which has been regarded as a premise of innovation research beyond the debate between resource-based theory and transaction cost theory. The Schumpeterian hypothesis is presented as a theory in innovation research but, at the same time, there is a contradiction in the empirical debate surrounding it. This study seeks to find clues to this contradiction in the heterogeneity of industry. In other words, this study seeks to find the cause of differences in the relationship between firm size and innovation in each country or industry from the essential point. The most fundamental reason that the ‘average’ rules are not applied is that there are significant differences between individuals. Therefore, this study considers the industry as a separate entity and focuses on the differences between the industrial characteristics of intra-industry heterogeneity. This suggests that discussion of the Schumpeterian hypothesis extends from the firm level to the industrial level, and that new solutions to the empirical limitations exist.

This study analyzes the Korean ICT industry. Korea has the most advanced ICT industry in the world and the highest level of ICT infrastructure. Also, Korea is one of

the countries with the highest government R&D expenditure on GDP in the world. Despite its short history of industrial development, the Korean ICT industry has innovative firms that have an important position in the global market. Therefore, analyzing the Korean ICT industry means analyzing one of the most innovative industries in the world. Considering that technology diversification in the modern market is centered on ICT technology, analyzing one of the most advanced ICT industries can provide important ideas for future ICT technology-centered innovation policies. Also, the results of this study can contribute to widening the understanding of the nature of firm behavior not only in Korea, but also in the ICT industry or other innovative industries around the world. Furthermore, this study can illustrate the simple but important patterns of complex interactions in the innovation ecosystem and bring them closer to the nature of cooperation between firms in competition.

This study consists of five chapters, including the introduction. Chapter 2 presents the first essay on intra-industry heterogeneity, government policy, and collaborative innovation. Chapter 3 offers a second essay dealing with the evolution of the collaborative innovation network in the Korean ICT industry. Chapter 4 consists of a third essay dealing with the effect of collaborative innovation on technological convergence. Finally, Chapter 5 presents the conclusions and implications of this study's conclusions and studies.

Chapter 2. [Essay 1] Intra-industry Heterogeneity, Government Policy, and Collaborative Innovation

2.1 Introduction

Inequality in size among firms in the industry has been regarded as affecting the innovation ecosystem, but these arguments have been discussed at a conceptual level. Many studies have made empirical efforts to identify stylized facts about the relationship between firm size and innovation performance since the Schumpeterian hypothesis on innovation was raised. However, these studies have failed to reach the same conclusion. There are many hypotheses about the causes, but the most common reason, that the "average" rule is not applied in general, is due to statistically significant heterogeneity among individuals (Zlowodzki et al., 2007). The reason that these factors hamper the establishment of stylized facts about the relationship between firm size and innovation performance can be found in the difference in characteristics between industries. In general, inter-firm interactions and innovation mechanisms within an industry are known to show significant differences between industries (Cantner & Hanusch, 2001). Previous studies have suggested that the effect of firm size on innovation performance varies according to industrial structure factors (Lee & Xia, 2006). Therefore, this study suggests that the limitations of the current research trends, which have mainly focused on the relationship between firm characteristics and innovation patterns, can be complemented by studies on the relationship between industrial characteristics and innovation patterns.

The innovation literature has rarely discussed the relationship between industrial characteristics and innovation patterns. However, the limitations of the Schumpeterian

hypothesis, which have continuously been reported by previous studies, indicate that the differences between the structural features of individual industries are more important than those perceived by researchers. Therefore, this study aims to explore how intra-industry heterogeneity in the firm size distribution (FSD) within an industry is related to the innovation patterns in the industry by extending the focus of the discussion from the firm level to the industry level.

This study concentrates on the FSD and intra-industry heterogeneity by expanding the focus of the current debate on firm size and innovation that has led innovation research since the Schumpeterian hypothesis from firms to industries. Previous studies on intra-industry heterogeneity have been monotonous, since they have focused on the determinants of intra-industry heterogeneity (Nelson, 1991; Noda & Collis, 2001). However, a few studies have suggested that intra-industry heterogeneity affects the economic performance of the industry, implying that intra-industry heterogeneity is a factor in promoting changes in industrial characteristics (Lee, 2009; Malerba, 2005). Therefore, this study examines the relationship between firm size and innovation performance posited by the Schumpeterian hypothesis at the industrial level and specifically explores how the collaborative innovation patterns differ according to the level of intra-industry heterogeneity. This study also investigates how the collaborative innovation pattern changes when governments use incentives and regulations to promote collaborative innovation.

The purposes of this study are as follows. First, it examines how collaborative innovation patterns are expressed differently depending on the heterogeneity level of the FSD in an industry. The relationship between firms in the industry is characterized by hierarchical features centered on market-dominant firms (Jung & Hong, 2015). Therefore, the level of intra-industry heterogeneity can affect inter-firm relationships

and interactions as well as industry performance. Indeed, previous studies have found that intensified intra-industry heterogeneity weakens industry returns (Lee, 2009). As such, the level of intra-industry heterogeneity can affect collaborative innovation as well as industry performance. Moreover, this possibility suggests a need to focus on industry-level characteristics that have rarely been considered in relation to the Schumpeterian hypothesis. This study therefore intends to explore the stylized facts about the relationship between intra-industry heterogeneity and innovation patterns by adding the intra-industry heterogeneity variable to the existing discussion.

Second, this study seeks to examine how government incentives and regulations affect collaborative innovation patterns in highly heterogeneous industries. Specifically, it analyzes changes in the pattern of collaborative innovation according to the level of incentives and regulations, identifies the more effective of the two policy instruments, and determines whether there is a positive interaction effect in the policy mix between incentives and regulations. With a properly designed policy mix, governments can avoid double financial burdens and increase policy efficiency. However, a defective policy mix can hinder policy effectiveness. It is therefore crucial for governments to have prior knowledge of the interactions of all the policy instruments (Sandu & Anghel, 2010).

The reason for the roughly inconsistent results obtained by the empirical studies that have explored the effect of collaborative innovation policies is the complexity of the policies and interactions (Uyarra & Ramlogan, 2012). Therefore, it is necessary to focus not only on the characteristics of agents but also on the relationships among agents when studying collaborative innovation. Agent-based modeling (ABM) is a methodology that is well suited to the fundamental purpose of social sciences, not only to understand individual behavior but also to understand the mechanisms by which

micro-interactions among individuals lead to macroscopic consequences (Axelrod & Tesfatsion, 2006). Representative early social science simulation studies, such as the bounded rationality of Simon (1955) and the garbage can model of Cohen et al. (1972), presented a bold new hypothesis that has not been captured by observations in the real world. Moreover, these hypotheses were established as the most important theories in social science by the empirical studies of their followers. The collaborative innovation model developed in this study can also contribute to the subsequent studies, because it can derive various application studies by presenting future innovation simulation studies and ABM studies with a basic model.

This study analyzes Korean ICT firms. To ensure the validity of the model, the characteristics data, patent data, and inter-firm collaborative innovation network data of Korean ICT firms are used. This study embodies the characteristics, behaviors, and interactions of agents using several theories of inter-firm collaborative innovation in model development.

The study consists of six chapters, including the introduction. Chapter 2 discusses theoretical discussions on intra-industry heterogeneity and collaborative innovation, as well as the Korean collaborative innovation policy, and reviews previous research related to collaborative innovation. First, the study proposes to focus on intra-industry heterogeneity by expanding the level of analysis from firms to industries as an alternative to the limitations of the Schumpeterian hypothesis. Based on this, it discusses the possibility of an independent variable of intra-industry heterogeneity that has been overlooked in previous innovation studies. Then, it examines the previous studies on intra-industry heterogeneity and collaborative innovation and presents theoretical propositions based on these studies. Second, this study examines the theoretical framework of innovation policy, which is the background of the study, and

reviews incentive and regulatory policies to promote inter-firm collaboration. Subsequently, it reviews the literature on the effects of incentives and regulations and then presents a proposition based on the theoretical discussions concerning interactions among policy instruments. Chapter 3 presents the theoretical propositions of this study, introduces agent-based modeling—which is the methodology of this study—and introduces the research design. This study introduces the research design and implements collaborative innovation using an agent-based model with empirical data. Specifically, this study specifies the agent, space, behavior rules, and payoff matrix, then establishes the model using these, and finally verifies the validity of the model. Chapter 4 presents the simulation results for each experiment. Finally, Chapter 5 summarizes the conclusions and presents the implications and limitations of the study.

2.2 Literature Review

2.2.1 Theoretical Background

2.2.1.1 Intra-industry Heterogeneity

The polarized distribution resulting from the observed size disparities in the FSD within an industry is called intra-industry heterogeneity (D'Este, 2005; Noda & Collis, 2001). Heterogeneity is defined by the concept of variety (Nelson, 1991) or the distributional disparity (Dosi, Lechvalier, & Secchi, 2010), but most of the studies on intra-industry heterogeneity have followed the latter definition (Na, Lee, & Baek, 2017). In this study, the concept of heterogeneity also follows the definitions of variability, variance, and skewness presented by Dosi et al. (2010). Intra-industry heterogeneity, as defined in this study, means the heterogeneity in the FSD in an industry, which is regarded as an inherent characteristic of the industry.

Intra-industry heterogeneity has long been a topic of interest to policy makers in relation to unfair trade practices (Axtell, 2001). The discussion of intra-industry heterogeneity begins with the work of Gibrat (1931). Gibrat (1931) presented a stylized fact relating to firm size, which concerns the size and growth of an enterprise and the manifestation of scale heterogeneity within an industry. These claims can be divided into two groups.

First, Gibrat (1931) stated that there is no significant relationship between firm size and growth. This claim, which regards corporate growth as a random process, is called Gibrat's Law and has been subject to verification by many researchers. Earlier empirical studies supported Gibrat's Law, because there was no significant relationship between firm size and growth (Mansfield, 1962; Simon & Bonnini, 1958). However, recent

studies using improved firm-level data sets have disproved Gibrat's Law (Evans, 1987; Sutton, 2005), revealing that growth slows as the firm size increases. Therefore, this claim that firm growth is a random process is not accepted at present. Instead, a variety of innovation and environmental factors are considered to affect firm growth.

Second, Gibrat (1931) presented a stylized fact about the size heterogeneity in industry. In other words, the FSD in a mature industry has a stable lognormal distribution, and the claim that size heterogeneity appears within the industry has led to efforts by many researchers to find hidden patterns of FSD distribution in an industry. Axtell (2001) reported that industries in developed countries consist of a small number of large firms and a large number of SMEs and that the FSD has an asymmetric structure with a right tilt. He also stated that this distribution is not affected by entry and bankruptcy. Unlike Gibrat's explanation for corporate growth, his explanations for the FSD remain valid hypotheses to date, and empirical studies have been conducted on various industries around the world.

Previous studies have explored the causes of intra-industry heterogeneity primarily from a resource-based perspective, in which intra-industry heterogeneity is expressed as a result of specific "ways of doing" according to firm capacity (Arrighetti, Landini, & Lasagni, 2014). D'Este (2005) analyzed the Spanish pharmaceutical industry and found that the diversity of firms' knowledge base is the main cause of intra-industry heterogeneity, and, as the knowledge of firms diversifies, innovation becomes more active. Noda and Collis (2001) explored the process of the emergence of heterogeneity among firms in an industry through a longitudinal study on the development of the cellular telephone service industry. They argued that intra-industry heterogeneity arises from the fact that each firm has a heterogeneous combination of assets and resources. Arrighetti et al. (2014) researched the Italian manufacturing sector. They found

heterogeneity in the investment patterns of intangible assets among firms, which could explain much of the emergence of intra-industry heterogeneity. Na et al. (2017) analyzed the FSD of Korea's service and manufacturing industries from 2008 to 2012 and found that there is heterogeneity in size. In particular, they stated that the service industry is more heterogeneous than the manufacturing sector.

In this way, many previous studies have mainly described intra-industry heterogeneity as size heterogeneity or performance heterogeneity among firms. However, there is no difference between the two, because both heterogeneity of size and heterogeneity of performance are measured by firms' sales. Therefore, size and performance heterogeneity within the industry can be seen as the same argument.

2.2.1.2 Schumpeterian Hypothesis and Industrial Characteristics

Innovation policies that do not take intra-industry heterogeneity into account are not likely to have the intended effect in an industry made up of heterogeneous firms (Na et al., 2017). Given that most industries in developed countries are formed by a small number of large firms and some SMEs, an innovation policy that does not consider intra-industry heterogeneity can lead to unexpected side effects (Axtell, 2001; Pavitt, 1987). However, researchers have focused primarily on firm-level characteristics rather than on the structural characteristics of the industry. In particular, firm size has been considered as an important factor for firms’ innovation. According to previous studies, firm size has a substantial effect on patents and affects ICT firms’ patent performance (Bound, Cummins, Griliches, Hall, & Jaffe, 1984: Hall & Ziedonis, 2001). Therefore, how does a firm's size affect its innovation? The debate regarding the effects of firm

size on firm innovation has been ongoing since the early days of innovation research.

The debate on the relationship between firm size and innovation begins with the Schumpeterian hypothesis. Schumpeter (1942) argued that large firms are more innovative than SMEs as they can secure the financing needed for innovation activities. Galbraith (1952) also asserted that market-dominant large firms lead innovation in an industry. This claim is called the Schumpeterian hypothesis and has been the subject of empirical analysis for a long time.

Schumpeterian economists have argued that an increase in firm size has a positive effect on innovation activities, and the innovation capacity of large firms is greater than that of SMEs. Schumpeter argued that large firms are more likely to innovate, because they spend more on R&D than SMEs do and they can use new technologies quickly and on a large scale regarding production levels, production capacity, marketing, and financing (Nelson & Winter, 1982). Galbraith (1952) also asserted that only a firm with a significant amount of resources can innovate, because innovation costs are high, which means that the larger the firm, the more innovative it is. Nelson and Winter (1982) suggested that the size of the firm, not the market power, is necessary for innovation. Acs and Audretsch (1988) argued that the larger the firm, the higher the total number of innovations is. They found that the total number of innovations is positively correlated with R&D, skilled labor, and the ratio of large firms in the industry (Acs & Audretsch, 1988). Cohen and Klepper (1996) analyzed the relationship between US firm size and patent performance and found that the larger the firm size, the higher the probability of performing innovation activities and the greater the frequency of innovation activities in the industry. Hoffman, Parejo, Bessant, & Perren (1998) noted that, in the UK, SMEs are considered to be innovative, but SMEs in many industries appear to be less innovative.

There is also a rebuttal to this claim. Some researchers have argued that, as a firm's size expands, its innovation capacity declines. Contrary to the Schumpeterian economists' argument that large firms have the advantages of being more efficient in research and development and of utilizing innovation on a larger scale, they have asserted that the bureaucratic control structures of large organizations can wholly or partially offset these potential advantages (Nelson & Winter, 1982). Acs, Morck, Shaver, and Yeung (1997) suggested that large firms are more successful innovators than SMEs, as the industries in which large firms are most active are high in innovation activity, but most of the innovation activities are conducted by small firms. They argued that radical innovations are more likely to occur in SMEs than in large firms and that SMEs lead Schumpeterian innovation. However, they asserted that the commercialization of innovation is likely to occur in large firms due to the availability of resources (Acs et al., 1997). Vossen (1998) also argued that large firms and SMEs play complementary roles in technological innovation processes, since large firms have stronger resources and SMEs have stronger innovation behaviors. They suggested that, while SMEs are more innovative than large firms, they have difficulty introducing innovation into the marketplace successfully, while large firms have had great success in introducing innovation into the marketplace.

In summary, there is a debate regarding how a firm's size affects its innovation activities. The empirical studies sustaining the Schumpeterian hypothesis have dealt with the effect of the size and market concentration of a particular firm on innovation. However, as mentioned above, these studies have not reached the same conclusion. Although various hypotheses can be raised about the causes, the most common reason for the 'average' rule not being applied is the presence of statistically significant heterogeneity among individuals (Zlowodzki et al., 2007). This argument can be

applied to investigate the cause of the difference between the results of the empirical tests of the Schumpeterian hypothesis. In other words, the effect of firm characteristics on innovation varies according to the industry because of the different characteristics of individual industries.

The claim that the inter-firm interaction and innovation mechanisms are different for each industry has already been raised by many previous studies (Cantner & Hanusch, 2001; Yurtseven & Tandoğan, 2012). However, the existing literature has not addressed the effect of the differences in industrial characteristics on innovation patterns. Lee and Xia (2006) conducted a meta-study of the effects of firm size on IT innovation using 54 correlations estimated from 21 empirical studies. They argued that the effect of firm size on innovation is adjusted differently depending on firm characteristics or industrial structure factors.

The limitations of the Schumpeterian hypothesis, which has continuously been reported by previous studies, indicate that the differences between the characteristics of structures among individual industries are more important than those discussed previously. Thus, the importance of the industrial structure itself emphasizes the need to move beyond the argument that the Schumpeterian hypothesis is applicable "on average" to all industries. In other words, it is necessary to shift the focus of the discussion beyond the current research trend, which focuses only on the firm, to the industry level. Therefore, this study aims to expand the Schumpeterian hypothesis to the industrial level and focus on how the FSD in an industry relates to the innovation patterns of the industry. It then suggests shifting the focus of the discussion from the firm level to the industry level.

2.2.1.3 Collaborative Innovation

Innovation is one of the firm's most important growth strategies and is closely related to firm performance. Firms build their technology portfolios through innovation activities and actively respond to market demand. Firms respond to market demand and build a technology portfolio through internal innovations. Sometimes, however, they collaborate strategically with other firms to conduct research and development. The theoretical basis for explaining this collaborative innovation is largely resource-based theory and transaction cost theory.

The resource-based theory assumes that firms have their own resources for innovation (Penrose, 1959). Firms use internal resources to perform internal innovation, but they cannot meet the market's technology needs with their own resources alone. Thus, firms use other firms' resources to survive in the market and gain an advantage in technology competition with other firms (Teece, 1986). Thus, the resource-based theory explains that mutual cooperation between firms with different technologies can meet various technology demands.

Transaction cost theory explains that firms prefer innovation types with lower costs associated with innovation activities (Williamson, 1981). Firms create R&D organizations and set up related facilities for internal innovation; in the case of certain technologies, the cost of such work may be greater than the cost of utilizing other firms' innovation capabilities. Therefore, firms choose collaborative innovation when the innovation cost reduction of collaborative innovation is greater than single innovation.

An innovative ecosystem with collaborative innovation can improve the inefficiency associated with internal innovation from the viewpoint of sharing innovation capability. Therefore, collaborative innovation improves the overall

innovation efficiency of the industry. Collaborative innovation also has broad external effects on the economy as a whole. In the recent technological environment in particular, where diversification of the technology demand in the market is rapidly proceeding due to the convergence of heterogeneous technologies based on ICT technology, this external effect positively affects the innovation performance of other industries. Therefore, many technologically developed countries have implemented various policies to engage firms in collaborative innovation to maximize the ripple effect of collaborative innovation.

The Korean government has also implemented policies to encourage firms to participate in collaborative innovation to create an open innovation ecosystem. The following sections examine government policies to promote collaborative innovation, focusing on theoretical grounds, policy instruments, and examples of Korean collaborative innovation policies.

2.2.2 Collaborative Innovation Policy

2.2.2.1 Theoretical Background of Innovation Policy

Firms have been regarded as the most important innovation actors, because they produce most of the innovation output in a country. Since innovation activities led by firms are considered to have widespread effects on national economic growth as well as knowledge and technology, governments have intervened in firms' innovation activities using a variety of policy instruments to improve their innovation performance. The legitimacy of such intervention can largely be divided into market failure and system failure.

According to the market failure approach of neo-classical economics, the knowledge of science and technology created through R&D activities has underprivileged characteristics because of its public nature, and investment in basic research with high externalities is insufficient (OECD, 2001). Therefore, government intervention is considered necessary to induce the optimal investment in innovation activities, and it is believed that governments can encourage innovation by giving incentives to firms. In other words, the market is the main stage of innovation activities, and government intervention in firms' innovation activities has been regarded as justified when market failures occur. However, despite governments' efforts to rectify market failures, criticism has been raised that the innovation failures are not improving, and a review of the innovation process has been made accordingly.

Evolutionary economists, such as Nelson and Winter (1982), have found that the market structure itself is an important factor in innovation through simulation studies using a history-friendly model. The need for government intervention in the market structure derived from their research exceeds the market failure approach. They pointed out that the extent to which the current policy instruments can reliably affect industrial structures is unclear (Nelson & Winter, 1982). As such, the importance of the overall innovation system, including the industrial structure, emerged, and the innovation system began to attract attention as a framework for explaining innovation failure in the market (Freeman, 1987). According to the innovation system theory, collaboration and networking among innovative agents in innovation activities have become important factors, and government intervention in innovation activities has been justified given that governments are responsible for promoting imperfect connections between innovation agents. That is, government intervention is needed to correct the system failure.

Freeman (1987) defined the national innovation system as an institutional network that promotes and spreads innovation and interaction between firms and governments. He argued that the rapid economic growth of Japan and the development of technological innovation stemmed from the national innovation system. The systematic approach to innovation emphasizes that firms rely extensively on collaboration and interaction with other agents (Broekel, Brachert, Duschl, & Brenner, 2015). The OECD Committee for Scientific and Technological Policy (CSTP) conducted the National Innovation System (NIS) project through the Working Party for Technology and Innovation Policy (TIP), and it pointed out that market failure approaches based on incentive schemes were limited (OECD, 2002). In addition, the CSTP concluded that interactions, including competition, trade, and networking, play an important role in the innovation process, particularly in clusters (OECD, 2002).

Edquist (2001) stated that the task of identifying the causes of innovation failure through the systems of innovation framework is the same as identifying errors in the system. He noted that the reason for the failure of an innovation system is that the functions, organization, and institutions of the innovation system may be inadequate or missing and that these components of the innovation system may not be connected or interact properly (Edquist, 2001). Therefore, it is considered that the government can intervene to prevent the omission of components of this innovation system and to promote networking and cooperation.

According to the viewpoint of innovation policy, the policy instruments of governments have also changed. Lundvall and Borrás (2005) classified the changes in government policy by the innovation paradigm into three categories: 'science policy,' 'technology policy,' and 'innovation policy.' The early government policy, called the 'science policy,' focused primarily on the correction of market failures through

incentives such as subsidies. Then, the 'science policy' changed to the 'technology policy,' and the commercialization aspect of scientific knowledge appeared. Finally, the 'innovation policy' paradigm emerged, emphasizing the importance of collaboration and networking among innovative agents, and the government policy also focused on promoting collaboration and networking among agents (Lundvall & Borrás, 2005). The innovation policy encompasses the science policy and technology policy and emphasizes the role of the government in focusing on the cluster policy, fair competition environment, and improvement of the intellectual property system compared with the existing incentive system.

2.2.2.2 Policy Instruments for Collaborative Innovation

Although inter-firm collaboration is a process that occurs voluntarily in the market as a result of interactions among firms, governments have introduced policies to encourage inter-firm collaboration to maximize the spillover effect on the industry, technology, and economic development. As the convergence among heterogeneous technologies has become active since the 2000s, inter-firm collaboration has been recognized as a means of promoting technological convergence, and governments have promoted inter-firm collaboration to promote technological convergence.

Incentives and regulations are the main policy instruments that governments can use to promote collaborative innovation between firms. Governments can provide firms participating in collaborative innovation with incentives, including financial, technical, and administrative support. Furthermore, they can prevent or punish opportunistic behavior by regulating the opportunistic behavior of firms in the collaborative

innovation process (Chiang, 1995).

First, governments can use incentive policies to promote collaborative innovation between firms. Incentives are defined as government support activities that range from economic to personal to promote activities that are thought to be beneficial to the economy or society (Myers & Kent, 2001). An incentive policy is a prime policy instrument for neo-classical economics, as it approaches market failure and aims to encourage voluntary participation in innovation activities (OECD, 2001). For example, governments can grant subsidies or relax regulations regarding technology, the workforce, money, and sales to firms participating in cooperation to achieve the goal of mutual growth through the activation of cooperation between firms. They can adopt an incentive system to encourage the voluntary cooperation of firms through these interventions (STEPI, 2007). These incentive systems are implemented in the form of regular schemes or short-term support programs.

Second, the most representative obstacle to collaborative innovation is firms' opportunistic behavior. According to Williamson (1975), opportunistic behavior in inter-firm relationships is defined as "self-interest seeking with guile." Opportunistic behavior includes "lying, stealing, distorting, disguise, cheating, and calculated efforts to mislead" (Wathne & Heide, 2000; Williamson, 1985). For example, some firms intentionally invest less, use more resources of other firms, or engage in collaborative innovation after signing contracts, resulting in legal disputes between firms and stopping collaborative innovation. Opportunistic behavior includes the deceptive behavior of a partner firm, malicious use of technical data after a predetermined period of return, and deception of a developer's source code. For example, a total of 526 technology leakages have occurred in 527 firms in Korea over the past 5 years, and the reported damage has amounted to 30,663 billion won (Lee, September 27, 2017).

Opportunism can also occur before fully fledged cooperation begins. For example, after Ford and Lear Corporation signed a sourcing contract, Lear deliberately misrepresented its design and production capabilities, despite its inability to comply with the contract, and Ford had to address direct management cost and quality issues (Walton, 1997; Wathne & Heide, 2000).

Opportunistic agents sacrifice honest partners for higher profits, which hampers collaboration in the market (Chiang, 1995). Therefore, governments can implement a system to prevent or punish such opportunistic behavior. Patent laws and the strengthening of intellectual property rights are representative regulations used in innovation policy (Rogge & Reichardt, 2015). Governments can prevent or punish firms' opportunistic behavior by broadening the scope of legally protected intellectual property or by strengthening the level of punishment.

So far, this study has examined the incentives and regulations that governments can use to promote collaborative innovation. The next section reviews the effectiveness of these policy instruments

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2.2.2.3 Collaborative Innovation Policy in Korea

(1) SMEs' Technological Competitiveness Enhancement Partnership Policy

The policy of promoting collaborative innovation between firms is a resource-based approach in that it mainly focuses on the complementary use of innovation capabilities among firms. For example, the Korean Government has focused on fostering collaborative innovation between firms to promote so-called 'collaborative cooperation' between large firms and SMEs. The Korean Government has also aimed to share the

achievements of collaborative innovation by both large firms and SMEs (STEPI, 2007).

Incentives for collaborative innovation have been provided mainly through direct subsidies. Specifically, R&D subsidies have been provided for innovative items. These policies are mainly focused on inter-firm collaborative innovation, among which the support for ICT technology is highest. Among the 18,411 projects supported by the SMBA from 2013 to 2015, 12,244, or 66.5%, were cooperative projects. By 2017, 65% of the total budget had been spent. Collaboration programs in ICT amounted to 52% of the projects. Inter-firm collaborative innovation accounts for about 9% of all collaborative innovation types. While firm–university and firm–university–government research institute (GRI) collaborative innovation is declining every year, inter-firm collaborative innovation is increasing (Kim & Yang, 2017).

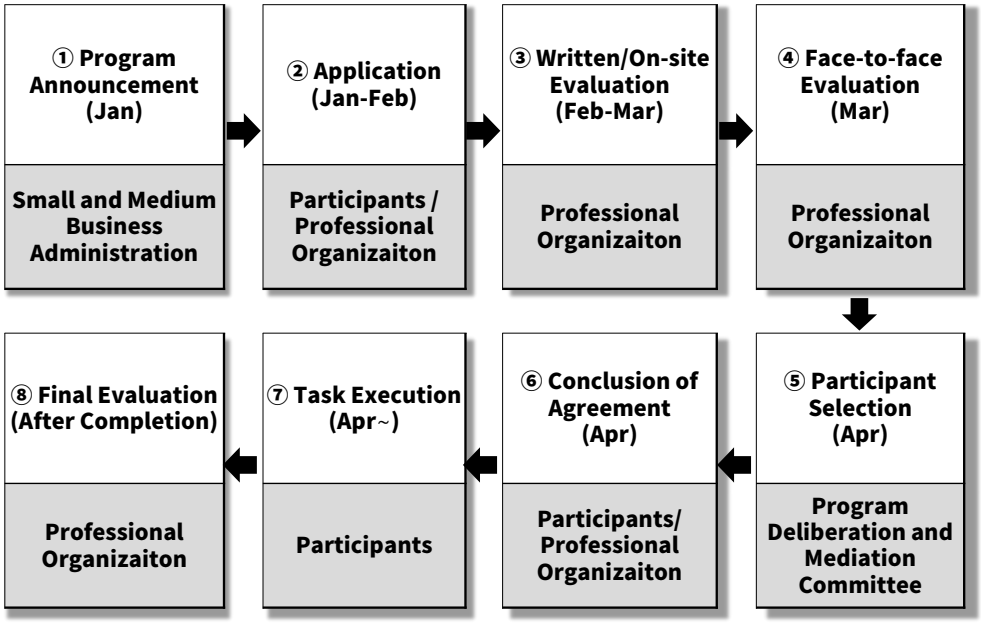
SMEs' technological competitiveness enhancement partnership policy, which is conducted under the supervision of the Small and Medium Business Administration (SMBA), aims to strengthen partnerships and to promote collaborative innovation between SMEs and mid-size firms. SMEs' technological competitiveness enhancement partnership policy supports the development of technology for strengthening the partnership between firms and the joint development model of global competency through small and medium firms’ cooperation.

The subsidy allocated by the government to this program is 3.195 billion KRW. Participants in the program are limited to SMEs and mid-size firms who want to participate in collaborative innovation. There are ten projects in total, including seven firm types and three research institute types. Among them, the firm-type project supports pre-planning and joint technology development, such as finding new growth items between SMEs. Firms can choose between technology-matching tasks and self-matching tasks. If the firm cannot find a partner firm, the firm applies for technology

matching support, forms a consortium with the support of the technology-matching support team, and performs collaborative innovation. The self-matching task is a collaborative innovation by the firm, which constructs a consortium by looking for a partner firm.

In the first stage, the government subsidizes innovation items through SMEs and a mid-size firm operating a consortium. In the second stage, R&D subsidies are paid to firms that perform collaborative innovation with innovation items selected in the first stage. The specific evaluation and implementation procedures of this program are shown in Figure 2.1 below.

Figure 2.1 Implementation and Evaluation Procedures for SMEs' Technological Competitiveness Enhancement Partnership Policy (SMBA, 2017)



The evaluation process for this program includes written and on-site evaluations

and face-to-face evaluations. Firstly, the professional organization is an expert in each field, and it establishes an evaluation committee to carry out a written evaluation on the business purpose, the compatibility, the technologicality, and the business performance. Secondly, the professional organization conducts an in-depth on-site evaluation of firms that have passed the written evaluation, including qualifications for applications, technology development, and commercialization capabilities. Thirdly, the professional organization is a specialist in each field, and it constitutes an evaluation committee. It evaluates the innovativeness, technologicality, and business feasibility of the program proposal submitted by the participants and selects it as a task to be recommended by the Program Deliberation and Mediation Committee according to the priority.

In this way, the Korean government subsidizes R&D for firms participating in collaborative innovation, thereby inducing SMEs to participate in collaborative innovation. R&D subsidies are a classic form of incentive (Lundvall & Borrás, 2005). Governments use aggressive consensus-building methods to build partnerships between firms, such as the firm's voluntary search for partners and the cost associated with this. In addition, the government can form a technology- matching support team consisting of experts to help SMEs mitigate information restrictions and collaborate with more appropriate partners.

(2) Damages System for Technology Theft

Governments can determine the level of punishment for firms that conduct opportunistic behavior. For example, the Korean Government has stipulated, in the Fair Trade Act, the Subcontracting Act, and the Act on the Promotion of Collaborative Cooperation between Large Enterprises and SMEs, the punishment of firms for

undertaking the exploitation and utilization of intellectual property in the collaborative innovation between firms. Specifically, the Korean Government has specified the penalty provisions in the Fair Transactions in Subcontracting Act and the Act on the Promotion of Collaborative Cooperation between Large Enterprises and SMEs. Through these regulations, it can impose penalties on opportunistic firms if opportunistic behavior appears hierarchically in collaborative innovation. Additionally, the Fair Trade Commission can extend the scope of technical data under the Fair Transactions in Subcontracting Act to prevent opportunistic firms from taking over technology and strengthen the protection of intellectual property rights.

The Korean government specifies by law the penalties to prevent technology theft that may arise from inter-firm collaborative innovation. For example, the Patent Act requires compensation for damage by patent infringement, and the Unfair Competition Prevention Act requires damages for trade secret infringement. Depending on the relationship between the firms, compensation for technology theft may be calculated differently. The Fair Subcontract Transactions Act requires that technology theft between subcontractors be repaid up by to three times the amount of the damage. In the case of SMEs, the amount of damage shall be reimbursed for technology theft. The compensation rules for technology theft in accordance with each of these laws are shown in Table 2.1 below.

Table 2.1 Damages Systems for Technology Theft in Korea (Ministry of SMEs and Startups (MSS), 2018)

Act	Target	Compensation Rules
Patent Act	Patent infringement	Actual damage
Unfair Competition	Infringement of trade secret	Actual damage

Prevention Act		
Fair Subcontract Transactions Act	Subcontractor relationship	Within three times the amount of actual damage
Act on the Promotion of Collaborative Cooperation Between Large Enterprises and SMEs	Consignment relationship	Actual damage
Industrial Technology Protect Act	Infringement of industrial technology	No Compensation Claims

The Korean government has increased the level of punishment to reduce the damage to SMEs by technology theft. In 2011, the Fair Subcontract Transactions Act introduced a punitive damages system that is liable to pay up to three times the amount of damage. However, despite the punitive damages, the current damages system has been criticized for not doing enough to prevent technology theft. Its limitations can be divided into two types as follows.

Firstly, the current system has the problem that it is difficult for SMEs to receive compensation. The minimum indemnity standard may apply to most SMEs that do not have sufficient legal capacity because of different legal provisions. Also, the Unfair Competition Prevention Act has civil and criminal provisions on trade secret infringement, but it takes a long time for a court decision for the SMEs. There is also a lack of safeguards against bargaining and negotiations (MSS, 2018).

Secondly, the criteria for calculating the loss amount itself are insufficient. SMEs often have difficulty proving technology theft damage due to a lack of legal capacity,

often not being recognized as trade secrets or lacking evidence. Although the Fair Subcontract Transactions Act stipulates punitive damages of up to three times the amount of damage, there is a limitation in the fact that it is difficult to prove damage and the criteria for calculating damage are not clear. SMEs are often unable to prove the facts of damage and are insufficiently compensated. The median value of patent infringement damages is 60 million KRW in Korea, 1/80th of that in the USA, which is 490 thousand USD, and one sixth when taking into account GDP (MSS, 2018).

In Korea, the damages system for technology theft sets the rules for compensation through various laws. Although the damages system for technology theft in Korea is presented in various laws, the fact that the actual damage may not be compensated entirely due to some limitations is a restriction (Choi, 2015).

The next section conducts a literature review to analyze the arguments underlying the collaborative innovation policy more critically. Specifically, this study examines prior studies on intra-industry heterogeneity and collaborative innovation, the effects of incentives and regulations, and interactions between policy instruments.

2.2.3 Literature Review

2.2.3.1 Intra-industry Heterogeneity and Collaborative Innovation

Since the study of Gibrat (1931), many researchers have sought the cause of intra-industry heterogeneity in the FSD. However, unlike firm size, studies related to the FSD tend to be limited (Nelson, 1991; Noda & Collis, 2001). Since Schumpeter (1942), firm size has been studied actively as an independent variable affecting innovation, whereas the FSD has been treated as a dependent variable. Some may argue that the FSD is

difficult to treat as an independent variable because it is an endogenous variable that is affected by several innovation factors. However, firm size has also played a role in innovation research as an independent variable for a long time, even though it is an endogenous variable that is affected by knowledge or firm competence factors. Instead, it has been argued that the FSD can affect innovation as well as firm size (Malerba, 2005). Intra-industry heterogeneity in the FSD is a result of various economic and technological factors, but it also has an effect on economic and technological change (Cantner & Hanusch, 2001). According to this perspective, intra-industry heterogeneity in the FSD cannot be simplified or neglected in the form of a mean, and it is an important variable to consider in innovation research.

Understanding of the effect of intra-industry heterogeneity on collaborative innovation is largely based on the literature that focuses on the conceptual discussion. Therefore, direct evidence for the relationship between the two is lacking. However, the relationship between intra-industry heterogeneity and collaborative innovation can be inferred through empirical studies on intra-industry heterogeneity and inter-firm interactions, and intra-industry heterogeneity and industry performance.

Firstly, some researchers have explored the effects of intra-industry heterogeneity on firms' interactions. Intra-industry heterogeneity affects inter-firm relationships, leading to changes in inter-firm interaction patterns. The interaction between heterogeneous agents within an industry plays an essential role in industrial evolution (Malerba, 2005). Specifically, intra-industry heterogeneity affects inter-firm relationships, leading to changes in inter-firm interaction patterns. The nature of the industry produced by its FSD is mainly due to the interactions between heterogeneous firms. For example, unfair trade between firms can be deepened by the level of the hierarchical relationship between large firms and SMEs, and this hierarchical

relationship can be exacerbated further when the size gap between firms is substantial. The National Assembly Research Service (NARS) (2013) notes that as the polarization between large firms and SMEs becomes higher, the hierarchical relationship between firms becomes worse, and the possibility of unfair transaction becomes higher. Therefore, the Korean government has been approaching a lower the level of polarization between large firms and SMEs as a fundamental solution to block the possibility of unfair transactions that may arise in the hierarchical relationship between large firms and SMEs (NARS, 2013). Also, some previous studies have shown that firms have a hierarchical relationship centered on market-dominant firms (Jung & Hong, 2015). In other words, inter-firm relationships and interactions, as well as industry performance, may be affected by the level of intra-industry heterogeneity.

Secondly, some researchers have explored the effects of firm size inequality on industry performance. These results are also related to the relationship between intra-industry heterogeneity and inter-firm interactions described in the previous paragraph. In general, the performance of the industry appears at a time lag from the start of the input. The input leads to performance through the various competencies and activities of the firm. Innovation is the factor most closely related to performance. Many studies have found that firms' innovation activities have a positive correlation with firms' financial performance (Gunday, Ulusoy, Kilic, & Alpkan, 2011; Mowery, 1983; Scherer, 1965). Therefore, inequality in firm size affects industry performance, suggesting that the firm's innovation activities may also be affected.

In summary, as intra-industry heterogeneity increases, inter-firm relationships become more hierarchical, and these hierarchical relationships affect inter-firm interactions. Innovation activities related to inter-firm interaction in collaborative innovation, and therefore hierarchical relationships among firms, can affect

collaborative innovation patterns. Given that innovation is closely related to earnings, studies showing that intensified intra-industry heterogeneity negatively affects industry revenues, suggesting that firms' innovation activities may also be negatively affected by intensified intra-industry heterogeneity. Collaborative innovation is very sensitive to inter-firm interaction patterns because it is based on inter-firm interaction. Based on these discussions, it can be inferred that intra-industry heterogeneity can change the aspect of inter-firm collaborative innovation in an industry.

2.2.3.2 Effect of Incentives and Regulations

This section examines the effects of government policies on collaborative innovation.

First, questions can be raised regarding whether government incentives to promote collaborative innovation have a positive effect on collaborative innovation. Research on the effect of incentives on collaborative innovation has recently started to be carried out by some researchers.[1] Broekel (2013) analyzed the effects of government subsidies to promote collaborative innovation using data from four German industry sectors from 1999 to 2003. The results showed that government subsidies for collaborative R&D

[1] Many countries have shifted their R&D subsidy allocation process to subsidized joint R&D projects since the mid-1980s (Broekel et al., 2015). However, scholars have criticized the fact that, in many countries, incentives have been paid to firms to encourage them to participate in collaborative innovation, but little research has been undertaken on whether such incentives work. Research on the effectiveness of government incentives to promote collaborative innovation among firms has been conducted by some researchers in recent years. LaRiviere (2014) argued that government subsidies for R&D collaboration reduce the total size of collaborative innovation among firms but that firms that have not previously participated in collaborative innovation are likely to participate in new collaborations. Bruhn and McKenzie (2017) found that government subsidies to promote collaborative innovation have the effect of increasing joint patenting, but they do not have the effect of increasing patents generated from unsubsidized projects. Therefore, they argued that a government's collaboration support program has a direct effect on promoting additional collaborative innovation.

activities increase the participation of firms in collaborative innovation activities and their interdependence on external agents but not in all industries.

LaRiviere (2014) presented a theoretical model for the effect of government R&D subsidies on collaborative innovation between firms engaging in R&D collaboration using the Cournot competition model. According to the model, government subsidies for R&D cooperation reduce the total size of the inter-firm collaborative innovation, but they have the effect of allowing a firm that has not previously undertaken collaborative innovation activities to participate in the new cooperation.

Bruhn and McKenzie (2017) empirically analyzed whether government incentives for collaborative innovation promote collaborative innovation. They analyzed survey data on 400 firms participating in Poland's In-Tech program using the regression discontinuity (RD) model. The analysis showed that government subsidies to promote collaborative innovation have the effect of increasing joint patenting but have no effect on increasing patents generated by projects that are not related to subsidies. Therefore, the authors stated that the government's collaboration support program has a direct effect on promoting further collaborative innovation.

Second, it is possible to raise questions about whether governments' regulations to reduce opportunistic behavior in a collaborative innovation process facilitate collaborative innovation. Some studies have shown that regulations concerning firms' opportunistic behavior actually reduce deceptive behaviors, such as free riding, in firm-to-firm transactions.

Popov and Simonova (2006) found that punitive systems for opportunistic behavior reduce the level of opportunistic behavior of agents through studies of Russian firms. In particular, they showed that, when punishments for opportunistic behavior were implemented, the opportunistic behavior of agents decreased by more than half.

Massimiliano (2015) analyzed the biotechnology field and argued that regulatory policies such as intellectual property protection could control firms' opportunistic behavior to some extent. However, he also pointed out that excessive regulations beyond the appropriate level could hinder innovation.

Niesten and Jolink (2012) analyzed the electricity industry in the Netherlands and France and found that regulations that reduce the incentives to adopt opportunistic behavior reduce operators' opportunistic behavior and transaction costs, thereby reducing uncertainty in inter-firm transactions.

In summary, studies dealing with the effects of regulations show that they reduce opportunistic behavior.

Third, questions can be raised about whether incentives or regulations, which are the policy instruments that governments can use to promote collaborative innovation, are more effective. Theoretically, incentives are known to be more effective than regulations. Popp (2006) argues that market-based instruments such as incentives are more effective in promoting firms' innovation than command-and-control schemes like regulation (Costantini, Crespi, & Palma, 2016). Also, Laffont and Tirole (1993) argue that government regulation can cause unforeseen adverse effects in oligopoly markets where information asymmetry exists. Thus, based on theoretical arguments, it is more effective for the government to provide incentives such as subsidies to promote firm innovation.

However, since incentives involve constant fiscal spending, governments are tempted to rely on regulations. In addition, since regulations act as a hidden tax, governments tend to prefer regulations to incentives (Posner, 1971). Indeed, governments prefer regulations to incentives because of the financial constraints of many sectors. In summary, incentives are more effective in promoting innovation than

regulations, but governments tend to prefer regulations because of budget constraints.

This section examined the previous studies on the effects of incentives and regulations. This section assumes incentives and regulations as independent policy instruments and compares them, but in reality incentives and regulations are often enforced simultaneously. The next chapter discusses the interaction effects between the two instruments when incentives and regulations are implemented simultaneously.

2.2.3.3 Interaction between Policy Instruments

As a means of promoting innovation, governments can implement various policy instruments, such as incentives, regulations, procurement, and education, simultaneously, which is called the policy mix (Nauwelaers & Wintjes, 2008). The policy mix can be categorized into two types: supply-side innovation policies include financial support, such as subsidies, tax incentives, and public venture capital, and demand-side policies include regulations or standard setting to promote innovation (Flanagan, Uyarra, & Laranja, 2011). The policy mix in an innovation policy emphasizes an integrated policy approach similar to policy integration, but it differs from policy integration in that it emphasizes the balance, linkage, and integration among policy instruments (Flanagan et al., 2011).

When various policy instruments are implemented to promote innovation, the effectiveness of the policy can be changed by the interaction between individual instruments (Uyarra & Ramlogan, 2012). If the level of the policy instruments that make up the policy mix is not properly adjusted, it can lead to unnecessary social costs, which are not originally intended to achieve the policy objectives. With a properly designed

policy mix, governments can avoid double financial burdens and increase the policy efficiency. On the contrary, it is important for governments to have preliminary information on the interactions of each policy instrument, because a defective policy mix hinders the efficiency of the policy (Sandu & Anghel, 2010).

A policy mix of incentives and regulations can also produce complex interactions between the two policy instruments. Thus, the question of whether this interaction effect is positive can be raised. However, researchers have pointed out that policy mix studies in innovation policy have rarely analyzed the effects of interactions between policy instruments (IEA, 2011; Rogge & Reichardt, 2015). The discussion on the policy mix in innovation research remains at the level of developing a conceptual framework, and little empirical verification of the effect of the policy mix has been performed (Rogge, Kern, & Howlett, 2017). The reason these studies have been insufficient is that the criteria for whether to restrict the policy to short-term business or to include the statute are ambiguous, and if there is a statute, the extent of the statute may be limited. Therefore, most studies have limited theoretical discussion to policy mix or design of policy mix for building an innovation system (Nauwelaers & Wintjes, 2008).

However, some researchers have demonstrated that there is a positive interaction effect between the policy instruments in the policy mix. Guerzoni and Raiteri (2015) analyzed the interaction effects of policy measures on 5238 firms located in 27 member states of the EU, Norway, and Switzerland from 2006 to 2008. Their findings demonstrated that the policy mix effects are greater than the sum of the individual policy effects on R&D subsidies, tax credits, and public procurement policies, indicating that an interaction effect takes place between policies. Thus, they argued that the interaction between different policy instruments in the innovation policy mix is strengthened. In a study on foreign direct investment by US firms in 44 countries, Min (2002) found that

there is a positive interaction effect between investment incentives and regulations in attracting foreign direct investment (FDI).

In summary, a well-designed policy mix in innovation policy is important for achieving policy goals, but most of the literature is limited to conceptual discussions rather than an exploration of interactions between policy instruments. However, some studies have found that government incentives for firms' innovation and investment have positive and interactive effects. In conclusion, this study examines the previous research on the interaction of incentives and regulations in innovation policy. The next section develops some theoretical propositions and presents the research design for reproducing these propositions through experiments.

2.3 Research Design

2.3.1 Theoretical Propositions

This study suggests several theoretical propositions in relation to intra-industry heterogeneity, government policy, and collaborative innovation.

Firstly, the level of intra-industry heterogeneity can affect collaborative innovation as well as industry performance. All the decisions that lead to collaborative innovation, such as the process of choosing a firm's cooperation actions and the selection of partners, can be affected by intra-industry heterogeneity when performing collaborative innovation. Thus, differences may arise in the patterns of collaborative innovation occurring at the industry level depending on the level of intra-industry heterogeneity.

As assumed by the Schumpeterian hypothesis, if market-dominant large firms lead innovations, the innovation gap between large firms and SMEs increases, resulting in asymmetrical innovation (Na et al., 2017; Nelson & Winter, 1982). Therefore, in the case of industries with high intra-industry heterogeneity, the level of collaborative innovation of all firms may not be high even though the market-dominant firm actively performs collaborative innovation. In addition, collaborative innovation will follow an asymmetrical pattern led by market-dominant firms, and the collaborative innovation among firms with low market concentration may not be relatively active. As a result, there will be patterns in which the collaborative innovation is concentrated on market-dominant firms, and this pattern will depend on the strategies of the market-dominant firms.

In this context, the level of intra-industry heterogeneity can affect the hierarchical relationships between innovation-led firms and the rest of the industry, which can also affect the collaborative innovation between firms. As intra-industry heterogeneity

increases, collaborative innovation can be concentrated more on market-dominant firms. Conversely, lower intra-industry heterogeneity will result in more collaborative innovation and a smaller share of market-dominant firms in the total collaborative innovation. Therefore, this study suggests that, as the level of intra-industry heterogeneity decreases, more firms will participate in collaborative innovation and collaborative innovation will become more active.

Proposition 1: Inter-firm collaborative innovation is more actively performed when the level of intra-industry heterogeneity is low.

Secondly, government incentives such as R&D subsidies can have a positive effect on collaborative innovation. Innovative industries, such as the ICT industry, are characterized by high R&D intensity, a short innovation cycle, and a diversified technology demand compared with other industries. These characteristics imply that innovative industries, including the ICT industry, have a greater demand for innovation than other industries and that government incentives such as R&D subsidies tend to lead to innovation performance. Likewise, if firms need collaborative innovation to respond to diversified technology needs and shortened innovation cycles, governments can encourage collaborative innovation by providing subsidized incentives.

Thirdly, regulation of opportunistic behavior can have a positive effect on collaborative innovation. As the opportunistic behavior of firms decreases, collaborative innovation is promoted as a result of decreased transaction costs in the process of partner selection for collaborative innovation. Especially in innovative industries like the ICT industry, innovation activity is an important growth strategy for firms. Therefore, as the transaction costs associated with collaborative innovation

decrease, firms are more likely to choose cooperation based on profit maximization incentives in a situation in which collaborative innovation performs better than individual innovation.

Therefore, this study suggests that government incentives to promote collaborative innovation have a positive effect on collaborative innovation. Also, this study suggests that government regulations to reduce opportunistic behavior facilitate collaborative innovation.

Proposition 2: Subsidized incentives to engage in collaborative innovation have a positive effect on collaborative innovation.

Proposition 3: The regulation of opportunistic behavior has a positive effect on collaborative innovation.

Fourthly, government incentives such as R&D subsidies may have a greater positive effect on collaborative innovation than regulations on opportunistic behavior. In industries such as Korea's ICT industry, in which both the market concentration and the FSD polarization are high, the focus of government regulations is mainly on reducing the unfair behavior of market-dominant large firms. This is similar to the regulatory situation for monopolies assumed by Laffont and Tirole (1993). They argued that regulating market-dominant firms in a situation in which they do not know all the necessary information about each firm can lead to unintended consequences and disadvantages for efficient firms. Thus, given this situation, it is considered that the regulation of market-dominant firms under imperfect information is partially offset by the ineffectiveness caused by information asymmetry at the industry level. Previous

research has also supported this theoretical argument that command-and-control schemes such as regulations are less effective in promoting firms' innovation than market-based instruments such as incentives (Costantini, Crespi, & Palma, 2016; Popp, 2006).

Incentives are an approach that enhances the benefits of collaborative innovation, and regulations are an approach that reduces the transaction costs between firms. Thus, regulations increase the cooperative behavior of firms that are reluctant to engage in collaborative innovation because of the entry barriers and transaction costs. On the other hand, incentives such as R&D subsidies can increase the cooperative behavior of firms that did not previously cooperate because the utility gained from participating in collaborative innovation was not large enough (LaRiviere, 2014). Firms can be divided into three groups according to their level of participation in collaborative innovation: (1) firms that do not participate in collaborative innovation; (2) firms that have participated in collaborative innovation but are passively involved; and (3) firms that have repeatedly participated in collaborative innovation. Most of the Korean ICT firms have no experience in participating in collaborative innovation, and, even if they do have experience of participating, the proportion of firms that repeatedly engage in collaborative innovation is small. The reduction of transaction costs caused by regulation may increase the cooperative behavior of firms that repeatedly collaborate on innovation, but it is thought that the increase in utility of collaborative innovation caused by incentives such as R&D subsidies can promote the cooperative behavior of firms that have passively participated in collaborative innovation (LaRiviere, 2014). Given the size of these two groups, this study assumes that incentives can affect firms more broadly than regulations. Therefore, this study suggests that incentives have a greater positive effect on collaborative innovation than regulations.

Proposition 4: Subsidized incentives have a greater positive effect on collaborative innovation than regulations of opportunistic behavior.

Finally, there may be positive interaction effects between incentives and regulations. Both incentives and regulations promote firm participation in collaborative innovation, but the mechanisms of these two instruments are different. Incentives such as R&D subsidies are implemented in the form of short-term business, while regulations on opportunistic behavior such as technology theft are implemented in the form of regular legislation. Incentives take the approach of increasing the benefits of participating in collaborative innovation more than single innovation, while regulation takes an approach that reduces the potential costs associated with participating in collaborative innovation. Therefore, both incentives and regulations affect the firm's decision to participate in collaborative innovation.

The fact that each policy instrument affects collaborative innovation in a different way suggests that there may be differences between the groups that are sensitive to each policy instrument. In previous research, government subsidies have led to the involvement of firms that have not participated in collaborative innovation, and regulators have been involved in collaborative innovation (LaRiviere, 2014). Low-level incentives and regulations have little impact on total utility, which is effective for groups that are each sensitive to increased benefits or reduced costs of collaborative innovation. However, as the level of the policy instrument increases, it can also be effective for groups that are less sensitive to the intervention, and thus the range of groups that respond substantially to policy can also be extended. In other words, more than a certain level of subsidy can cause firms that have been passively involved in collaborative

innovation and that are less sensitive to the cost of collaborative innovation to participate in collaborative innovation. In addition, regulations above a certain level can cause firms that are less sensitive to the net profit of collaborative innovation and that have not previously participated in collaborative innovation participate in collaborative innovation. In other words, under a certain level of policy, the scope of the target group that is affected by the policy may be widened, which may lead to a positive interaction effect between complementary policy instruments. Therefore, this study suggests that interactions between incentives and regulations positively affect the collaborative innovation in the ICT industry.

Proposition 5: There is a positive interaction effect between incentives and regulations on collaborative innovation.

There are some limitations in verifying some theoretical propositions in relation to the collaborative innovation proposed in this study. Although firms constantly interact with each other in an industry, the mechanism of this interaction is hardly known (Yurtseven & Tandoğan, 2012). Despite the differences in the factors, mechanisms, and interactions that affect innovation in each industry, there has been insufficient exploration of the industry-level variables that affect innovation. Unlike firm-level research, industry-level research is difficult to control for innovation mechanisms, and it is challenging to find comparable groups that are similar in all conditions and differ only in the FSD in reality.[2]

[2] Some studies, such as that by Lee and Xia (2006), have used meta-analysis to compare indirect industry indices. However, these studies have limitations not only in the selection of control variables and the measurement of industrial characteristics but also in the estimates derived from the methodology itself.

Therefore, this study produces counterfactuals in which all the conditions except the FSD are homogeneous and then tries to establish theoretical propositions by comparing their collaborative innovation patterns through simulations. The next section discusses agent-based modeling—which is the methodology of this study—and discusses the applicability of collaborative innovation to the context of this study.

2.3.2 Methodology

2.3.2.1 Agent-Based Modeling

Since an economic system is a complex system that encompasses agents' behavioral rules, interactions, and accompanying macroscopic patterns, researchers must deal with difficult real-world problems such as strategic interactions, competition, and organizational learning (Tesfatsion, 2006). ABM can be a new approach for analyzing these problems because it can model dynamic systems where interactions among agents occur (Tesfatsion, 2006).

ABM is a computer program that creates a virtual world in which interactions among heterogeneous agents occur. The ABM allows an exploration of how agents interact with various factors, including time, space, and other agents, and how macroscopic patterns appear in the real world (Hamill & Gilbert, 2015). The origin of the ABM dates back to the microsimulation of the 1960s. Microsimulation is useful for modeling the effects of policy changes by allowing heterogeneity of various agents, but it does not allow interactions among agents (Gilbert & Troitzsch, 2005). The ABM overcomes these limitations of microsimulation by implementing interactions among agents.

Tesfatsion (2006) pointed out that an important feature of ABM is that when the initial conditions are specified, subsequent events occur only by interactions among agents. ABM has the advantage of being able to better explain the process by which agents are moving toward balance, rather than the balance itself, and can better understand the relationships among agents within the system (Tesfatsion, 2006)

Representative early social science simulation studies, such as the bounded rationality of Simon (1955) and the garbage can model of Cohen et al. (1972), present a bold new hypothesis that has not been captured by observations in the real world. And these hypotheses were established as the most important theories in social science by empirical studies of followers. In this way, ABM is complementary to other social science methodologies, including empirical research (Choi & Robertson, 2013). For example, in the case of experimental economics using game theory, there are cases where a virtual experiment is conducted by reproducing the experimental situation with ABM.[3]

2.3.2.2 Modeling Collaborative Innovation

Simulation methodology can be a basic tool for reviewing innovation models, and analytical results can be obtained especially for simple innovation cases (Nelson & Winter, 1982). From this perspective, ABM can be a useful tool for analyzing collaborative innovation.

Watts and Gilbert (2014) presented two strengths of ABM over other methodologies in research in innovation. First, innovation is a very complex process,

[3] Johnston, Hicks, Nan, & Auer (2011) implemented Weber's (2006) experiment with ABM based on N-person coordination game and experimented with new intervention.

and ABM can explain the behavior of heterogeneous agents with various mechanisms that are difficult to explain with mathematical models. Yun, Won, & Park (2016) also suggested that collaborative innovation should be analyzed using ABM because it appears in complex adaptive systems (CAS) such as National Innovation System (NIS), Regional Innovation System (RIS), and Sectoral Innovation System (SIS). Second, ABM can easily simulate experiments that are subject to cost or ethical constraints through virtual space, and it is relatively free from various constraints (Watts & Gilbert, 2014).

Watts and Gilbert (2014) also stated that ABM should be used to simulate the innovation to explain the stylized facts and patterns of the general mechanism at the micro level. Specifically, first, ABM can be used to bridge the gap between the micro and macro by explaining the process in which the microscopic mechanism of innovation leads to a macro pattern (Schelling, 1971). Second, ABM can demonstrate sufficient reasons for the cause of certain patterns appearing in the process of innovation, even if alternative explanations exist. Third, ABM can demonstrate various conditions in which emergence, such as network structure, behavior among agents, and environmental dynamics, occurs (Watts & Gilbert, 2014).

There are many ways to implement collaborative innovation within the framework of ABM. Considering that collaboration among agents is a strategy for survival in the market, a similar approach can be used for game theory. Participation in collaborative innovation has been actively analyzed using game theory, since it has been perceived as a process by which firms choose the optimal strategy of collaboration and non-collaboration (Suzumura, 1992). Moreover, analysis using game theory can be implemented through ABM, which serves as a point of linking ABM with the theoretical foundation of innovation economics.

Axelrod (1984) found through simulations that a collaborative strategy emerges among agents in the iterated prisoner's dilemma game. Thanks to his ideas, the iterated prisoner's dilemma game has been used as a tool to illustrate the emergence of collaboration in repeated interactions among various levels of agents, not just for individuals but also organizations, nations, and firms. Gulati, Khanna, & Nohria (1994) suggested that modeling can be done with prisoner's dilemma or an assurance/coordination game because inter-firm collaboration, like strategic alliance, is a social dilemma problem. They pointed out that the prisoner's dilemma game is the most popular model for inter-firm collaboration. Arend and Seale (2005) also noted that the formation of alliances among firms is essentially a prisoner's dilemma game. In fact, many previous studies that have analyzed strategic alliances and collaborative innovations have been based on the prisoner's dilemma game (Arend & Seale, 2005; Axelrod, 1997; McMillan, Mauri, & Casey, 2014, Yun, Won, & Park, 2016).

Not all collaborative innovation studies utilize the same game model, and there are differences in the models that are used, according to the type of innovation in detail. Baniak and Dubina (2012) suggested that when using game theory in innovation research, different methods should be used depending on the extent of the model. They classified the types of games used in innovation research into intra-organizational, inter-organizational, and meta-organizational games. According to Baniak and Dubina (2012), first, the intra-organizational game represents the most microscopic level of interaction and explains the interactions among individual agents in the innovation organization. Second, the inter-organizational game accounts for a medium-level interaction and describes inter-organizational interaction. Third, the meta-organizational game shows the highest level of interaction and demonstrates the effect of the innovation policymaker's intervention on the innovation ecosystem. Table 2.2

presents the summary of previous studies according to their classification.

Table 2.2 Previous Innovation Studies according to the Game Model

Game Model	Level	Previous Studies	Problem
IPD Game	Intra-Org.	Yang & Wu (2008)	Knowledge Sharing
	Inter-Org.	Arend & Seale (2005)	Alliance Activity
		Arend (2009)	Alliance Activity
		Yun et al. (2016)	Open Innovation
PD Game	Inter-Org.	Furrer & Thomas (2000)	Competition
	Meta-Org.	Chiang (1995)	Collaborative R&D
Non-Cooperative Game, Cooperative Game	Inter-Org.	Martin (2002)	Spillovers in R&D Races
Nash Bargaining Game	Inter-Org.	Arsenyan, Büyüközkan, & Feyzioğlu (2015)	Collaborative Product Development
Two-stage Game	Inter-Org.	Li, Nguyen, & Yu (2016)	Competition, Collaboration

Table 2.2 shows that the PD game is most widely used to implement innovation among the various types of games. In particular, many studies use IPD games to model interactions in innovation. Since this study performs policy simulation, it is evident that the level of interaction between agents is Meta-organizational level. This study aims to infer the optimal policy alternative through policy simulation, so the level of interaction among agents should be considered as the meta-organizational level as shown in Table 2.2 above. Also, this study aims to implement collaborative innovation at the inter-organizational level. An iterated prisoner's dilemma game is considered to be the most suitable for this study because it focuses on watching the progress of cooperation aspect

over time among many innovators. At the meta-organizational level, an N-player game is also appropriate to implement interactions among multiple innovation agents. In conclusion, this study use an N-player game based on the iterated prisoner's dilemma game. This type of game is commonly known as the "N-person iterated prisoner's dilemma (NIPD) game."

The NIPD game has been used as a model to analyze the emergence of cooperation in the interaction among various agents. For example, Schweitzer, Behera, & Muhlenbein (2002) analyzed the evolution of collaborative strategies using a spatial NIPD game based on cellular automata. There are cases where the NIPD game is used in strategic collaboration research as well as general cooperation. For example, researchers such as Arend and Seale (2005) and Waltman (2011) analyzed inter-firm collaboration based on iterated PD game. The NIPD game has also been used in research on collaborative innovation among firms as well as strategic alliances. For example, Yun et al. (2016) analyzed the results of adopting open innovation strategies in the smartphone market by using an agent-based model based on an NIPD game.

2.3.2.3 Validation Issues

Sargent (1999) classified the modeling process into three stages: problem entity, conceptual model development, and computerized model development. He suggested that the conceptual model validity should be secured in the analysis and modeling process, the operational validity should be secured in the experimental process, and verification of the model should be carried out in the process of implementing the conceptual model on the computer. And ensuring data validity is the core of the validation process (Sargent, 1999). After that, David (2009) developed the conceptual

framework of Sargent and presented a generalized model development process in social science simulation. If the framework of Sargent (1999) shows the process from problem recognition to model development and simulation, the framework of David (2009) includes the process of checking how much the simulation results are compatible with the social theory or phenomenon. In this framework, pre-computerized models represent the conceptual model, and post-computerized models represent the base model in which the model construction is completed. The validation process goes through two stages. First, it confirms how well the model reflects the context of the phenomenon in the conceptualization phase of the model. Second, it confirms how well the model reflects reality or theory after building the base model. Specific validation and verification strategies for each step are presented in Table 2.3 below (David, 2009).

Table 2.3 Approaches for Validation and Verification in the Simulation Studies (David, 2009)

	Pre-computerized models	**Post-computerized models**
Validation	Formal Modelling Theory-driven Discourse Empirical Methods Participative-based Approaches	Statistical Signatures Stylized Facts Participative-based Approaches Cross-Model Validation ("Model-to-Model")
Verification	Structured Programming (e.g., modularity, object-oriented programming) Model Embedding (e.g., compilation, software reuse of components) Static Methods (e.g., code walk-throughs)	Dynamic Methods (program testing, sensitivity analysis) Replication for Alignment Participative-based Approaches

ABM studies often rely on empirical data for validation. For example, Campbell, Kim, & Eckerd (2015) constructed a model using U. S. Census data and performed validation by verifying whether the base model produces common patterns consistent with reality. The validation technique that utilizes empirical data is called empirical validation. Empirical validation has been done differently according to the ABM's specific topics, researchers, and models. Windrum, Fagiolo, & Moneta (2007) categorized three types of empirical validation in ABM. This classification is shown in Table 2.4 below.

Table 2.4 Previous Simulation Studies according to Validation Process (Retrieved from Windrum et al., 2007)

	Validation Process	**Application of Data**	**Previous Studies**	**Research Domain**
Indirect Calibration Approach	Use empirical data to restrict the initial conditions	1) Assisting in model building 2) Validating simulated output	Fagiolo & Dosi (2003)	Economic Growth
			Fagiolo et al. (2004)	Labor and Output Market
Werker-Brenner Approach	1) Theoretical and empirical realizations (Percentage) 2) Use empirical parameters to the model	1) Assisting in model building 2) Calibrating initial conditions and parameters 3) Validating simulated output	Brenner & Murmann (2003)	Intellectual Property Rights
			Brenner (2004)	Learning Process
History-Friendly Approach	History-replicating simulation using historical data	1) Empirical data 2) Causal, historical and anecdotic knowledge	Malerba, Nelson, Orsenigo, & Winter (1999)	Computer Industry
			Malerba & Orsenigo (2002)	Pharmaceutical Industry
			Kim & Lee (2003)	DRAM Industry

			Yoon & Lee (2009)	Semiconductor Industry

According to Windrum et al. (2007), as presented in Table 2.4, the indirect calibration approach provides the weakest validation, and it becomes more robust towards the Werker–Brenner approach and the history-friendly approach. However, even with a history-friendly approach, it is not possible to calibrate a particular pattern fully. Nelson and Winter's (1982) evolutionary economics study did not calibrate the patterns of the entire industry; it only calibrated Intel's patterns. As shown in these examples, unlike mathematical forecasting, innovation simulation cannot be evaluated regarding how well the historical records are reproduced. This is because the purpose of innovation simulation is not to predict the future but to derive strategic and policy implications by comparing the effects of various interventions on innovation (Watts & Gilbert, 2014). Although Table 2.4 presents the criteria by classifying validation into three categories according to robustness, not all studies fit this classification. Therefore, researchers can refer to these criteria in determining the level of validation that is consistent with the purpose of the study.

Since this study is intended to calibrate the initial conditions and parameters, the Werker–Brenner approach and the history-friendly approach can be used. The major difference between the Werker-Brenner approach and the history-friendly approach is whether it involves tracking a specific historical record to correct the model (Windrum et al., 2007). The Werker-Brenner approach does not involve this process called ‘history replication’, whereas the history-friendly approach involves this process.

This study does not perform optimization, such as curve fitting, to track specific time series records but performs a parameterization process to verify which combination of parameters produces the most similar values to the actual observations.

Therefore, it performs mid-to-high-level validation that is lower than the level suggested by the history-friendly approach but higher than that suggested by the Werker–Brenner approach.

2.3.3 Research Design

2.3.3.1 Conceptual Framework and Data Source

This section presents a conceptual framework based on the theories and empirical studies discussed above. The purposes of this study are as follows. First, it examines how the collaborative innovation patterns emerge according to the level of FSD heterogeneity in the industry. Second, it explores how government incentives and regulations affect collaborative innovation patterns in industries with high intra-industry heterogeneity. Specifically, it analyzes the changes in the collaborative innovation patterns according to the levels of incentives and regulations, identifies which of the two instruments is more effective, and investigates whether there is a positive interaction effect in the policy mix of incentives and regulations.

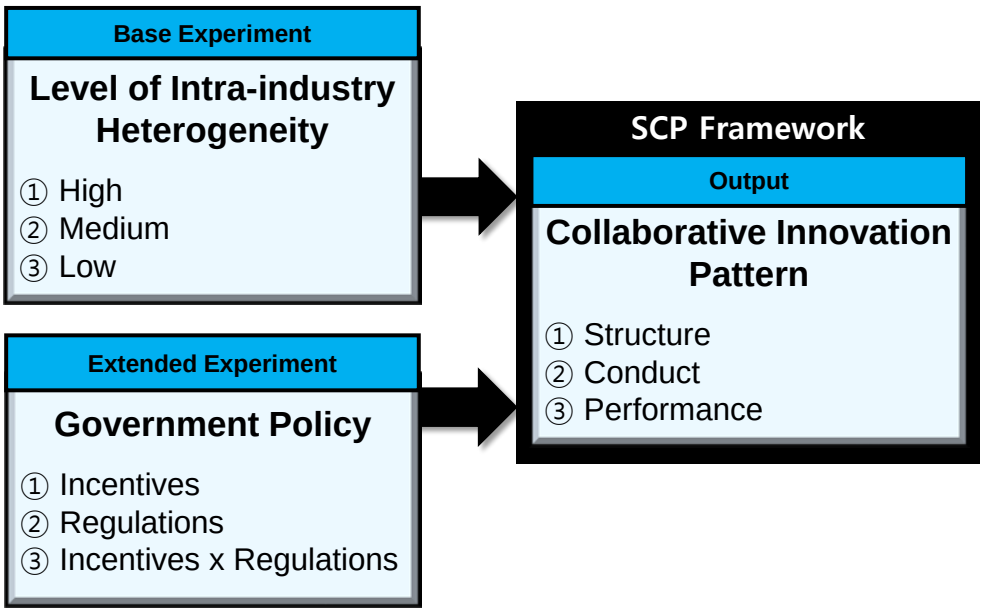
This study analyzes the innovation patterns of the industry based on the structure–conduct–performance (SCP) framework. The SCP framework is a classic model of industrial organization research and one of the most actively used tools for industry analysis. It is based on the paradigm that the performance of a particular industry is affected by the firms' actions in the market and the behavior of the firms is linked to the industry structure. Thus, this framework is an appropriate tool to investigate how the micro-actions of firms interacting within an industry lead to the macro-industry structure and performance (Porter, 1980). In the SCP framework, the structure

represents the market concentration and the structure of the industry, the conduct represents firms' strategic behavior in inter-firm interaction, and the performance represents the industry-level performance of the firms. This study analyzes the changes in the collaborative innovation structure, firms' cooperative behavior, and collaborative innovation performance within the SCP framework.

In the computational model developed for this study[4], firms perform collaborative innovation by interacting with other firms according to their resources, their strategy, and the surrounding environment. In the virtual space implemented in the computational model, firms interact with each other according to the spatial NIPD game[5] and decide whether to perform collaborative innovation. The mechanism of interactions among agents are based on the Huff model (Huff, 1964). In this model, the inter-firm interaction module based on the Huff model is implemented in three stages. Firstly, firms randomly select another firm and then calculate the probability of partnering with the firm based on the Huff model. Secondly, after calculating the partnering probability, firms randomly generate numbers. Thirdly, when the random number generated by the firm is located within the partnering probability interval, a partnership between the two firms is created and the game is executed. Collaborative innovation is achieved when firms choose to collaborate in the game. This study examines the propositions by capturing changes in the industry structure, firms' cooperative behavior, and the collaborative innovation performance derived from this process. The conceptual framework of this study is presented in Figure 2.2 below.

[4] This study builds an agent based model using Netlogo 6.0.2 software (Wilensky, 1999). The model was developed in Logo language.
[5] The basic module of the NIPD game follows Wilensky (2002).

Figure 2.2 The Conceptual Framework of Simulation in the Context of Collaborative Innovation



The firm-level data for this study are collected from KISVALUE and the annual report published in the Financial Supervisory Service's (FSS) Digital Analysis, Retrieval and Transfer System (DART: https://dart.fss.or.kr/). In addition, inter-firm collaborative innovation data are collected from the patent data registered with the Korean Intellectual Property Office published in the National Digital Science Library (NDSL: http://www.ndsl.kr).

2.3.3.2 Agents and Space

(1) Agents: Korean ICT Firms

This study analyzes the collaborative innovation ecosystem among firms in the ICT industry in Korea. Therefore, the agents of this study are ICT firms in Korea. As defined by the KIS-Industry Classification (KIS-IC), as of May 2016, a total of 525 Korean firms were classified as ICT firms. Among them, 524 firms, excluding 1 firm headquartered in Japan, are analyzed. Each of these firms is given a unique ID and has the characteristics of region, sales, and strategy based on empirical data on firm characteristics.

First, the firms are located in 17 provinces and cities (Seoul Metropolitan City, Incheon, Daejeon, Sejong, Daegu, Ulsan, Busan, Gwangju, Gyeonggi, Gangwon, Chungcheongbuk, Chungcheongnam, Gyeongsangbuk, Gyeongsangnam, Jeonbuk, Jeollanam, and Jeju) of Korea based on empirical data representing the headquarters' location. In this model, the location of the firm is assumed to be fixed. In fact, most of the headquarters of the ICT firms in Korea have been maintained without transfer until now.

Second, the sales distribution of the firms follows the distribution of 2015. It is assumed that the sales of firms are also fixed. The distribution of ICT firms in Korea has been maintained for the past 30 years, as a small number of large firms have accounted for the majority of the total sales.[6]

Third, firms have their own strategies, and when they interact with other firms, they choose cooperation and defection according to their situation and strategy.

[6] The annual sales is used to calculate the firms' attractiveness probability, which is determined by the relative size (distribution) of the annual sales. Therefore, if the annual sales distribution among firms is kept constant, the increase does not affect the probability calculation. Therefore, assuming that the annual sales distribution does not vary significantly by year, the remaining fluctuations can be considered to be constant.

(2) Space: A GIS-based Virtual Space

The spatial background of this study is Korea. This model uses GIS data[7] to make a GIS-based virtual space to enhance the reality of the model by using empirical data. The so-called 'virtual Korea' is divided into 17 provinces and cities. In this GIS-based virtual space, firms are located according to a random normal distribution based on the center of each region.

Figure 2.3 shows how the firms are located within the GIS-based virtual space, respectively

[7] The GIS data were collected from Geoservice (http://www.gisdeveloper.co.kr).

Figure 2.3 A GIS-based Virtual Korea Implemented in the Computational Model

As shown in the picture above, most firms are concentrated in the metropolitan areas including Seoul, Gyeonggi-do, and Incheon. The colors of the firms are light gray or dark gray. The light gray refers to Pavlovian firms, and the rest are defective firms.

2.3.3.3 Behavior Rules

(1) Overview

The operating mechanism of this agent-based model is controlled by five rules: initial condition setting, a stochastic process for partner searching, interaction with partners, expected payoff calculation, and reset and update ticks. Specific behavior rules for each rule are presented at the bottom.

Rule 1 (Initial Conditions)

The 524 ICT firms have several unique characteristics and are located in the GIS-based virtual space using actual Korean geographic information.

1-a (Location): The firms are located within 17 provinces and cities according to the empirical data and are distributed as a random normal distribution similar to the actual variance based on the center of each region.

1-b (Sales): The firms have the same sales distribution as the empirical data.

1-c (Strategy): The firms are divided into Pavlovian firms that are willing to cooperate and defective firms that are not. The defective firms include non-innovative firms that have never carried out innovation.

Rule 2 (A Stochastic Process for Partner Searching)

All the firms except non-innovative firms randomly select another firm to explore potential partners.

2-a (Partnering Probability Calculation): The probability of becoming a partner of a selected firm is calculated using the sales of the two firms, the Euclidean distance between the firms, and calibration parameters according to the Huff model.

2-b (Random Number Generation): Firms generate unique random numbers. The random numbers are randomly generated within the probability interval in which

the minimum value is zero and the maximum value is the maximum partnering probability among the partnering probabilities of all the firms of the corresponding tick.

2-c (Stochastic Process): When both random numbers generated by firms are located within the interval calculated with the Huff model, a partnership is made between the two firms.

Rule 3 (Interaction with a Partner)

Partnered firms run one simultaneous game with each other's partners according to the prisoner's dilemma game.

3-a (Behavior Choice): Each firm decides whether to cooperate with the other depending on its own strategy and the size of the expected payoff from cooperation.

3-b (Pavlovian Firms): Pavlovian firms collaborate when the expected payoff from cooperation is higher than the expected payoff from defection.

3-c (Defective Firms): Defective firms do not cooperate regardless of the expected payoff.

3-d. (Mutual Cooperation): When firms cooperate with each other, an edge is created between firms and one collaborative innovation is generated.

Rule 4 (Expected Payoff Calculation)

Firms receive a payoff according to their behavior and the behavior of their partners in a simultaneous game.

4-a (Payoff Record): Firms record all their payoffs from their cooperative or defective behavior.

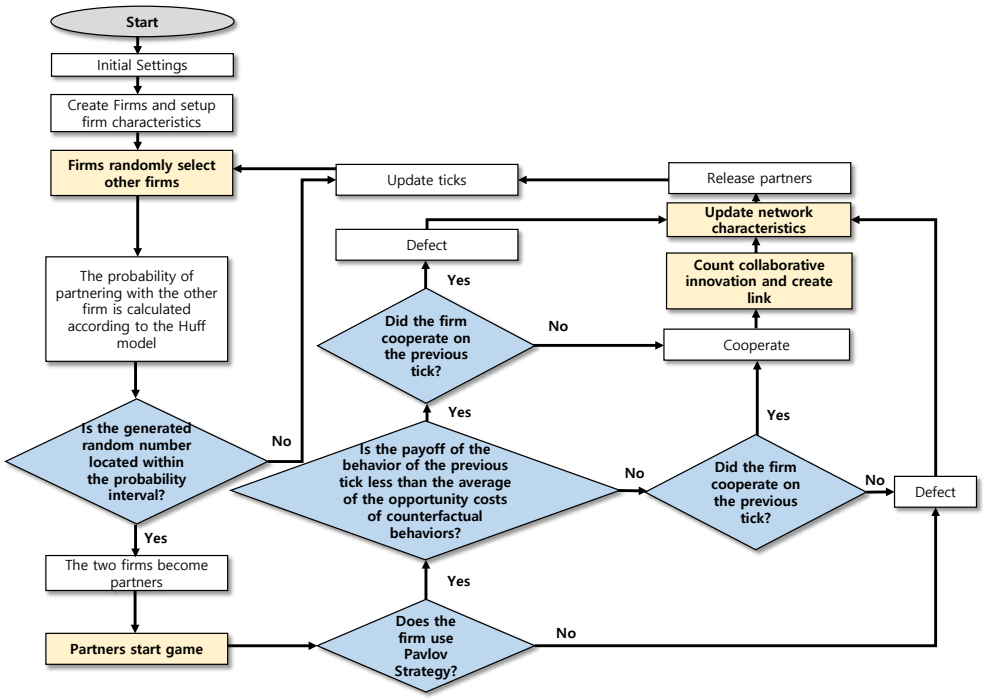
4-b (Expected Payoff Calculation): Firms use the accumulated payoff records to obtain the expected payoff for each action.

Rule 5 (Reset and Update Ticks)

After interacting with the partner, the partnership is invalidated, the random number that the firm created is deleted, and the tick is updated.

An algorithm of this model is presented in Figure 2.4.

Figure 2.4 An Algorithm of the Agent-Based Model



(2) The Huff Model: A Probabilistic Gravitation Model

This study applies the Huff model, a probabilistic gravitation model, as a partner

selection mechanism. The Huff model introduces the concept of probability into the gravity model, and is also called the Huff gravity model. The gravity model explains bilateral trade using the entity size and the distance between entities and has been considered as a successful experience model in economics (Frankel & Rose, 2002; Picci, 2010). The gravity model has been used in various fields, such as inter-firm transactions, international trade, and knowledge flows. Researchers have used the gravity model to analyze collaborative innovation. For example, Maggioni and Uberti (2007) analyzed the collaborative innovation among the EU member countries using the gravity model. Picci (2010) also analyzed the collaborative innovation among European countries through the gravity model with European patent data. In addition, many studies have used the gravity model to analyze collaborative innovation between several countries or firms (Montobbio & Sterzi, 2013; Morescalchi, Pammolli, Penner, Peterson, & Riccaboni, 2015; Scherngell & Barber, 2009).

The gravity model has also been used to implement inter-firm collaborative innovation as an agent-based model. For example, Heshimati and Lenz-Cesar (2015) developed an agent-based model of collaborative R&D between firms through the gravity model using the annual turnover and distance between firms to explore the conditions for the emergence of cooperation. These studies indicated that the gravity model is a good model for analyzing collaborative innovation.

In this study, the Huff model is used to determine the probability that a partnership will be established between two firms. Like the gravity model, the Huff model assumes that the probability of inter-firm interaction is proportional to the firm size and inversely proportional to the distance between firms (Huff, 1964). The equation for the Huff model is presented below.

$$P_{ij} = \frac{U_{ij}}{\sum_{j=1}^{n} U_{ij}} = \frac{\frac{S_j^{\alpha}}{T_{ij}^{\beta}}}{\sum_{j=1}^{n} \frac{S_j^{\alpha}}{T_{ij}^{\beta}}}$$

n: A set of competing firms;

P_{ij}: The probability that firm i will meet firm j;

U_{ij}: The utility of firm i for firm j;

S_j: The size of firm j;

T_{ij} : The distance between firm i and firm j;

α, β: Parameters.

The probability of interaction is calculated as the ratio of the utility of interaction with the partner firm to the utility of interaction with all the firms. The utility of the firm is proportional to the firm size and inversely proportional to the distance between firms. Annual sales data from firms are used to measure firm size (Heshimati & Lenz-Cesar, 2015). This study also calculates P_{ij} using the empirical annual sales data and the Euclidean distance between firms in the virtual model.

In the Huff model, as the number of firms increases, the expected value of P_{ij} decreases, because $\sum_{j=1}^{n} U_{ij}$ increases in a situation in which U_{ij} is constant. In other words, as the number of firms increases under the same conditions, the probability that firm i will interact with firm j decreases. These characteristics can cause an error that increases the probability of not interacting with the partner firm when implementing the Huff model as an agent-based model using a one-to-one matching algorithm. Under these conditions, as the number of firms increases, the probability that firm i will not interact with anyone increases, which is unrealistic. To compensate for this discrepancy, this study automatically assigns a weight to each tick to keep the maximum value of

P_{ij} at 1 at all times. Therefore, the probability distribution of this model satisfies the following condition:

$$\max_{ij}(P_{ij}) = 1$$

This correction can eliminate errors that occur when implementing the Huff model as an agent-based model.

(3) Firm Strategy

The most widely accepted explanation for firms' decision-making mechanisms is that firms act for profit maximization. In other words, firms strategically choose cooperation and defection for their own benefit, and the evolution of cooperation takes place in this process. This study assumes the Pavlov strategy as the most useful and realistic strategy for analyzing the evolution of cooperation.

The Pavlov strategy, also called the win–stay–lose–shift strategy, is a strategy in which an agent chooses one of the behaviors of collaboration or defection, and if the result is successful, it retains the behavior; otherwise, it changes it to another behavior. Under the payoff of a typical PD game, the Pavlov strategy repeats its behaviors in two situations: mutual cooperation and the situation in which the firm defects and the partner cooperates. Conversely, firms change their behavior in two situations: mutual defection or the situation in which the firm cooperates and the other defects.

Therefore, the Pavlov strategy is highly realistic in that it can choose cooperation or defection flexibly according to the change in payoff, unlike other strategies, including tit-for-tat (TFT), which depend only on the behaviors of the partner agents. In particular,

the Pavlov strategy explains the profit-seeking behaviors of firms regarding the selection of behavior according to payoffs. Pavlovian agents are the most realistic automata for analyzing the evolution of cooperation (Szilagyi & Szilagyi, 2002). In fact, the Pavlov strategy has been widely used in ABM as a tool for analyzing the evolution of cooperation in rational choice (Power, 2009). It is also known that the Pavlov strategy is effective and superior to the TFT strategy when agents make mistakes (Nowak & Sigmund, 1993).

The Pavlov strategy assumes that an agent's behavior depends on the payoff gained from the action of his choice in the previous game. Therefore, the agent maintains the behavior of the previous interaction when satisfied with the payoff of the previous transaction and changes the behavior when dissatisfied. However, a firm's decision-making process differs from that of an individual. First, firms have all their past transaction records. Second, firms predict the payoffs from each action based on their historical transaction records. Third, in a simultaneous PD game situation in which the opponent does not know what to do, the firm chooses the action with a high payoff expectation at the current point of cooperation and distribution based on the results of all the past transactions. Therefore, it is reasonable to assume that firms depend on the expected value of the payoff from past actions at present rather than the payoff from the previous action.

This study revises the assumptions that are not consistent with reality in the Pavlov strategy to be close to firms' decision-making process. Specifically, it assumes that Pavlovian firms calculate the expected value of payoffs for each behavior based on past transactions and select a behavior with high expectations for the payoff at the current point in time.

The behaviors of Pavlovian firms can be expressed in simple equations. The

behavior that Pavlovian firm i can adopt at time t is cooperation (C) or defection (D).

$$Pav_{it} = \{ C, D\}$$

Transaction records I_{it} at time t are recorded by each firm (Yamamoto, Ishida, & Ohta, 2004).

$$I_{it} = \{F_{ik} \mid k \in (0, 1, \dots, t)\}$$

Based on the transaction records, each firm calculates the expected value by collecting the payoff information from the past interaction. The expected value of cooperative behavior at time t of firm i $E(C)_{it}$ and the expected value of defective behavior $E(D)_{it}$ can be expressed by the following equation:

$$E(C)_{it} = \frac{1}{(Rn + Sn)}\left(\sum_{k=1}^{r} R_{ik} + \sum_{k=1}^{s} S_{ik}\right)$$

$$E(D)_{it} = \frac{1}{(Tn + Pn)}\left(\sum_{k=1}^{t} T_{ik} + \sum_{k=1}^{p} P_{ik}\right)$$

R is the payoff obtained from mutual cooperation, and ***Rn*** is the number of mutual cooperations until t-1. ***S*** is the payoff obtained when the player cooperates and the opponent defects, and ***Sn*** is the number of ***S*** games played until time t-1. ***T*** is the payoff obtained when the player defects and the other cooperates, and ***Tn*** is the number of ***T*** games played until time t-1. Finally, ***P*** is the payoff obtained from mutual defection and ***Pn*** is the number of mutual defections until t-1.

$$Pav_{it} = \begin{cases} C & if\ E(C)_{it} > E(D)_{\mathrm{it}} \\ D & if\ E(C)_{it} < E(D)_{\mathrm{it}} \end{cases}$$

This study also assumes that, when $E(C)_{it} = E(D)_{it}$, the firm retains the behavior selected in the immediately preceding tick based on path dependency.

In addition to firms that use Pavlov strategies, some firms never consider cooperation with other firms because of the potential costs, such as transaction costs. Firms that follow this defective strategy will choose unconditional defective behavior regardless of the expected value of the payoff. This can be expressed by the following equation:

$$Def_{it} = \{D\}$$

In addition, this study assumes that there are non-innovative firms that do not interact with other firms among the firms that use defective strategies. In this model, only Pavlovian firms and defective firms except non-innovative firms are designed to interact.

(4) Payoff Matrix

In a collaborative innovation game, the payoff between firms follows a general payoff of the prisoner's dilemma game (Chiang, 1995; Majeski, 1986). Since the model of this study is based on the spatial NIPD game, it also follows the general payoff of the prisoner's dilemma game. The payoff matrix of the prisoner's dilemma game in which

Firm A and Firm B interact simultaneously is presented in Table 2.5.

Table 2.5 Payoffs in the Prisoner's Dilemma Game

		Firm B	
		Cooperate	**Defect**
Firm A	**Cooperate**	(R, R)	(S, T)
	Defect	(T, S)	(P, P)

Since this study assumes the general prisoner's dilemma game situation, the payoff between firm A and firm B is set to be symmetric (Chiang, 1995; Majeski, 1986). R represents the payoff to be obtained with mutual cooperation, and P represents the payoff to be obtained with mutual defection. S represents the payoff that an agent receives when the agent cooperates and the partner defects, and T represents the payoff that the agent takes when the agent defects and the partner cooperates. The payoffs listed in Table 2.5 above satisfy all of the conditions below (Yamamoto et al., 2004).

$$\begin{cases} \boldsymbol{T > R > P > S} \\ \boldsymbol{2R > T + S} \end{cases}$$

The most common payoff satisfying the above condition is T = 5, R = 3, P = 1, and S = 0. Furthermore, the payoff matrix is presented in Table 2.6 below. This study sets the payoff matrix shown in Table 2.6 as the default value for the simulation.

Table 2.6 Default Payoff for the Prisoner's Dilemma Game in the Agent-Based Model

	Firm B	
	Cooperate	**Defect**

Firm A	**Cooperate**	(3, 3)	(0, 5)
	Defect	(5, 0)	(1, 1)

In collaborative innovation, cooperative firms are likely to cooperate with other firms and defective behaviors can be seen as a lack of cooperation with other firms. Mutual cooperation indicates that two firms perform collaborative innovation, and mutual defection indicates that they do not perform collaborative innovation. When a firm cooperates and the partner firm does not cooperate, it is evident that the partner firm is acting opportunistically. This opportunistic behavior is defined as a defective firm attempting to innovate with the core skills and skilled workforce of a cooperative firm without sharing its core skills and skilled workforce. In this case, the collaborative innovation is broken, the firm that has cooperated suffers losses, and the firm that has taken opportunistic actions gains benefits (Chiang, 1995).[8]

2.3.3.4 Model Validation

This study performs validation through the optimization process, which minimizes the error between the empirical data and the agent-based model for the indicators that characterize the structure of the collaborative innovation network structure. The indicators that present the characteristics of the network include the number of edges

[8] Chiang (1995) explains this situation in the case of SEMATECH and MCC, a US private R&D consortium, which began in 1984. He argued that opportunistic behavior among firms in SEMATECH and MCC continued to hamper collaborative innovation, while Japan's VLSI and 5GC programs could successfully sustain collaborative innovation because few firms adopted opportunistic behavior. He cited cultural characteristics and government intervention as the reasons for the differences between the United States and Japan. He argued that the Japanese Government actively enforced policies to reduce opportunistic behavior from the beginning of the programs, in contrast to the US Government's early observation that the consortium's continued mismanagement prompted passive intervention.

and the number of connected firms. These are used to calculate the density of the network. There is also a degree indicating the number of nodes that are directly connected to a node.

Various centrality measurements are also important indicators of network characteristics. First, betweenness centrality is measured as the degree to which one node is "between" the other points of the network (Freeman, 1979). Betweenness centrality is a measure of the importance of a node as a link that connects other nodes across the network. Nodes with high betweenness centrality are considered to play an important role in the inter-network interaction. Second, closeness centrality is defined as the reciprocal of the sum of the minimum steps required from one node to another node. Nodes connecting the different nodes through the smallest steps are considered to have high closeness centrality and play an important role in spreading information between the nodes.

Finally, the clustering coefficient is an indicator of the clustering tendency of the nodes in the network. The whole network is formed through a small number of nodes connecting the various clusters. The clustering coefficient is measured by dividing the ratio of the number of actual connections to the number of connections when each node is connected to neighboring nodes divided by the total number of nodes. A node with a high clustering coefficient is highly likely to belong to a cluster.

To summarize, a total of seven indicators are selected. This study performs validation using network indicators such as edges, linked firms, degree, betweenness centrality, closeness centrality, and clustering coefficient. It uses mean values for all the node-level measurements. In addition, since the degree has a similar distribution to the exponential distribution, not only the mean but also the maximum value is added to the

indicator.[9]

This study performs the validation process by calibrating two parameters, α and β, of the Huff model. It explores the most similar combination of empirical data among the combinations of α from 0.01 to 4 and β from 0.01 to 2. The simulation is performed 30 times[10] each with the maximum tick = 1,000 according to the combinations of the coefficients in the initial setting without an edge, and then it is possible to confirm whether the network characteristic values are similar to those of the actual network.

The range of each parameter is set from 0.01 to 4 for α and from 0.01 to 2 for β. This is because the edge is not generated sufficiently at the maximum tick = 1,000 when the β value exceeds 1. The parameter settings for validation are shown in Table 2.7.

Table 2.7 Parameter Settings for Validation

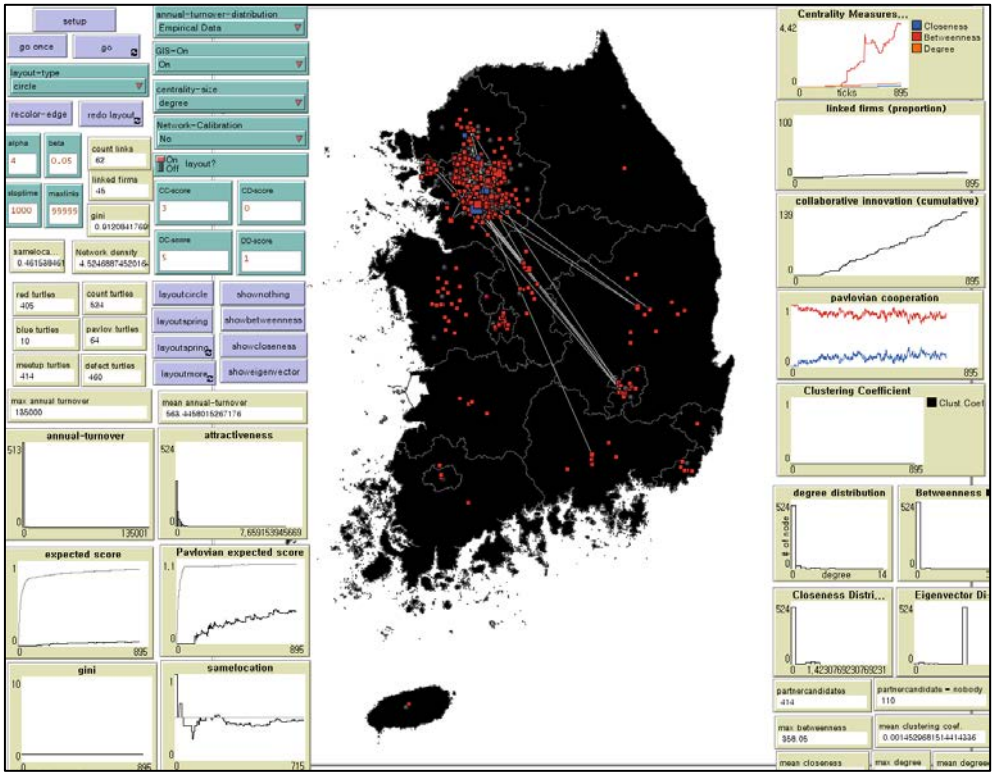
Type	Name		Description
Input	Huff Parameter	α	0.01, 0.05, 0.1, 0.5, 1, 1.5, 2, 2.5, 3, 3.5, 4
		β	0.01, 0.05, 0.1, 0.5, 1, 1.5, 2
Output	Network Characteristics		Edges
			Linked Firms
			Max. Degree
			Mean Degree
			Mean Betweenness Centrality
			Mean Closeness Centrality
			Mean Clustering Coefficient

[9] It is inappropriate to measure the maximum value of closeness centrality, because it reaches a maximum value of one when independent one-to-one connections occur regardless of the network characteristics. Furthermore, if the measurement of the maximum value under the network in which the outlier exists in the degree distribution is used as several indicators, like the present network, the outliers are repeatedly weighted in calculating the MAPE value.

[10] This study performs 30 iterations per simulation to obtain a minimum number of sa mples with statistical power according to the Central Limit Theorem (CLT).

Since the coefficients for validation are composed of 10 α and 6 β, the total number of possible combinations is 60. Each combination is simulated up to 1,000 ticks through 30 iterations. Therefore, the simulation is performed 1,800 times in total. The screenshot of the simulation run on Netlogo is shown in Figure 2.5.

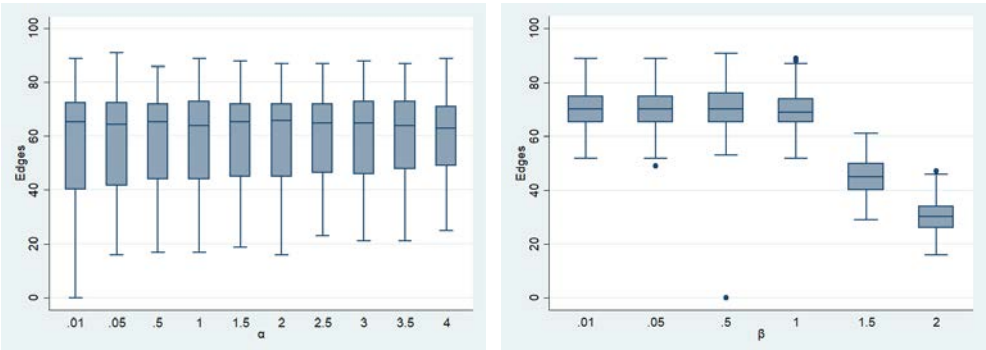
Figure 2.5 Screenshot of the Simulation



The following figures show the simulation results of each indicator according to the combination of the two parameters. Each figure presents the value at the time when the average of the edges is 70, which is the same as the observed value, at the time of 30 iterations. Through these figures, it is possible to capture the tendency of the change in the network characteristic according to each parameter. First, the tendency of edge

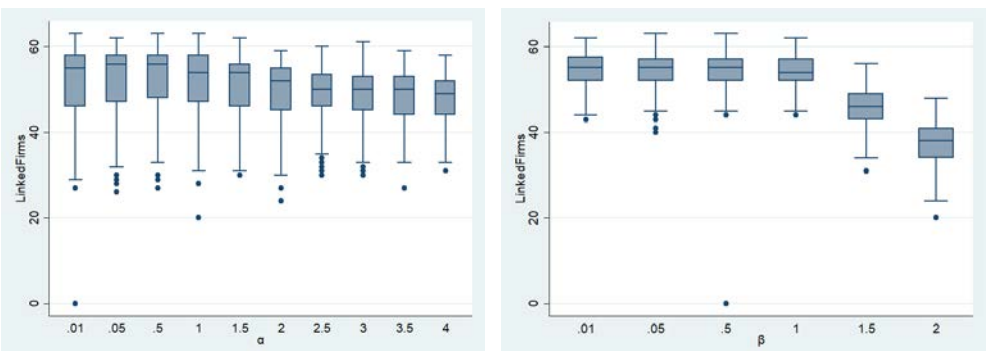
generation by α and β is shown in Figure 2.6.

Figure 2.6 Edges by α and β



First, a clear change in the edge by α is not observed. However, when β is 1 or more, edges are generated at 70 or less at the maximum tick, and, as β increases, the number of generated edges also decreases gradually. Next, the change in the linked firms by α and β is presented in Figure 2.7.

Figure 2.7 Linked Firms by α and β

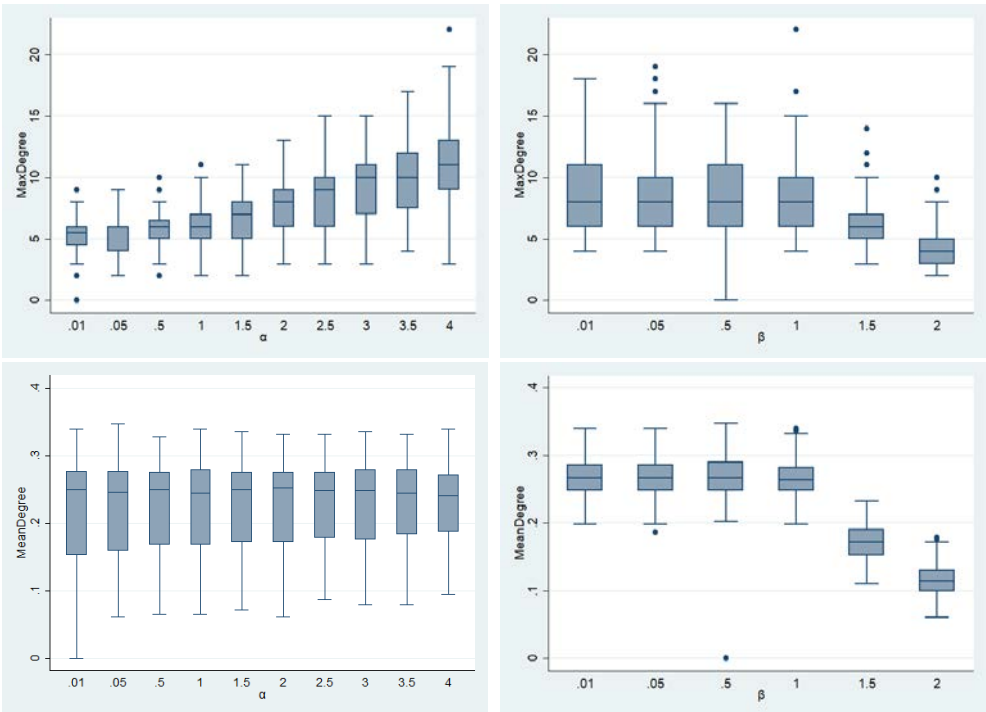


The number of linked firms is more than 50 regardless of α, and the average value tends to decrease slightly with an increasing α. On the other hand, the number of firms

linked to β tends to decrease rapidly from 1 and decreases to less than 40 when β is 2.

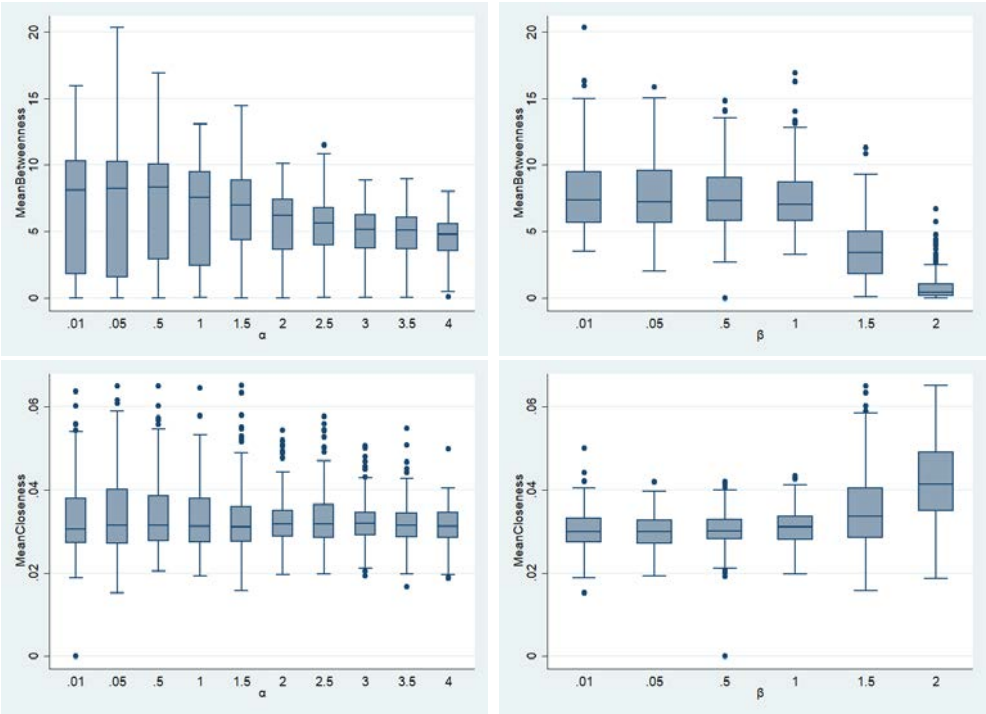
The number of edges and the number of linked firms are shown to be more affected by β than by α. Next, the changes in the maximum degree and mean degree by α and β are shown in Figure 2.8 below.

Figure 2.8 Maximum Degree and Mean Degree by α and β



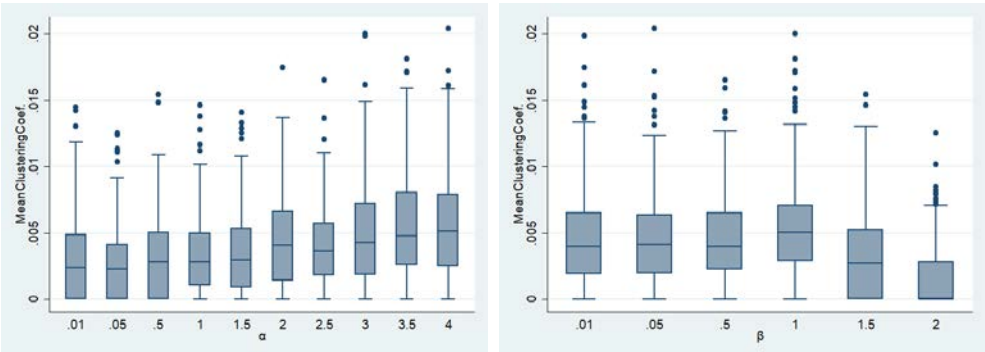
Unlike edges or linked firms, the maximum degree tends to increase as α increases but tends to decrease as β increases. The mean degree has a pattern similar to the edge or linked firms. It responds to β more sensitively than α and decreases sharply when β is greater than 1. The changes in the mean betweenness centrality and the mean closeness centrality by α and β are shown in Figure 2.9 below.

Figure 2.9 Mean Betweenness Centrality and Mean Closeness Centrality by α and β



The mean betweenness centrality decreases as the value of α increases and decreases sharply when β is higher than 1. The mean closeness centrality does not change with the α value, and it increases when β is 1 or more. Finally, the change in the mean clustering coefficient by alpha and beta is shown in Figure 2.10.

Figure 2.10 Mean Clustering Coefficient by α and β



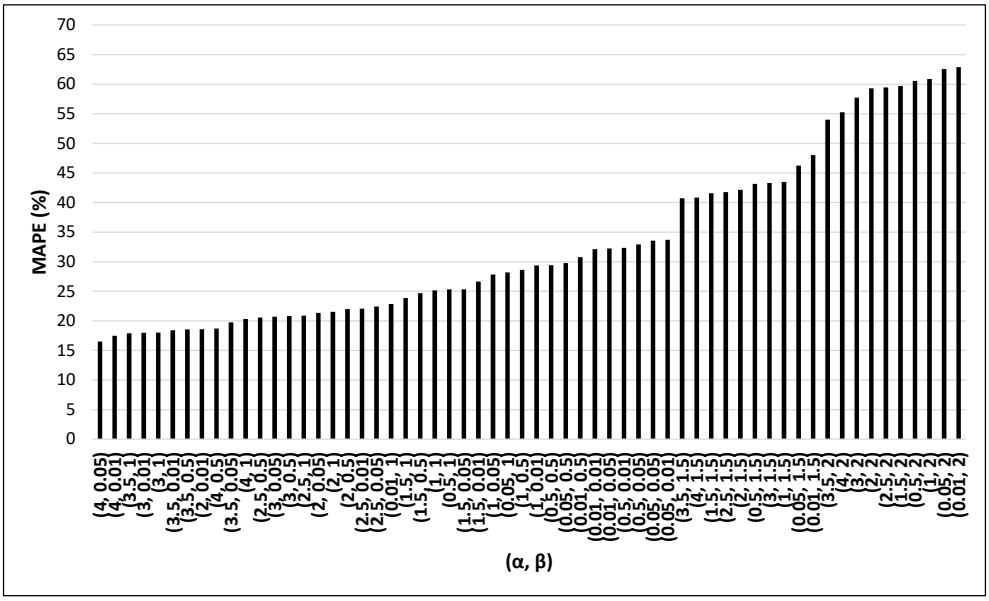
The mean clustering coefficient tends to increase slightly as α increases and decrease sharply when β exceeds 1.

This study searches for the combination of parameters with the lowest absolute value of the difference ratio between the simulation results and the observations for the above seven indicators. This method is similar to the procedure for obtaining the mean absolute percentage error (MAPE) for measuring the accuracy of a general forecasting model. The equation for the MAPE is as follows:

$$MAPE = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{Y_i - S_i}{Y_i}\right|$$

n is the number of observations used as indicators, Y_i is the observed value, and S_i is the simulated value. The lower the MAPE value is, the more likely the predicted performance is, because the values calculated by the model are similar to the actual data. The MAPE values for the 60 combinations used in the validation are presented in order from the lowest value in Figure 2.11.

Figure 2.11 MAPE by Combinations of α and β



The average MAPE for 60 combinations is 33.22%. When A is 4 and β is 0.05, the MAPE is the smallest at 16.54%. On the other hand, when α is 0.01 and β is 2, the MAPE is the largest at 62.89%. Therefore, this study adopts α = 4 and β = 0.05, which is the smallest combination of the MAPE among all the combinations of parameters. The comparison between the mean of the simulation results and the empirical data when α = 4 and β = 0.05 at tick = 996 is presented in Table 2.8.

Table 2.8 Validation Result of the Base Model (Tick = 996, α = 4, and β = 0.05)

Network Characteristics	Empirical Data	Simulated Data (30 Iterations)	
		Mean	SD
Edges	70	70.06667	8.23337
Linked Firms	64	50.80000	2.92904
Max. Degree	18	12.53333	2.48767

Mean Degree	0.26667	0.26743	0.03143
Mean Betweeneness Centrality	7.10095	5.31190	0.98984
Mean Closeness Centrality	0.04758	0.03211	0.00377
Mean Clustering Coefficient	0.00841	0.00785	0.00433
MAPE	16.54%		

The validation results indicate that inter-firm collaborative innovation is affected more by firm size factors, such as sales, than by geographic distance. In other words, even if the distance between the firms is not large, it does not affect the collaborative innovation. However, if the firms' sales are high, the probability of collaborative innovation increases exponentially.

This study performs validation on the same basis as the general mathematical forecasting model. However, the MAPE of this validation result needs to be interpreted carefully. The purpose of the validation process of this study is to determine the difference between the observations for the n indicators and the simulation estimates. Therefore, it is difficult to apply the criterion of the good prediction model, which is normally used in the time series forecasting model: less than 10% is highly accurate, and less than 20% is good (Lewis, 1982)[11]. This is because these forecasting models minimize the MAPE through optimization processes such as curve fitting, including NLS. The mathematical forecasting model minimizes the MAPE for one continuous time series variable, but this study optimizes the discontinuous variables. Given the nature of this data, the MAPE value of 16.54 percent is considered to have high explanatory power.

[11] MAPE < 10 : Highly accurate forecasting
10 < MAPE < 20 : Good forecasting
20 < MAPE < 50 : Reasonable forecasting
50 < MAPE : Inaccurate forecasting (Lewis, 1982)

Validation is a highly controversial concept in simulation studies and is not easy to perform (Campbell et al., 2015); therefore, validation is not performed on all simulation models. However, validated models have several advantages.

Firstly, Windrum et al. (2007) suggest that the model is accurate and consistent as researchers have more knowledge of the initial assumption. Therefore, the closer the results of empirical validation are to reality, the more accurate and consistent the model is. However, researchers need to find trade-offs between ease of analysis and accuracy of description. The concrete and complex model explains the reality better, and the more abstract and straightforward the model, the easier it is to deal with analytically. It is neither impossible nor productive to construct a fully embodied model of complex social phenomena (Windrum et al., 2007).

Secondly, Popper says that phenomena that cannot be replicated cannot be used in a scientific way (Wilensky & Rand, 2007). According to this logic, validation can be interpreted as an instrument to use phenomena with scientific methodology. A virtual model such as an agent-based model can be used to represent and intervene in social phenomena (Morrison & Morgan, 1999). Thus, a well-validated model can be regarded as one that has the potential to explore a phenomenon scientifically.

Thirdly, validation helps to clarify whether there is sufficient correspondence between the conceptual model and the real world (Wilensky & Rand, 2007). Since the model with low MAPE value is considered to be highly accurate for future prediction, the simulation of this study can be interpreted as having relatively high explanation power of reality.

In sum, the validation results indicate that the model is appropriate for exploring the phenomenon of coherent and collaborative innovation in a scientific way, and that the explanatory power and accuracy of future predictions are high.

This study performs two experiments using the base model constructed through validation. Each experiment is performed by manipulating different conditions in the same base model. The following sections describe the experimental design in detail.

2.3.3.5 Experimental Design

(1) Base Experiment: Intra-industry Heterogeneity Simulation

The first experiment attempts to analyze how the collaborative innovation patterns emerge differently due to the level of intra-industry heterogeneity. This experiment investigates how collaborative innovation and network characteristics are changed by creating counterfactuals through simulations, assuming that early innovations start in different distributions from the empirical data. Specifically, this experiment analyzes the effect of the annual sales distribution among firms on the network characteristics, firms' cooperative behavior, and collaborative innovation.

This study selects empirical distribution, exponential distribution, and normal distribution as independent variables. The mean values of these distributions are the same, but there is a difference in the polarization level of the annual sales between firms. The characteristics of these independent variables are summarized in Table 2.9.

Table 2.9 Summary of the Independent Variables

	Firm Size Distribution (Annual Sales Distribution)		
	Empirical	**Exponential**	**Normal**
Description	Empirical distribution	Random exponential distribution	Random normal distribution
	Mean 563.45	Mean 563.45	Mean 563.45

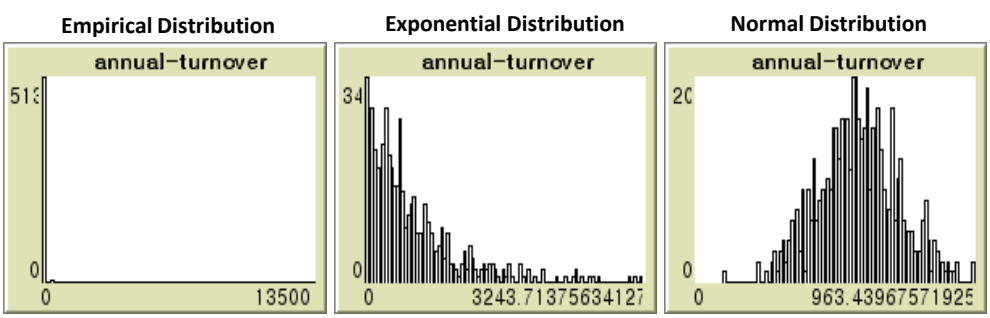
	Max 13,500		SD: 25% of mean
Gini Index	0.9121	0.5024	0.1409
Intra-Industry Heterogeneity	High	Medium	Low

First, the empirical distribution is similar to the exponential distribution but has a more skewed distribution. The maximum annual sales is 13,500, and the mean is 563.45. Most firms are located in the lowermost section of the tenth quartile, and the Gini coefficient is 0.9121. Therefore, the empirical distribution is extremely polarized, and the level of intra-industry heterogeneity is high.

Second, the exponential distribution is a random exponential distribution with a mean equal to the empirical distribution but a smaller variance. The Gini coefficient is 0.5024, and the levels of polarization and intra-industry heterogeneity are medium.

Third, the normal distribution is the random normal distribution with the mean being equal to the empirical distribution and the standard deviation being 25% of the mean. The Gini coefficient is 0.1409, which is a relatively even distribution, and the level of intra-industry heterogeneity is low. The histogram for each distribution is shown in Figure 2.12.

Figure 2.12 Histograms of the Independent Variables



The level of intra-industry heterogeneity for each distribution is evident in the above histograms. Especially in the empirical distribution, the level of intra-industry heterogeneity seems to be very high. Most firms are located at the bottom of the distribution, and only a few firms are located at the top. In the exponential distribution, the intra-industry heterogeneity is moderated, and the normal distribution has a very low level of heterogeneity.

The dependent variables of this study adopt the structure, conduct, and performance of the industry based on the SCP framework. The structure of the industry is measured by the network density, conduct by the cooperative behavior of Pavlovian firms, and performance by collaborative innovation.

First, the network density is an indicator of network cohesion and is defined as the ratio of potential connections to actual connections. In an undirected network with N nodes, as in this study, when the actual connections are A, the network density is defined as follows:

$$D = \frac{2A}{N(N-1)}$$

High network density indicates that the members of a network are closely connected.

Second, cooperative behavior is measured as the percentage of agents performing cooperative behavior at specific time points. Since this study focuses on the behavior of Pavlovian agents, cooperative behavior is calculated as the ratio of cooperative Pavlovian agents to all Pavlovian agents. When the number of Pavlovian agents at time t is PA_t, and when the number of Pavlovian agents performing cooperative actions at

time t is PC_t, cooperative behavior CB is defined as follows:

$$CB = \frac{100 * PC_t}{PA_t}$$

As the cooperative behavior of agents increases, the probability of collaborative innovations among agents also increases.

Third, collaborative innovation occurs when Pavlovian agents cooperate mutually. When mutual cooperation between two agents occurs repeatedly, a new edge does not occur between them, but the collaborative innovation accumulates. Collaborative innovation is measured as the sum of collaborative innovation of all agents.

The simulations are performed up to 996 ticks with an average edge count of 70 in the empirical distribution, and 30 iterations are performed for each distribution. Therefore, a total of 90 simulations are performed. The manipulation settings for the simulation are shown in Table 2.10 below.

Table 2.10 Manipulation Settings for the Base Simulation

Type	Variable	Description	Measurement
Dependent Variable	Structure	Network Density	$D = \frac{2A}{N(N-1)}$
	Conduct	Cooperative Behavior (Pavlovian Cooperation)	$CB = \frac{100 * PC_t}{PA_t}$
	Performance	Collaborative Innovation	Sum of Collaborative Innovation
Independent Variable	Level of Intra-industry Heterogeneity	FSD (Annual Sales Distribution)	Empirical Distribution (High Heterogeneity)
			Exponential Distribution (Medium Heterogeneity)

			Normal Distribution (Low Heterogeneity)
Control Variable	Payoff	Payoff (R, T, S, P)	R = 3
			T = 5
			S = 0
			P = 1
	Partnering Mechanism	Huff Parameter	α =4
			β=0.05

The initial conditions for this simulation assume that collaborative innovation has not yet been performed. Therefore, the simulation starts in a condition in which the network has not yet been formed and the network characteristics are all zero.

This study divides firms into Pavlovian firms and defective firms depending on whether they are willing to engage in collaborative innovation. First, firms that have once participated in collaborative innovation during the past 35 years as of 2015 are included in the potential firms that can act in a cooperative manner. This study sets them as Pavlovian firms. Second, firms that have not participated in collaborative innovation over the past 35 years are set as "defective firms" that are not willing to cooperate. Third, firms that have not performed innovation activities in the last 35 years among the defective firms are classified as non-innovative firms. They do not engage in innovation activities and therefore do not participate in firm-to-firm interactions. The initial settings for the simulation are shown in Table 2.11 below.

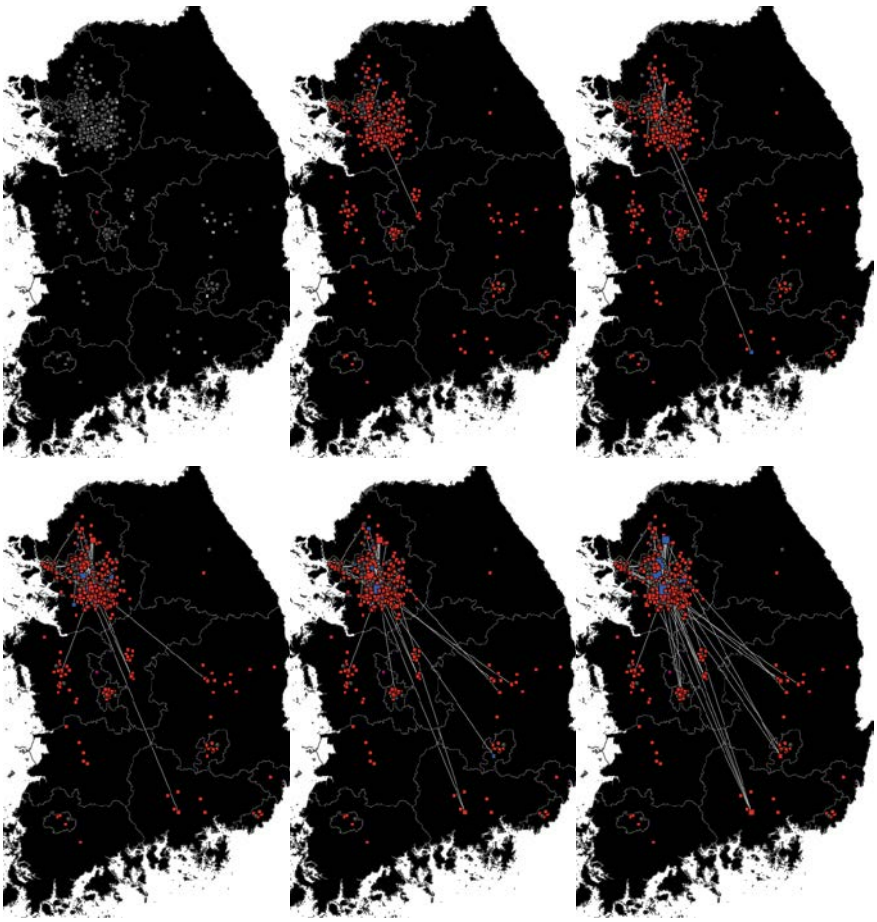
Table 2.11 Initial Settings for the Base Simulation

Type	Name	Initial Value
Agent	Firms	524
	Pavlovian Firms	64 (Initial Pavlovian Cooperation = 0)

	Defective Firms	460 (Non-innovative Firms = 109)
Space	GIS	South Korea
	Number of Regions	17 Cities and Provinces
	Geographical Distribution of Firms	Seoul (179), Gyonggi (219), Incheon (21), Sejong (1), Daejeon (17), Gangwon (2), Daegu (12), Ulsan (1), Gwangju (5), Busan (6), Chungbuk (12), Chungnam (23), Jeonbuk (4), Jeonnam(1), Gyungbuk (13), Gyungnam (6), Jeju (2)
Network	Edges	0
	Linked Firms	0
	Max Degree	0
	Mean Degree	0
	Mean Betweenness Centrality	0
	Mean Closeness Centrality	0
	Mean Clustering Coefficient	0

This study uses one-way ANOVA to determine whether there is a statistically significant difference between the dependent variables for each distribution. Screenshots of the simulation process over time are presented in Figure 2.13.

Figure 2.13 Screenshots of the Base Simulation (Tick = 0, 100, 250, 500, 750, and 996)



At the beginning of the simulation, the network is not formed, but, as time passes, the edges are created due to the cooperation between the firms. The red agents represent firms that have acted defectively, while the blue agents represent firms that have acted cooperatively. The size of the agent increases in proportion to its degree. At the endpoint of 996 ticks, a small number of firms are found to be relatively larger than the other firms, indicating that the polarized distribution of degrees observed in the real world is

successfully reproduced through this agent-based model.

(2) Extended Experiment: Policy Simulation

The second experiment attempts to analyze how government incentives and regulatory policies affect collaborative innovation patterns in industries with high intra-industry heterogeneity. This experiment assumes incentives and regulatory scenarios and explores how collaborative innovation and network characteristics change in the future through simulation starting from the present.

This study sets up four incentive scenarios (no incentives, low incentives, medium incentives, and high incentives) by the level of incentives for collaborative innovation and four regulatory scenarios (no regulation, weak regulation, moderate regulation, and strong regulation) by the level of regulation of opportunistic behavior.[12] Thus, the independent variables in this study are the sixteen policy scenarios, which are a combination of four incentive scenarios and four regulatory scenarios.

Chiang (1995) argued that governments' policy should focus on shifting the payoff from T > R > P > S to R > T > S > P. He noted that governments can increase R or suppress T. For example, governments can increase R by providing financial, technical, and administrative support to firms participating in collaborative innovation. They can also suppress T by preventing or punishing the opportunistic behavior of firms (Chiang, 1995). Therefore, this experiment also manipulates the independent variable by setting the payoff differently by the policy level of the government.

The payoffs are R = 3, T = 5, P = 1, and S = 0 in the basic situation without

[12] No incentives indicate no additional incentives, and no regulation indicates no additional regulation. In other words, these scenarios represent the current levels of incentives and regulations.

incentives and regulations. The incentive policy increases R, and the regulation of opportunistic behavior suppresses T.

First, incentive scenarios can be implemented by increasing R. The intensity of the incentive is set to increase by 2 for each level. Low incentives are R = 5 scenarios, where R = T, which receive the same payoff as T in the base model. In this situation, when a partner cooperates, the payoff of the agent becomes the same regardless of the behavior, so the incentive for the agent to choose opportunistic behavior is reduced. However, since P > S, the expected payoff of defective behavior is higher than the expected payoff of cooperative behavior. Medium incentives are R = 7 scenarios, where R > T in the base model. In this situation, when the partner cooperates, the partner also becomes the dominant strategy. Finally, high incentives are a scenario with R = 9, and, in this situation, when partners work together, the agent also becomes a dominant strategy. In addition, compared with the medium-incentive scenario, agents are more likely to choose cooperation.

Second, the regulatory scenario can be implemented by suppressing T. The intensity of regulation is also set to decrease by 2 for each level. Weak regulation is a scenario with T = 3, which is R = T in the base model. In this situation, when a partner cooperates, the payoff of the agent is constant regardless of the behavior, so the incentive for the agent to choose opportunistic behavior is reduced. However, since P > S, the expected payoff of defective behavior is still higher than the payoff of cooperative behavior, considering the defection by the partner. Moderate regulation is a scenario in which T = 1, which is a situation in which R > T = P, where the expected value obtained when a payoff is lower than R in the base model is 1. In this situation, when the partner cooperates, the partner also becomes the dominant strategy. Finally, strong regulation is a scenario in which T = -1. In this situation, the punishment for defection is substantial

and the incentive for opportunistic behavior is highly reduced. The policy mix reflecting this in the payoff is presented in Table 2.12 below.

Table 2.12 Scenario Settings for the Extended Simulation

		Level of Regulation			
		No Regulation	**Weak Regulation**	**Moderate Regulation**	**Strong Regulation**
Level of Incentives	**No Incentives**	(R = 3, T = 5)	(R = 3, T = 3)	(R = 3, T = 1)	(R = 3, T = -1)
	Low Incentives	(R = 5, T = 5)	(R = 5, T = 3)	(R = 5, T = 1)	(R = 5, T = -1)
	Medium Incentives	(R = 7, T = 5)	(R = 7, T = 3)	(R = 7, T = 1)	(R = 7, T = -1)
	High Incentives	(R = 9, T = 5)	(R = 9, T = 3)	(R = 9, T = 1)	(R = 9, T = -1)

The dependent variable in this study is the same as in experiment I. The simulation runs up to 1,000 ticks and performs 30 iterations per scenario. Therefore, a total of 480 simulations are performed. The manipulation settings for the simulation are shown in Table 2.13 below.

Table 2.13 Manipulation Settings for the Extended Simulation

Type	Variable	Description	Measurement
Dependent Variable	Structure	Network Density	$D = \frac{2A}{N(N-1)}$
	Conduct	Cooperative Behavior (Pavlovian Cooperation)	$CB = \frac{100 * PC_t}{PA_t}$
	Performance	Collaborative	Sum of Collaborative

		Innovation	Innovation
Independent Variable	Level of Incentives	No Incentives	R = 3
		Low Incentives	R = 5
		Medium Incentives	R = 7
		High Incentives	R = 9
	Level of Regulation	No Regulation	T = 5
		Weak Regulation	T = 3
		Moderate Regulation	T = 1
		Strong Regulation	T = -1
Control Variable	Payoff	Payoff (S, P)	S = 0
			P = 1
	Partnering Mechanism	Huff Parameter	α =4
			β=0.05
	Level of Intra-industry Heterogeneity	FSD (Annual Sales Distribution)	Empirical Distribution (High Heterogeneity)

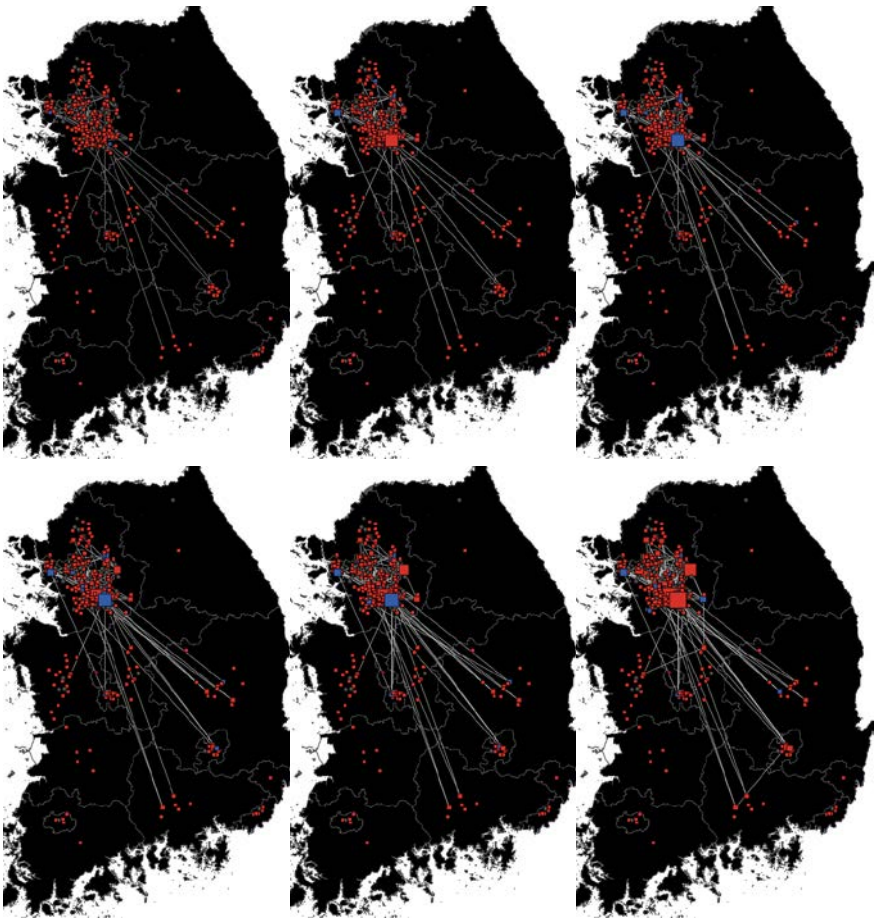
This simulation focuses on exploring how government policies will change in future collaborative innovation based on the year 2015. Therefore, the initial conditions for the simulation are set equal to the empirical data of the network in 2015. In addition, the percentage of Pavlovian firms that have cooperated in 2015 should be reflected. However, there is a problem that cooperative behavior is unilateral and difficult to measure in the real world. This study sets the percentage of Pavlovian firms as 18.177% (SD = 5.39), which is the simulation result obtained when the condition is the closest to reality (α = 4 and β = 0.05). Randomly selected from among 64 Pavlovian firms, 12 Pavlovian firms are set to cooperate at tick = 0. The initial settings for the simulation are shown in Table 2.14 below.

Table 2.14 Manipulation Settings for the Extended Simulation

Type	Name	Initial Value
Agent	Firms	524
	Pavlovian Firms	64 (Initial Pavlovian Cooperation = 12)
	Defective Firms	460 (Non-innovative Firms = 109)
Space	GIS	South Korea
	Number of Regions	17 Cities and Provinces
	Geographical Distribution of Firms	Seoul (179), Gyonggi (219), Incheon (21), Sejong (1), Daejeon (17), Gangwon (2), Daegu (12), Ulsan (1), Gwangju (5), Busan (6), Chungbuk (12), Chungnam (23), Jeonbuk (4), Jeonnam(1), Gyungbuk (13), Gyungnam (6), Jeju (2)
Network	Edges	70
	Linked Firms	64
	Max Degree	18
	Mean Degree	0.26717
	Mean Betweenness Centrality	7.11450
	Mean Closeness Centrality	0.0047667
	Mean Clustering Coefficient	0.0084275

This study uses two-way ANOVA to determine whether there is a statistically significant difference between the dependent variables for each policy scenario. This study also tests whether there is a positive interaction effect between incentives and regulations. Screenshots of the simulation process over time are presented in Figure 2.14.

Figure 2.14 Screenshots of the Extended Simulation (Tick = 0, 100, 250, 500, 750, and 1000)



At the beginning of the simulation, the network is the same as the empirical network of 2015. Over time, the network is expanded with the addition of edges according to mutual cooperation among firms.

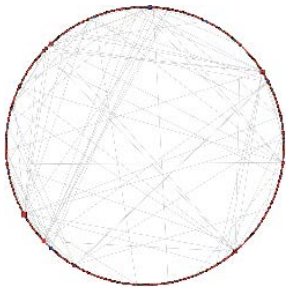
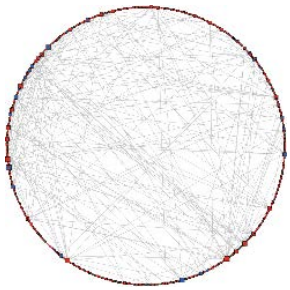
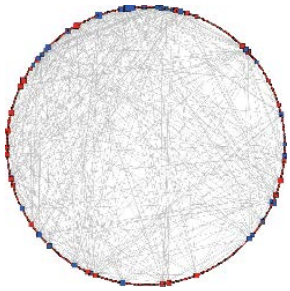
2.4 Simulation Results

2.4.1 Base Experiment: Intra-industry Heterogeneity Simulation

2.4.1.1 Network Density

This experiment investigates changes in structure, conduct, and performance of collaborative innovation according to changes in FSD. The first simulation determines whether the network density differs by the level of intra-industry heterogeneity. Table 2.15 shows the topology of the collaborative innovation network formed at tick = 996 in a circular layout.

Table 2.15 Network Topology in a Circular Layout by FSD

Empirical	Exponential	Normal
		

The density of the network is higher with the exponential distribution than with the empirical distribution and seems to be the highest with the normal distribution. The large nodes indicate an increased degree of a network. In the case of normal distribution, the large nodes occur the most frequently among the three distributions.

This study examines the summary statistics of the network density for each FSD

before the ANOVA. This study calculates Cohen's d for standardized mean comparisons. The summary statistics are presented in Table 2.16.

Table 2.16 Summary Statistics of Network Density by FSD

Variable	FSD	Mean	SD	Cohen's d	Freq.
Network Density	Empirical	5.113e-04	6.009e-05	0	30
	Exponential	1.308e-03	1.897e-04	5.6621	30
	Normal	2.894e-03	1.545e-04	20.3267	30

The simulation is iterated 30 times for each FSD. The summary statistics show that the average network density is the lowest in the empirical distribution, higher in the exponential distribution, and the highest in the normal distribution. The results of the ANOVA on network density by FSD are shown in Table 2.17 below.

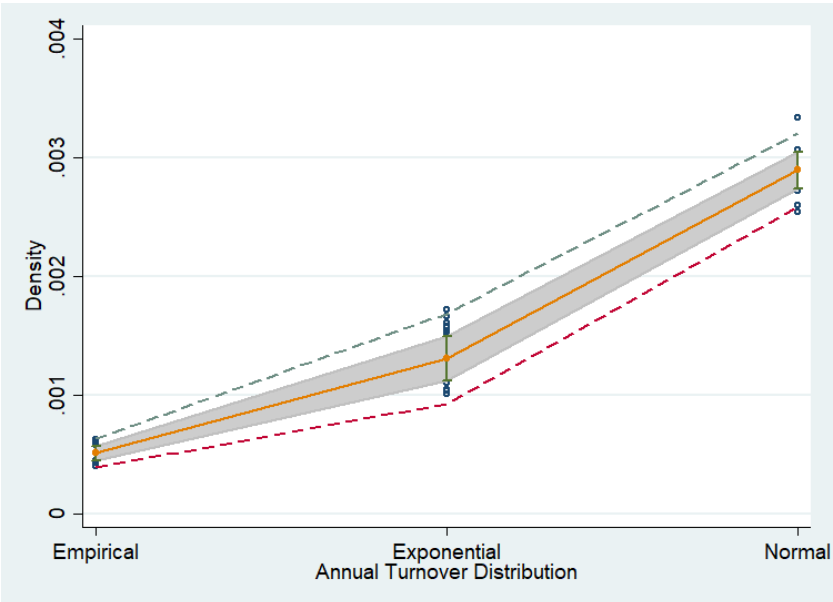
Table 2.17 Results of the One-way ANOVA

Variable	Source	SS	df	MS	F	Prob.>F
Network Density	Between Groups	8.8306e-05	2	4.4153e-05	2086.27***	0.0000
	Within Groups	1.8412e-06	87	2.1164e-08		
	Total	9.0147e-05	89	1.0129e-06		

Note: $^{*}p < 0.05$p < 0.1, $^{**}p < 0.01$, $^{***}p < 0.001$

The ANOVA results show that the effect of intra-industry heterogeneity on the network density is statistically significant at the 99.9% significance level. The effects are presented in Figure 2.15 below.

Figure 2.15 Effect of Intra-Industry Heterogeneity on Network Density

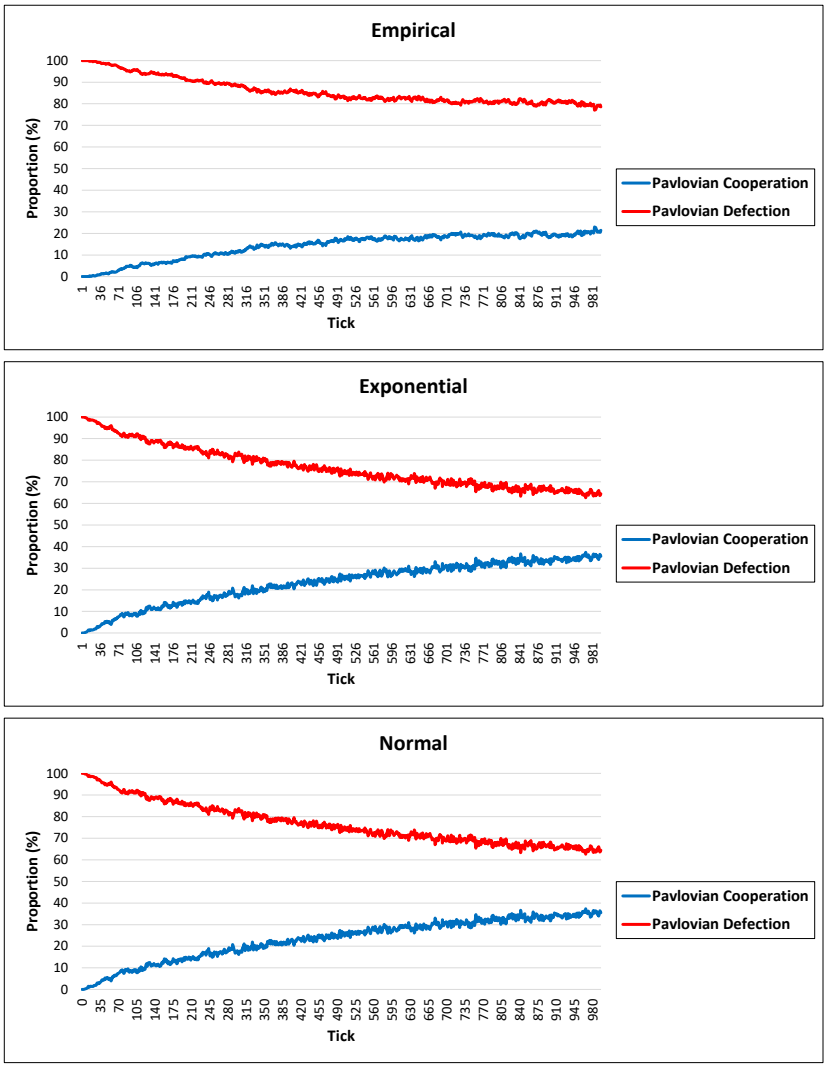


According to Table 2.9, the Gini coefficient is 0.91 for the empirical distribution, 0.50 for the exponential distribution, and 0.14 for the normal distribution. As the FSD changes from the empirical distribution to the normal distribution, the intra-industry heterogeneity gradually decreases. Therefore, Figure 2.15 shows that the diversity of partner selection in inter-firm collaborative innovation is reduced under the high intra-industry heterogeneity. However, as the intra-industry heterogeneity becomes lower, firms cooperate with more diverse partners. The results of this analysis also suggest that the intensification of intra-industry heterogeneity can be a barrier to collaborative innovation among various partners.

2.4.1.2 Cooperative Behavior

The second simulation analyzes whether the cooperative behavior differs by the level of intra-industry heterogeneity using the ANOVA for the proportion of Pavlovian cooperation at tick = 996. The changes in the proportion of Pavlovian cooperation and Pavlovian defection by each FSD over time up to tick = 996 are shown in Figure 2.16 below.

Figure 2.16 Changes in Pavlovian Cooperation and Pavlovian Defection by FSD over Time (Average of 30 Iterations)



The proportion of Pavlovian cooperation increases and the proportion of Pavlovian defection decreases in all the FSDs. The increasing slope of the proportion of Pavlovian cooperation is the lowest in the empirical distribution and the highest in the normal

distribution.

This study examines the summary statistics of the proportion of Pavlovian cooperation for each FSD before the ANOVA. The summary statistics are presented in Table 2.18.

Table 2.18 Summary Statistics of Pavlovian Cooperation by FSD (Proportion)

Variable	FSD	Mean	SD	Cohen's d	Freq.
Pavlovian Cooperation	Empirical	18.177	5.389	0	30
	Exponential	35.521	6.628	2.8714	30
	Normal	42.240	6.243	4.1263	30

The simulation is iterated 30 times for each FSD. The summary statistics show that the mean of the proportion of Pavlovian cooperation is the lowest in the empirical distribution, higher in the exponential distribution, and the highest in the normal distribution. The results of the ANOVA on the proportion of Pavlovian cooperation by FSD are shown in Table 2.19.

Table 2.19 Results of the One-way ANOVA

Variable	Source	SS	df	MS	F	Prob.>F
Pavlovian Cooperation	Between Groups	9249.512	2	4624.756	123.93***	0.0000
	Within Groups	3246.582	87	37.317		
	Total	12496.094	89	140.406		

Note: $^{*}p < 0.05$p < 0.1, $^{**}p < 0.01$, $^{***}p < 0.001$

The ANOVA results show that intra-industry heterogeneity has a statistically significant effect on firms' cooperative behavior at the 99.9% significance level. The effects are presented in Figure 2.17 below.

Figure 2.17 Effect of Intra-Industry Heterogeneity on Pavlovian Cooperation

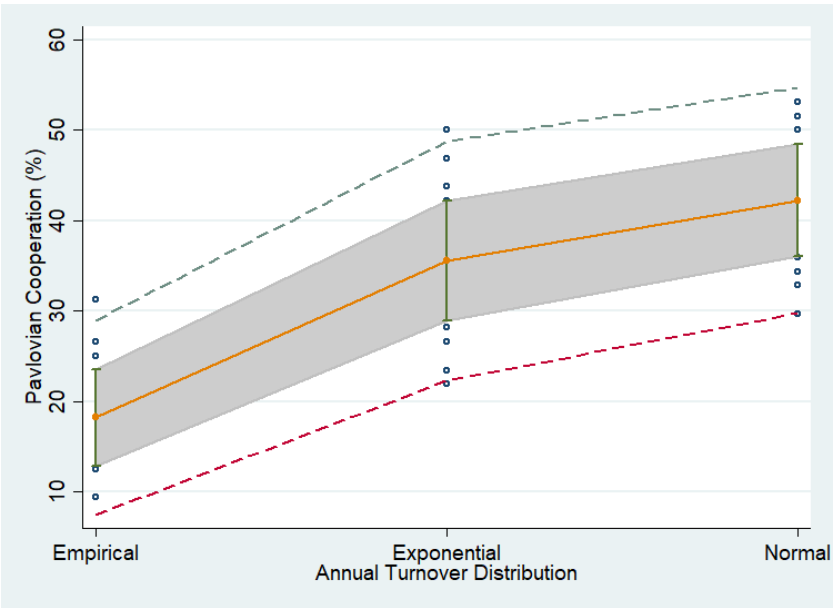


Figure 2.17 shows that firms' cooperative behaviors are low when the intra-industry heterogeneity is high and, conversely, as the intra-industry heterogeneity decreases, firms' cooperative behavior increases. This indicates that firms tend to cooperate with their counterparts when the size distribution of firms in the industry is relatively uniform rather than when the size variation among firms is large. Therefore, as the intra-industry heterogeneity decreases, firms tend to prefer collaborative innovation. This result implies that the intra-industry heterogeneity can be a factor that

interferes with the open innovation ecosystem in the industry by reducing the cooperation tendency among the firms.

2.4.1.3 Collaborative Innovation

The third simulation investigates whether there is a difference between the firms' collaborative innovation by the level of intra-industry heterogeneity using the ANOVA for the sum of the frequencies of collaborative innovation performed by all firms until tick = 996. This study examines the summary statistics of collaborative innovation for each FSD before the ANOVA. The summary statistics are presented in Table 2.20.

Table 2.20 Summary Statistics of Collaborative Innovation by FSD

Variable	FSD	Mean	SD	Cohen's d	Freq.
Collaborative Innovation	Empirical	143.133	16.414	0	30
	Exponential	371.200	54.392	5.6770	30
	Normal	848.733	49.036	19.2973	30

The simulation is iterated 30 times for each FSD. The summary statistics show that the mean of the cumulative collaborative innovation until tick = 996 is the lowest in the empirical distribution, higher in the exponential distribution, and the highest in the normal distribution. The results of the ANOVA on collaborative innovation by FSD are presented in Table 2.21.

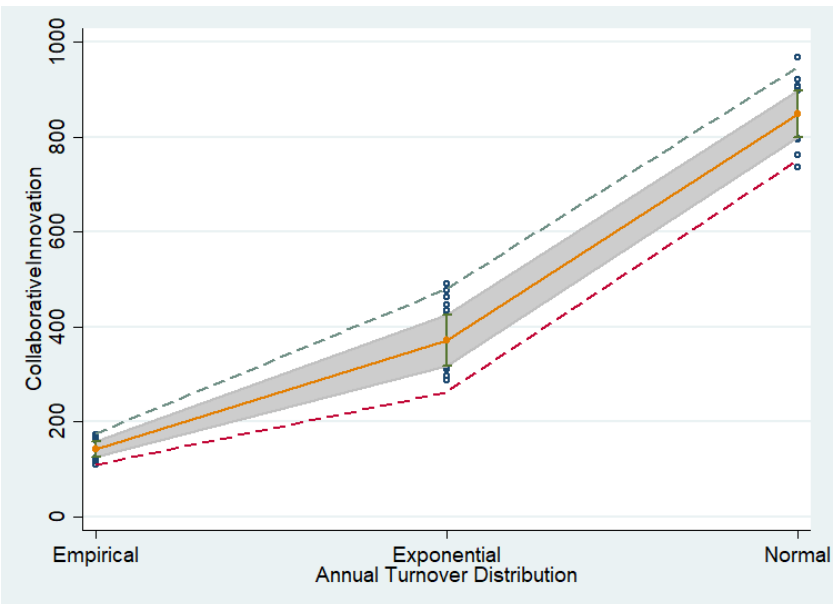
Table 2.21 Results of the One-way ANOVA

Variable	Source	SS	df	MS	F	Prob.>F
Collaborative Innovation	Between Groups	7779238.49	2	3889619.24	2071.71***	0.0000
	Within Groups	163342.13	87	1877.50		
	Total	7942580.62	89	89242.48		

Note: $^{*}p < 0.05$p < 0.1, $^{**}p < 0.01$, $^{***}p < 0.001$

The ANOVA results show that the effect of intra-industry heterogeneity on collaborative innovation is statistically significant at the 99.9% significance level. The effects are presented in Figure 2.18 below.

Figure 2.18 Effects of Intra-Industry Heterogeneity on Collaborative Innovation



Collaborative innovation increased about 2.6 times more in the exponential distribution and 5.9 times more in the normal distribution than in the empirical distribution, indicating that it is highly sensitive to the level of intra-industry heterogeneity. Figure 2.18 shows that, while collaborative innovation is reduced under conditions of high intra-industry heterogeneity, collaborative innovation increases as intra-industry heterogeneity decreases. This indicates that collaborative innovation is performed more when the FSD in the industry is relatively uniform than when the FSD is large. Therefore, as the intra-industry heterogeneity decreases, the tendency to engage in collaborative innovation among firms is relatively high. Given the high sensitivity of the intra-industry heterogeneity of the collaborative innovation, the results imply that intra-industry heterogeneity can be a key factor in inhibiting collaborative innovation.

In conclusion, the results of this analysis suggest that, as the intra-industry heterogeneity decreases, the collaborative innovation structure becomes more complicated, the cooperation behavior of firms increases, and the collaborative innovation performance in the industry becomes higher. The next section analyzes the effects of government incentives and regulatory policies on collaborative innovation patterns in industries with high intra-industry heterogeneity through an extended experiment.

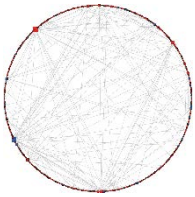
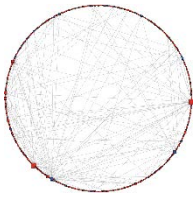
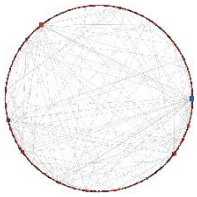
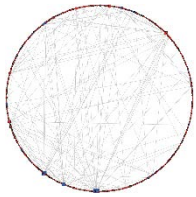
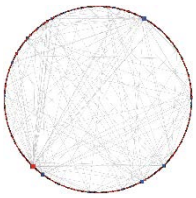
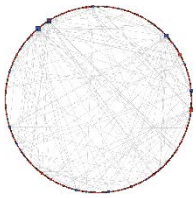
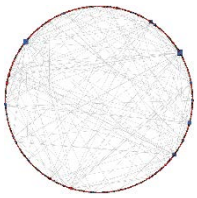
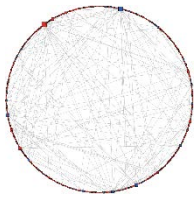
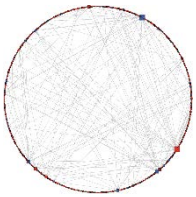
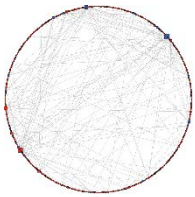
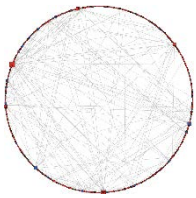
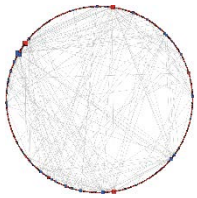
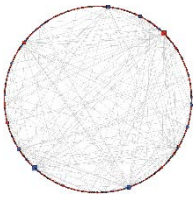
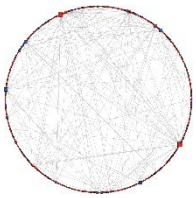
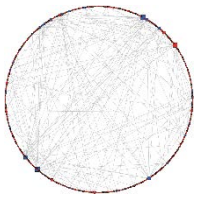
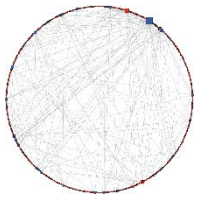
2.4.2 Extended Experiment: Policy Simulation

2.4.2.1 Network Density

This experiment investigates how the collaborative innovation pattern varies in each policy scenario when a total of 16 policy scenarios consisting of different levels of

incentives and regulatory combinations are implemented, assuming the current policy situation as the default. The first simulation considers whether the network density differs according to the level of incentives and regulations. Table 2.22 shows the topology of the collaborative innovation network formed at tick = 1,000 in a circular layout.

Table 2.22 Network Topology in a Circular Layout by Policy Scenario

		Level of Regulation			
		No Regulation	Weak Regulation	Moderate Regulation	Strong Regulation
Level of Incentives	No Incentives				
	Low Incentives				
	Medium Incentives				
	High Incentives				

The results of dividing the network by the 16 policy scenarios show that no noticeable change is observed, unlike the base experiment. This indicates that there is no significant difference in network density in most scenarios. This study examines the summary statistics on the network density for each policy scenario before the ANOVA. The summary statistics are presented in Table 2.23.

Table 2.23 Summary Statistics of Network Density by Policy Scenario

			Level of Regulation			
			No Regulation	**Weak Regulation**	**Moderate Regulation**	**Strong Regulation**
Level of Incentives	**No Incentives**	Mean (SD)	1.040e-03 (5.000e-05)	1.030e-03 (5.000e-05)	1.040e-03 (6.000e-05)	1.070e-03 (6.000e-05)
		Cohen'sd	0	-0.2000	0	0.5432
		Freq.	30	30	30	30
	Low Incentives	Mean (SD)	1.050e-03 (6.000e-05)	1.060e-03 (7.000e-05)	1.080e-03 (8.000e-05)	1.120e-03 (9.000e-05)
		Cohen'sd	0.1811	0.3288	0.5996	1.0989
		Freq.	30	30	30	30
	Medium Incentives	Mean (SD)	1.100e-03 (8.000e-05)	1.110e-03 (9.000e-05)	1.140e-03 (9.000e-05)	1.300e-03 (1.300e-04)
		Cohen'sd	0.8994	0.9615	1.3736	2.6399
		Freq.	30	30	30	30
	High Incentives	Mean (SD)	1.180e-03 (9.000e-05)	1.190e-03 (1.300e-04)	1.330e-03 (1.600e-04)	1.560e-03 (2.500e-04)
		Cohen'sd	1.9230	1.5230	2.4466	2.8844
		Freq.	30	30	30	30

The simulation is iterated 30 times for each policy scenario. The summary statistics show that the network density is the lowest in the scenario with 'no incentives and weak

regulations' and highest in the scenario with 'high incentives and strong regulations.' As the level of incentives and regulations increases, the network density tends to increase. However, the magnitude of the policy effect appears to be small when compared with the FSD simulation results.

This study examines whether there is an interaction effect as well as the main effect of incentives and regulations through a two-way ANOVA. The ANOVA results for the main and interaction effects of incentives and regulations on the network density are shown in Table 2.24.

Table 2.24 Results of the Two-way ANOVA

Source	SS	df	MS	F	Prob. > F
Model	8.933e-06	15	5.956e-07	50.37***	0.0000
Incentives	5.283e-06	3	1.761e-06	148.93***	0.0000
Regulation	2.242e-06	3	7.473e-07	63.21***	0.0000
Interaction	1.409e-06	9	1.565e-07	13.24***	0.0000
Residual	5.486e-06	464	1.182e-08		
Total	1.440e-05	479			
Observations	480				
R-Squared	0.6195				
Adj. R-Squared	0.6072				

Note: $^{*}p < 0.05$p < 0.1, $^{**}p < 0.01$, $^{***}p < 0.001$

The ANOVA results show that the main effect of incentives and regulations on the network density is statistically significant at the 99.9% significance level. The interaction effect of incentives and regulations is also statistically significant at the 99.9%

significance level. These effects are presented in Figure 2.19 below.

Figure 2.19 Effects of Policy Scenarios on the Network Density

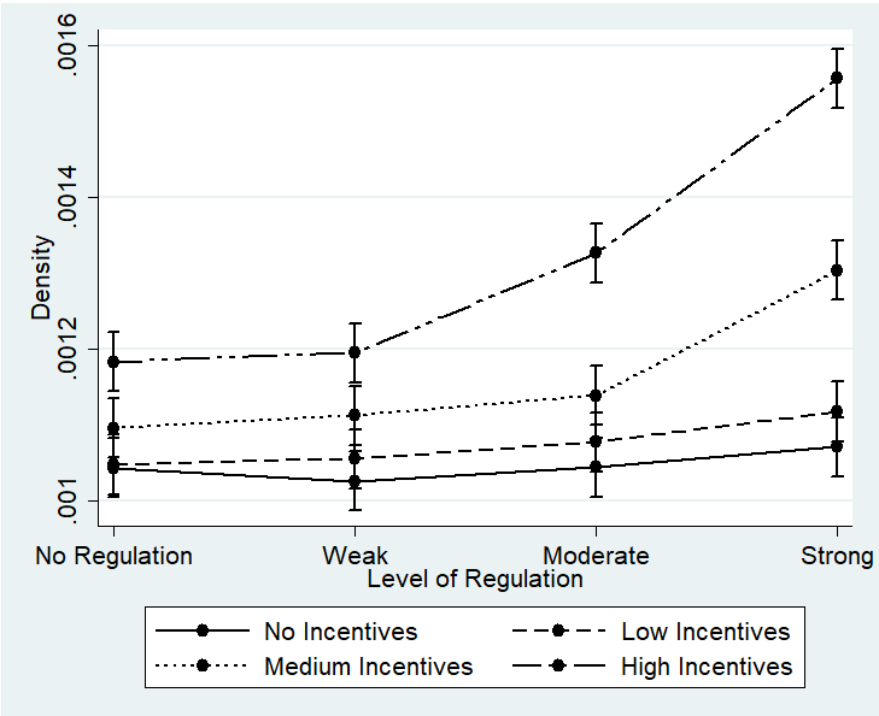
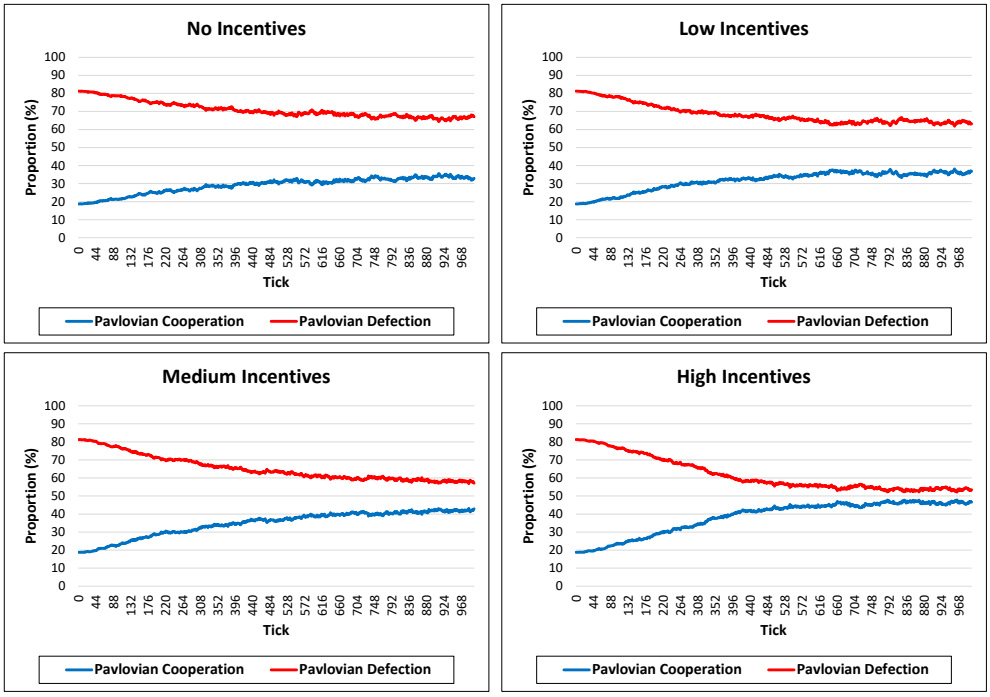


Figure 2.19 shows that the effect of incentives on the network density is higher than the effect of regulations. In particular, the network density is larger in the scenario with 'high incentives and no regulations' than in the scenario with 'no incentives and strong regulations.' The simulation results show that it is more effective to increase the level of incentives one step higher than to increase the level of regulation by two steps. In addition, the results show that there is a positive interaction effect in which the effect of regulations increases as the level of incentives increases and the effect of incentives increases as the level of regulation increases. Finally, the results indicate that the network density increases more with the incentive policy than with regulations.

2.4.2.2 Cooperative Behavior

The second simulation analyzes whether the cooperative behavior of firms differs according to the level of incentives and regulations, with an ANOVA for the proportion of Pavlovian cooperation at tick = 1,000. Assuming no additional regulations in the current situation, the changes in the proportion of Pavlovian cooperation and Pavlovian defection by each level of incentives over time up to tick = 1,000 are shown in Figure 2.20 below.

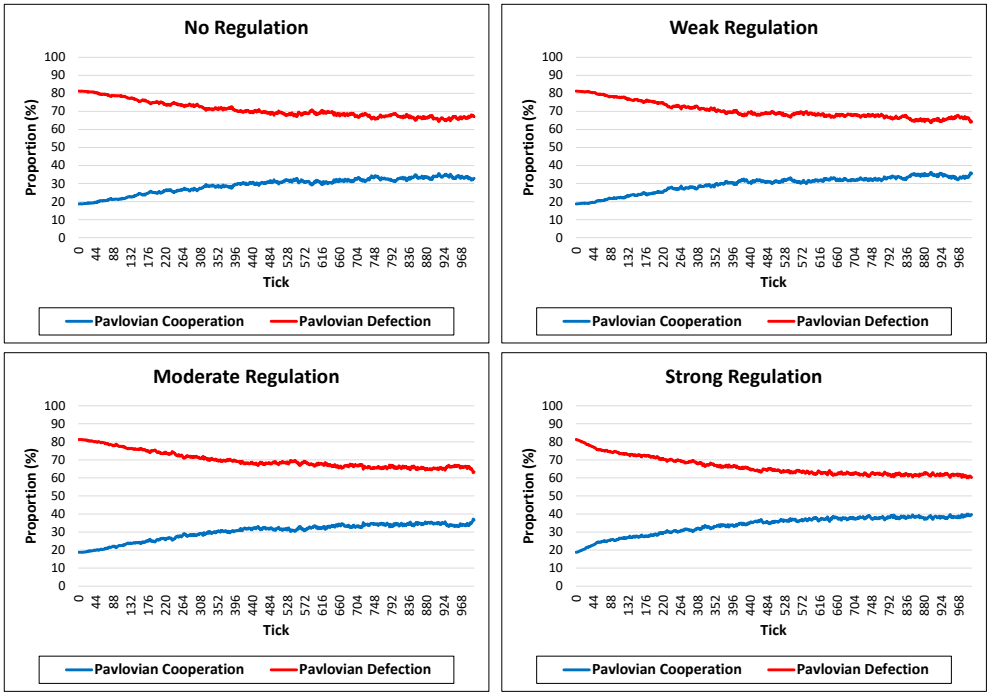
Figure 2.20 Pavlovian Cooperative Behavior without Additional Incentives (Average of 30 Iterations)



Under all the conditions, the proportion of Pavlovian cooperation increases and the proportion of Pavlovian defection decreases. In particular, as the level of incentives increases, the proportion of Pavlovian cooperation increases. In the high-incentive scenario, the proportion of Pavlovian cooperation at tick = 1,000 is the highest.

Assuming that no additional incentives exist in the current situation, the changes in the proportion of Pavlovian cooperation and Pavlovian defection by each level of regulation over time up to tick = 1,000 are shown in Figure 2.21 below.

Figure 2.21 Pavlovian Cooperative Behavior without Additional Regulations (Average of 30 Iterations)



Under all the conditions, the proportion of Pavlovian cooperation increases and the proportion of Pavlovian defection decreases. In particular, as the level of regulation

increases, the proportion of Pavlovian cooperation increases gradually. In the strong-regulation scenario, the proportion of Pavlovian cooperation at tick = 1,000 is the highest, but the proportion of Pavlovian cooperation is relatively low compared with the high-incentive scenario in Figure 2.20.

This study examines the summary statistics of the proportion of Pavlovian cooperation for each policy scenario before the ANOVA. The summary statistics are presented in Table 2.25.

Table 2.25 Summary Statistics of Pavlovian Cooperation by Policy Scenario (Proportion)

			Level of Regulation			
			No Regulation	**Weak Regulation**	**Moderate Regulation**	**Strong Regulation**
Level of Incentives	**No Incentives**	Mean (SD)	32.969 (4.756)	35.625 (4.631)	36.667 (5.393)	39.740 (3.593)
		Cohen'sd	0	0.5658	0.7273	1.6065
		Freq.	30	30	30	30
	Low Incentives	Mean (SD)	36.823 (5.054)	36.875 (4.796)	39.479 (4.143)	44.792 (4.756)
		Cohen'sd	0.7854	0.8178	1.4596	2.4859
		Freq.	30	30	30	30
	Medium Incentives	Mean (SD)	42.865 (5.755)	43.385 (5.003)	45.781 (5.583)	57.708 (5.550)
		Cohen'sd	1.8745	2.1340	2.4705	4.7867
		Freq.	30	30	30	30
	High Incentives	Mean (SD)	46.563 (5.952)	49.635 (6.713)	58.333 (6.697)	70.469 (7.367)
		Cohen'sd	2.5233	2.8649	4.3670	6.0480
		Freq.	30	30	30	30

The simulation is iterated 30 times for each policy scenario. The summary statistics show that the proportion of cooperative behavior of Pavlovian agents is the lowest in the scenario with 'no incentives and no regulations' and highest in the scenario with 'high incentives and strong regulations.' As the level of incentives and regulations increases, cooperative behavior tends to increase.

This study examines whether there is an interaction effect as well as the main effect of incentives and regulations through a two-way ANOVA. The ANOVA results for the main effects and interaction effects of incentives and regulations on the proportion of Pavlovian cooperation are shown in Table 2.26 below.

Table 2.26 Results of the Two-way ANOVA

Source	SS	df	MS	F	Prob. > F
Model	45374.268	15	3024.951	102.08***	0.0000
Incentives	28716.919	3	9572.306	323.03***	0.0000
Regulation	12825.724	3	4275.241	144.27***	0.0000
Interaction	3831.624	9	425.736	14.37***	0.0000
Residual	13749.674	464	29.632		
Total	59123.942	479	123.432		
Observations	480				
R-Squared	0.7674				
Adj. R-Squared	0.7599				

Note: $^{*}p < 0.05$p < 0.1, $^{**}p < 0.01$, $^{***}p < 0.001$

The ANOVA results show that the main effect of incentives and regulations on

cooperative behavior is statistically significant at the 99.9% significance level. The interaction effect of incentives and regulations is also statistically significant at the 99.9% significance level. These effects are presented in Figure 2.22.

Figure 2.22 Effects of Policy Scenarios on Pavlovian Cooperation

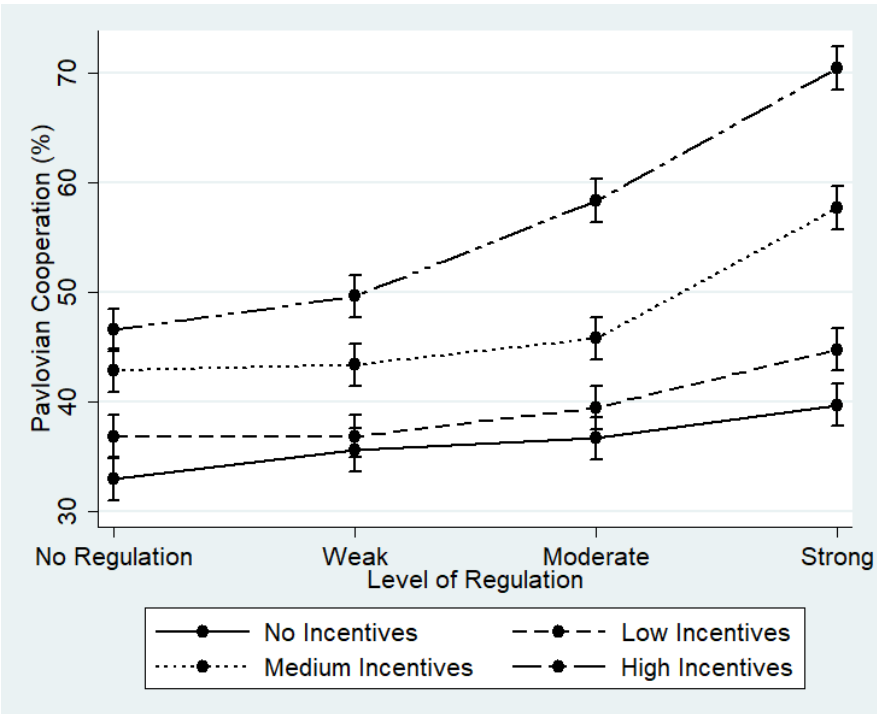


Figure 2.22 shows that the effect of incentives on cooperative behavior is greater than the effect of regulations. In particular, the proportion of Pavlovian cooperation appears to be larger in the scenario with 'high incentives and no regulations' than in the scenario with 'no incentives and strong regulations'. The simulation results show that it is more effective to raise the level of incentives one step more than to raise the level of regulation by two steps.

In addition, there is a positive interaction effect in which the effect of regulations

increases as the level of incentives increases and the effect of incentives increases as the level of regulation increases. However, the positive interaction effect occurs under medium or high levels of incentives or regulations. This implies that there is synergy between policies when implementing incentives or regulations that are at least at the medium level. Since incentives and regulations above the medium level mean R > T, the synergy of the policy mix is visible when the policy intervention is strong enough to reverse the T > R relationship.

In conclusion, the simulation results suggest that incentives are more effective policy instruments to promote firms' cooperative behavior than regulations. Furthermore, to achieve synergies between incentives and regulations, they should not be implemented at a weak level but at a level at which the payoff from mutual cooperation is higher than the payoff obtained by adopting opportunistic behavior.

2.4.2.3 Collaborative Innovation

The third simulation analyzes whether the collaborative innovation between firms differs according to the level of incentives and regulations using an ANOVA for the sum of the frequencies of collaborative innovation performed by all firms until tick = 1,000. This study examines the summary statistics of collaborative innovation for each FSD before the ANOVA. The summary statistics are presented in Table 2.27.

Table 2.27 Summary Statistics of Collaborative Innovation by Policy Scenario

	Level of Regulation			
	No	Weak	Moderate	Strong

			Regulation	Regulation	Regulation	Regulation
Level of Incentives	No Incentives	Mean (SD)	180.400 (15.071)	173.133 (18.154)	177.333 (21.873)	192.267 (24.233)
		Cohen'sd	0	-0.4356	-0.1633	0.5881
		Freq.	30	30	30	30
	Low Incentives	Mean (SD)	178.867 (17.457)	182.533 (23.500)	189.000 (26.862)	201.867 (33.692)
		Cohen'sd	-0.0940	0.1081	0.3949	0.8225
		Freq.	30	30	30	30
	Medium Incentives	Mean (SD)	193.133 (28.656)	201.000 (29.584)	211.533 (30.916)	272.600 (56.914)
		Cohen'sd	0.5562	0.8775	1.2801	2.2147
		Freq.	30	30	30	30
	High Incentives	Mean (SD)	226.533 (29.337)	229.867 (40.836)	277.933 (63.017)	372.467 (96.198)
		Cohen'sd	1.9781	1.6072	2.1288	2.7896
		Freq.	30	30	30	30

The simulation is iterated 30 times for each policy scenario. The summary statistics show that collaborative innovation between firms is the lowest in the scenario with 'no incentives and weak regulations' and the highest in the scenario with 'high incentives and strong regulations.' Except for the scenario with 'no incentives,' collaborative innovation tends to increase as the level of incentives and regulations increases. However, the magnitude of the policy effect appears to be small when compared with the FSD simulation results.

This study examines whether there is an interaction effect as well as the main effect of incentives and regulations through a two-way ANOVA. The ANOVA results for the main effects and interaction effects of incentives and regulations on collaborative

innovation are shown in Table 2.28 below.

Table 2.28 Results of the Two-way ANOVA

Source	SS	df	MS	F	Prob. > F
Model	1235456.60	15	82363.773	50.72***	0.0000
Incentives	686086.09	3	228695.360	140.84***	0.0000
Regulation	329960.36	3	109986.790	67.73***	0.0000
Interaction	219410.14	9	24378.905	15.01***	0.0000
Residual	753446.00	464	1623.806		
Total	1988902.60	479	4152.1975		
Observations	480				
R-Squared	0.6212				
Adj. R-Squared	0.6089				

Note: $^{*}p < 0.05$p < 0.1, $^{**}p < 0.01$, $^{***}p < 0.001$

The ANOVA results show that the main effect of incentives and regulations on collaborative innovation is statistically significant at the 99.9% significance level. The interaction effect of incentives and regulations is also statistically significant at the 99.9% significance level. These effects are presented in Figure 2.23.

Figure 2.23 Effects of Policy Scenarios on Collaborative Innovation

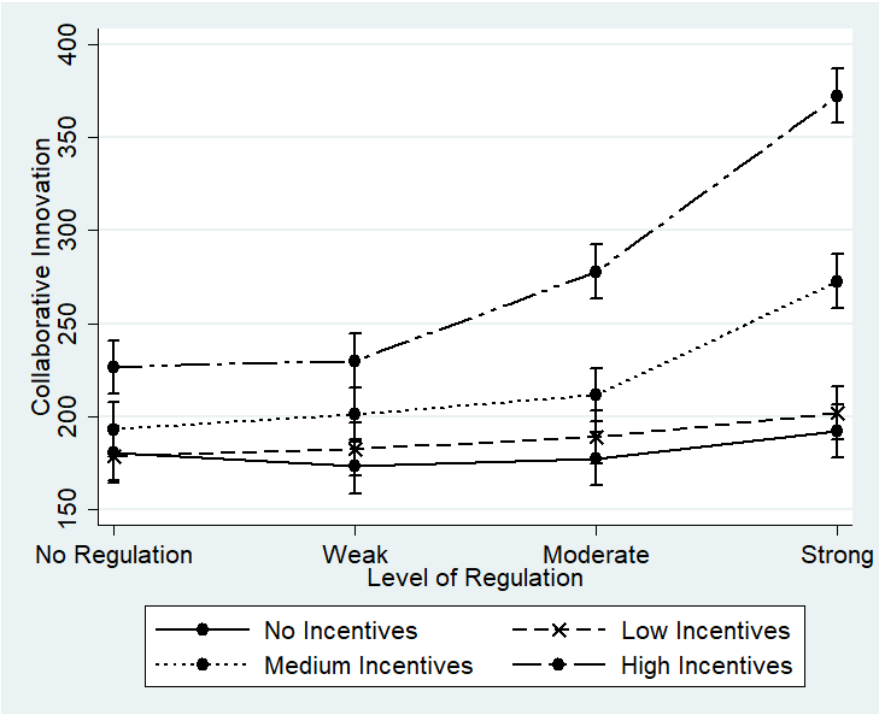


Figure 2.23 shows that the effect of incentives on collaborative innovation is higher than the effect of regulations.[13] In particular, more collaborative innovation takes place in scenarios with 'high incentives and no regulations' than in scenarios with 'no incentives and strong regulations.' The simulation results show that it is more effective to increase the level of incentives one step more than to increase the level of regulation by two steps.

The simulation results show that when the same level of incentives is given, the effect of the incentives is amplified as the level of regulation increases. Except for no incentives and no regulation scenarios, the higher the level of regulation, the higher the

[13] For the robustness check of the analysis results, see Appendix 2-A.

increase in collaborative innovation. This tendency is particularly evident in the high incentives curve of Figure 2.23, which shows that the collaborative innovation in the high regulation scenario increased by about 64 percent in the no regulation scenario.

Simulation results also imply that the policy effect of regulation is amplified as the level of incentive increases. This tendency is particularly evident in the high regulation curve, which shows that collaborative innovation in the strong incentives scenario increased by about 93 percent in the no incentives scenario.

To compare the effects of incentives amplifying the effects of regulation and the effects of regulation amplifying the effects of incentives, we graphically show the rate of increase of collaborative innovation per scenario. Figure 2.24 shows the growth rate of collaborative innovation per policy scenario according to the level of other policy instruments.

Figure 2.24 The Increase Rate of Collaborative Innovation by Each Policy Scenario according to the Level of Other Policy Instruments

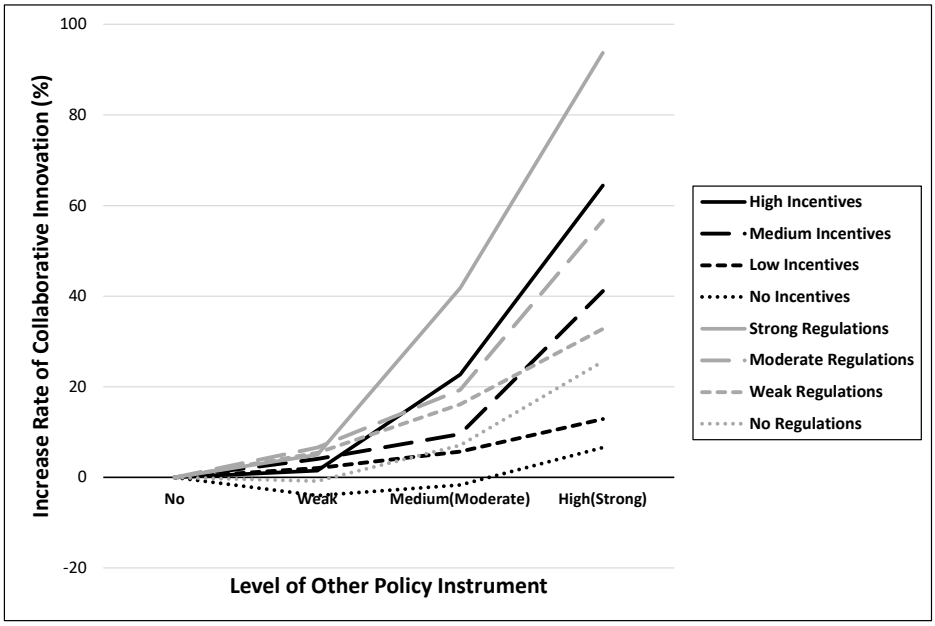


Figure 2.24 shows that the incentive is more effective in amplifying the regulation than the regulation is in amplifying the incentive. When implementing the same level of incentives, the effectiveness of incentives increased by up to 64 percent, depending on the level of regulation. However, when implementing the same level of regulation, the effect of regulation increased by up to 93 percent, depending on the level of incentives. This increase in collaborative innovation is more exponential as the level of execution of other policy instruments increases. This indicates that the higher the level of incentives and regulations in the policy mix, the higher the interaction effect between them.

Specifically, the collaborative innovation rate of the high regulation scenario compared to the no regulation scenario is 7 percent for the no incentives curve, 13

percent for the low incentives curve, 40 percent for the medium incentives curve, and 64 percent for the high incentives curve. The rate of collaborative innovation in the high incentives scenario is 25 percent for the no regulation scenario, 32 percent for the weak regulation scenario, 57 percent for the moderate regulation scenario, and 93 percent for the high regulation scenario.

The incentive implies that the main effect and the effect of amplifying the effects of other policy instruments are also greater than the regulation, which is the most important policy instrument. However, regulation is a policy instrument that is less effective than incentives when considering net effects alone, though it can play an important role in the policy mix in that it maximizes the effect of incentives. Therefore, it can be inferred that regulation is also an important factor that maximizes the effect of incentives.

However, in certain circumstances, regulation creates adverse effects. Among the scenarios with 'no incentives,' when weak regulations are implemented, the degree of collaborative innovation is rather reduced, indicating that regulations in the absence of incentives can lead to adverse effects that interfere with collaborative innovation. This indicates that the adverse effect of the regulatory regime on proprietary firms, assumed by Laffont and Tirole (1993), is also reproduced in this simulation. This result strengthens the theoretical argument that there is a possibility of side effects from regulations for industries with high market concentration. Therefore, this study suggests that regulations should be implemented together with incentives in the form of a policy mix rather than regulations alone.

In addition, there is a positive interaction effect in which the effect of regulations increases as the level of incentives increases and the effect of incentives increases as the level of regulations increases. However, the positive interaction effect does not occur in

the no-incentives scenario. This suggests that synergy between policies occurs when at least the 'low'-level incentives defined in this study are implemented. The 'low' level of incentives defined in this study means that R = T. Therefore, the interaction effect of the policy mix becomes visible when the policy is implemented at a level at which the payoff of collaborative innovation and opportunistic behavior becomes virtually indiscriminate. However, since there is not much difference between the no-incentives scenario and the low-incentives scenario, it can be concluded that the government should implement a medium-level incentive policy of at least R > T to promote collaborative innovation. Specifically, the amount of subsidy paid to firms participating in collaborative innovation can be different based on the potential value of the technology. This is because the higher the value and the better the technology, the higher the unfair profit to be obtained from technology theft, and the higher the incentive for opportunistic behavior. Therefore, to pay subsidies exceeding the incentive for opportunistic behavior, it is necessary to carry out feasibility studies on the collaborative tasks in advance and to allocate more subsidies to those technologies with more business value based on the evaluation results. Therefore, it is more effective to pay bigger subsidies to those projects that are high in business efficiency and high in technology theft incentives rather than current the incentive schemes that pay subsidies of 630 million KRW for up to two years per project.

However, this method has some limitations. Firstly, there is a high possibility that the feasibility evaluation criteria are ambiguous, which may lead to equity issues. Secondly, allocating a lot of the budget to some high-tech technologies will reduce the budget that can be allocated to the remaining technologies, which may be against the policy of encouraging more firms to participate in collaborative innovation. Thirdly, incentives are limited by budget and have financial problems. Thus, although incentives

such as R&D subsidies are more effective than regulations, the government actually tends to prefer regulations. Also, governments prefer regulations over subsidies because of the 'hidden tax' function (Posner, 1971).

Therefore, the government can implement the medium-level regulatory policy at the same time as the incentive to make R higher than T. Specifically, the amount of compensation for the unfair advantage obtained in technology theft can be estimated based on the benefit obtained in the collaborative innovation. The current damages system shall settle damages based on actual damage. Specifically, the Patent Act requires compensation for damage, and the Fair Subcontract Transactions Act provides punitive damages that set the amount of compensation up to three times the amount of damage. However, most SMEs abandon their lawsuits because the criteria for calculating losses are not clear and damages are insufficient. In particular, the median value of Korean patent infringement damages is 60 million KRW, which is 1/80th of that in the US. Therefore, the current regulation to set the amount of compensation based on the actual damage is limited, even though the punitive damages system is specified, and the amount of damages actually paid by SMEs is meager. In particular, considering that the subsidy amount is 600 million KRW, it is shallow that the amount of damages is one tenth of the government investment cost. Therefore, based on the value and business capability of the technology, the government can estimate the benefits of collaborative innovation and the benefits gained through an internal innovation and use more compensation than the difference between these two benefits. Since the difference between the two is substantially the difference between the profit distribution and the management cost, the profit distribution and management cost can be relatively clear, even though the standard of the profit is ambiguous. Therefore, the government can adopt the method of paying the difference of net profit in the two

situations together with the actual loss.

In summary, the simulation results suggest that incentives are a more effective policy instrument to promote inter-firm collaborative innovation than regulations. However, regulation plays an important role in the policy mix in that it maximizes the effect of incentives. To achieve the interaction effect between incentives and regulations, incentives should be implemented at least to make the payoff from mutual cooperation equal to the payoff from engaging in opportunistic behavior. However, to maximize the effectiveness of the policy, incentives of at least the medium level should be accompanied by the effect of regulations. If the minimum incentives are not accompanied, the effect of regulations can be very small, and regulations can inhibit collaborative innovation. In addition, low incentives in the absence of regulations are ineffective. In conclusion, this study suggests that medium-level or high-level incentives accompanied by regulations can be a marginal solution for promoting collaborative innovation. However, as subsidies are difficult to expand due to budget constraints, governments can use subsidies to expand compensation for opportunistic behavior such as technology theft. In other words, a more realistic alternative would be to include not only the actual loss, but also the difference in the net profit between internal innovation and collaborative innovation, rather than the existing regulations that set the compensation amount based on the actual loss only.

2.5 Conclusions

This study discusses the empirical limitations of the Schumpeterian hypothesis on the relationship between firm size and innovation and suggests focusing on the FSD at the industrial level, which has not been widely discussed as an independent variable. This study suggests a theoretical proposition on the relationship between intra-industry heterogeneity and collaborative innovation from the previous literature on the market structure, inter-firm relationships, and innovation. Then, it analyzes and compares the effects of government incentives and regulations on collaborative innovation in industries with high intra-industry heterogeneity and investigates whether there is a positive interaction effect in the policy mix of incentives and regulation.

To this end, this study analyzes the changes in the collaborative innovation structure, firms' cooperation behavior, and collaborative innovation performance according to the SCP framework. Specifically, it analyzes the density of the collaborative innovation network, the cooperative behavior of Pavlovian firms, and the changes in collaborative innovation performed in the industry. This study collects data on Korean ICT firms and develops an agent-based model. This agent-based model, based on the spatial NIPD game, reproduces the collaborative innovation between 524 firms in the ICT industry in GIS-based virtual space.

The results can be summarized as follows. First, a decrease in the intra-industry heterogeneity appears to have a positive effect on the structure, conduct, and performance of collaborative innovation in the industry. Specifically, as the intra-industry heterogeneity decreases, the cooperative behavior of firms increases and cooperation among various firms is performed, increasing the frequency of collaborative innovation and the network density. This implies that an increase in the intra-industry heterogeneity can reduce firms' cooperative behavior and collaborative

innovation and further impede the open innovation ecosystem in the industry.

Second, depending on the level of incentives and regulations, the structure, conduct, and performance of collaborative innovation in the industry change differently. Incentives are more effective than the same level of regulations, and regulations at a certain level can have adverse effects.

Third, there is a positive interaction effect between incentives and regulations in the policy mix, and this interaction effect depends on the level of incentives and regulations. This indicates that incentives are more effective than regulations and that an optimized policy mix that enforces incentives and regulations at an appropriate level can lead to firms' collaborative behavior and improve the collaborative innovation performance in the industry. However, the regulation also plays an important role in policy mix in that it maximizes the effect of incentives.

The results of this study can contribute to the theoretical development of innovation research. First, this study confirms that intra-industry heterogeneity, which has not previously been considered as an independent variable, is an important variable for collaborative innovation in industries. Intra-industry heterogeneity appears to have a relatively large effect on the collaborative innovation structure, conduct, and performance in an industry rather than the government's payoff adjustment approach through incentives or regulations. The FSD has previously been suggested by some researchers to be an important independent variable that affects performance within an industry (Malerba, 2005) but has failed to advance further from the theoretical discussion due to some limitations, such as the limitations of empirical studies by analytical units. This study attempts to complement the empirical limitations of the Schumpeterian hypothesis by using the agent-based model to mitigate the methodological constraints and show its potential as an independent variable in the

study of intra-industry heterogeneity innovation.

Second, this study presents some propositions about the relationship between intra-industry heterogeneity and collaborative innovation. Specifically, it argues that, as the intra-industry heterogeneity decreases, the collaborative innovation structure becomes more complex, firms' cooperative behavior increases, and the collaborative innovation performance in the industry is enhanced. Previous studies have attempted to present stylized facts about the relationship between the market structure and the firm characteristics and innovation. Typically, the stylized facts presented by Schumpeter (1942) and Gibrat (1931) contributed significantly to the growth of knowledge in the innovation field by producing numerous follow-up studies, suggesting empirical testing tasks for subsequent researchers. Although some of these hypotheses have been dismissed or remain controversial, their hypotheses have contributed to the development of scholarship by leading the study as the central axis of innovation research for decades. This study finds answers to the empirical limitations of the Schumpeterian hypothesis proposed by Schumpeter (1942) from the industrial characteristics presented by Gibrat (1931). Therefore, it is assumed that industry characteristics, such as the FSD as well as firm characteristics, also affect the innovation performance in an industry. The results of this study suggest not only that these assumptions fit but also that intra-industry heterogeneity may be a major factor affecting the collaborative innovation in an industry. In particular, this study has the significance of presenting more detailed theoretical propositions by analyzing not only collaborative innovation achievements but also structural and behavioral changes through the SCP framework, which is a classical model of industrial organization theory.

Third, this study sheds light on the effects of incentives and regulations on the collaborative innovation in an industry and shows the positive interaction effect

between incentives and regulations. In particular, this study reaffirms the hypothesis that market-based instrument incentives are more effective than the regulation of the command-and-control scheme (Popp, 2006; Costantini et al., 2016). Furthermore, the adverse effects associated with the regulation of monopolistic firms, assumed by Laffont and Tirole (1993), are reproduced in the simulation results, which strengthen the existing theoretical discussion.

The results of this study can contribute to the government policy to create an open innovation ecosystem in an industry. First, the reason why collaborative innovation is not actively carried out in an industry with high intra-industry heterogeneity can be attributed not only to the payoffs as pointed out in previous studies (Chiang, 1995; Majeski, 1986) but also to structural problems. The results of this study show that the collaborative innovation structure, conduct, and performance in the industry are more sensitive to intra-industry heterogeneity than to government policy. Therefore, there is a limit to governments' approach to creating an open innovation ecosystem by adjusting the payoffs of firms' behavior. This limitation is due to the high level of intra-industry heterogeneity. The results of this study show that the effect of intra-industry heterogeneity on collaborative innovation is relatively large. Therefore, to create an open innovation ecosystem in an industry, governments need to recognize that intra-industry heterogeneity is an important factor as well as the adjustment of payoffs through incentives and regulations, and they should aim to mitigate the intra-industry heterogeneity.

Various claims have been made about the solution to the polarization between large firms and SMEs. These claims can be summarized in three categories. Firstly, governments can mitigate polarization by restricting the unfair practices of large firms. Specifically, the government can eliminate the polarization between large firms and

SMEs by strengthening the protection of SME business areas and formalizing subcontracting transactions (NARS, 2013). For example, governments can strengthen the protection of software intellectual property rights of SMEs in the ICT industry to prevent unfair practices such as large firms' software imitation and technology theft. Secondly, the government can mitigate polarization through direct support for SMEs. It is hard for SMEs to participate in the commodity market, which is dominated by large firms, because they have low marketing capabilities and difficulty in paying advertising costs (Kim, 2012). Therefore, the government can expand SME-eligible industries and items in the field of ICT such as software through public procurement. Thirdly, it is argued that not only the regulation of large firms' unfair practices but also the improvement of the structure of large firms' labor force and the opportunities for SMEs entering the market through public procurement should be expanded. Kim (2012) points out that the widening gap between large firms and SMEs is not because of the high value-added capacity of large firms but because large firms have reduced their human resources. Therefore, to resolve polarization, it is necessary to expand the protection of irregular workers while at the same time improving the working environment of SME workers.

Second, the results suggest that incentives are more effective than regulations. Governments prefer regulations because the financial burden is less than that of incentives (Posner, 1971). However, the results of this study show that regulations alone are insufficient and that regulations at a certain level cause adverse effects. This represents the risk of enforcing regulations alone. Therefore, regulations should be implemented with a proper level of incentives in the form of a policy mix to prevent adverse effects and to expect policy effects. This study can contribute to the design of the optimal policy mix by presenting the appropriate level of incentives and regulations

considering the interaction effect in the policy mix. In other words, the government can pay subsidies that are higher than T. The current subsidy system supports 630 million KRW for a maximum of two years per project. However, technologies with high potential and business value are more likely to attract opportunistic behaviors such as technology theft than other technologies. Therefore, the current incentive system that pays subsidies equally for all technologies has the limitation that it cannot eliminate incentives for opportunistic behavior, such as technology theft of technologies with high business value. Therefore, to eliminate the incentive for opportunistic behavior for high-tech technology, it is necessary to consider a feasibility evaluation and to pay the subsidy differently depending on the result. To do this, the government can conduct a feasibility evaluation in advance to evaluate the technology value and business level, and pay the subsidy differently based on the evaluation results. This approach has the advantage of being able to reduce incentives for opportunistic behavior more effectively than current incentive schemes that provide the same subsidy regardless of business performance.

However, this approach has some limitations. Firstly, the evaluation criteria for business feasibility are ambiguous, which may raise the issue of equity. Secondly, assigning large subsidies to highly functional technologies under a fixed budget reduces the subsidies allocated to some remaining technologies. As a result, the budget that can be allocated to the rest of the technology is reduced, which is against the policy of encouraging more firms to participate in collaborative innovation. Thirdly, maintaining the number of participating firms and increasing the amount of subsidy adds to the budget burden. This approach has limitations regarding implementation difficulties under budget constraints. Therefore, the government can implement the medium-level regulatory policy at the same time as the incentive to make R higher than T.

The Patent Act, a current regulation for opportunistic behavior such as technology theft, measures the amount of compensation based on actual damage, and is the punitive damages system provided by the Fair Subcontract Transactions Act. However, the criteria for calculating losses are not clear, the SMEs' legal capacity is not sufficient, and the various costs involved in litigation are obstacles to compensation. Because of these limitations, the median value of the patent infringement damages in Korea is 60 million KRW (MSS, 2018), which is 1/80th of that in the US. This amount is very small—about one tenth the amount of the government's collaborative innovation incentives. Therefore, when calculating the amount of compensation for unfair profit, the government can make an approach based on expected profit as well as actual loss. In other words, the government can compare the expected profit from the collaborative innovation with the expected profit from the single patent through technology theft and set the compensation amount equal to or more than the difference between them. In conclusion, the government can subsidize collaborative innovation while at the same time settling the compensation for technology theft by adding the difference between the net profit from collaborative innovation and internal innovation to the actual loss. Also, the government can streamline legislation to prevent conflicts of law, stating the amount of compensation, and can simplify administrative and litigation procedures for reimbursement, thereby reducing the time and cost of reimbursement.

This study also has limitations. It utilizes empirical data on firm characteristics and collaborative innovation to create and analyze virtual models that are close to reality. However, as with other simulation studies, the results of this study are hypothetical for social phenomena and need to be proven based on empirical data. Therefore, further studies should be conducted to verify the propositions presented in this study.

Bibliography

Acs, Z., & Audretsch, D. B. (1988). Innovation in Large and Small Firms: An Empirical Analysis. *American Economic Review*, 78(4): 678-690.

Acs, Z., Morck, R., Shaver, J. M., & Yeung, B. (1997). The Internationalization of Small and Medium-Sized Enterprises: A Policy Perspective. *Small Business Economics*, 9: 7–20.

Arend, R. J., & Seale, D. A. (2005). Modeling Alliance Activity: An Iterated Prisoners' Dilemma with Exit Option. *Strategic Management Journal*, 26(11): 1057–1074.

Arend, R. J. (2009). Reputation for Cooperation: Contingent Benefits in Alliance Activity. *Strategic Management Journal*, 30(4): 371-385.

Arrighetti, A., Landini, F., & Lasagni, A. (2014). Intangible Assets and Firm Heterogeneity: Evidence from Italy. *Research Policy*, 43(1): 202-213.

Arsenyan, J., Büyüközkan, G., & Feyzioğlu, O. (2015). Modeling Collaborative Formation with a Game Theory Approach. *Expert Systems with Applications*, 42 (4): 2073-2085.

Axelrod, R., & Tesfatsion, L. (2006). *A Guide for Newcomers to Agent-Based Modeling in the Social Sciences.* in L. Tesfatsion & K. L. Judd (eds.), Handbook of Computational Economics, Vol. 2: Agent-Based Computational Economics. Amsterdam: North-Holland.

Axelrod, R. (1984). *Evolution of Cooperation*. New York: Basic Books.

Axelrod, R. (1997). *The Complexity of Cooperation: Agent-Based Models of Competition and Collaboration. Princeton*, NJ: Princeton University Press.

Axtell, R. L. (2001). Zipf Distribution of US Firm Sizes. *Science*, 293(5536): 1818-

1820.

Baniak, A., & Dubina, I. (2012). Innovation Analysis and Game Theory: A Review. *Innovation: Management, Policy & Practice*. 14(2): 178-191.

Bound, J., Cummins, C., Griliches, Z., Hall, B. H., & Jaffe, A. B. (1984). *Who Does R&D and Who Patents?* in R&D, Patents and Productivity, edited by Zvi Griliches. Chicago: Univeristy of Chicago Press.

Broeke, G. T., Voorn, G. V., & Ligtenberg, A. (2009). Which Sensitivity Analysis Method Should I Use for My Agent-Based Model?. *Journal of Artificial Societies and Social Simulation*, 19(1): 5.

Broekel, T. (2013). Do Cooperative Research and Development (R&D) Subsidies Stimulate Regional Innovation Efficiency? Evidence from Germany. *Regional Studies*, 49(7): 1087-1110.

Broekel, T., Brachert, M., Duschl, M., & Brenner, T. (2015). Joint R&D Subsidies, Related Variety, and Regional Innovation. *International Regional Science Review*, 40(3): 297-326.

Brenner, T., & Murmann, J. P. (2003). *The Use of Simulations in Developing Robust Knowledge about Causal Processes: Methodological Considerations and an Application to Industrial Evolution*. Papers on Economics and Evolution. Jena: Max Planck Institute.

Brenner, T. (2004). *Agent Learning Representation - Advice in Modelling Economic Learning, Papers on Economics and Evolution*. Jena: Max Planck Institute.

Bruhn, M., & McKenzie, D. J. (2017). *Can Grants to Consortia Spur Innovation and Science-Industry Collaboration? Regression-Discontinuity Evidence from Poland*. St. Louis: Federal Reserve Bank of St Louis.

Campbell, H. E., Kim, Y., & Eckerd, A. (2015). *Rethinking Environmental Justice in*

Sustainable Cities: Insights from Agent-Based Modeling. New York: Routledge.

Cantner, U., & Hanusch, H. (2001). *Heterogeneity and Evolutionary Change: Empirical Conception, Findings and Unresolved Issues*. In Foster J and Metcalfe J S (eds.), Frontiers of Evolutionary Economics. Competition, Self-Organization and Innovation Policy, Chentelham, UK, Northampton, Massachusetts, USA: Edward Elgar.

Chiang, J-T. (1995). Application of Game Theory in Government Strategies for Industrial Collaborative Research and Development. *Technology in Society*, 17(2): 197-214.

Choi, T., & Robertson, P. J. (2014). Deliberation and Decision in Collaborative Governance: A Simulation of Approaches to Mitigate Power Imbalance. *Journal of Public Administration Research Theory*, 24 (2): 495-518.

Choi, S. J. (2015). A Study for the Effective Protection of the Intellectual Properties of the Small and Medium Sized Company in terms of the Damage Action. *The Journal of Intellectual Property*, 10 (2): 69-98.

Cohen, M. D., March J.G., & Olsen, J. P. (1972), A Garbage Can Model of Organizational Choice. *Administrative Science Quarterly*, 17: 1-25.

Cohen, W., & Klepper, S. (1996). Firm Size and the Nature of Innovation within Industries: The Case of Process and Product R&D. *The Review of Economics and Statistics*, 78(2): 232-243.

Costantini, V., Crespi, F., & Palma, A. (2015). *Characterizing the Policy Mix and Its Effect on Eco-Innovation in Energy-Efficient Technologies.* SEEDS Working Paper.

David, N. (2009). *Validation and Verification in Social Simulation: Patterns and Clarification of Terminology.* In: Squazzoni, F. (eds.) Epistemological Aspects

of Computer Simulation in the Social Sciences, Second International Workshop, EPOS 2006, Brescia, 5–6 Oct 2006, Revised Selected and Invited Papers (Lecture Notes in Computer Science), vol. 5466. Berlin: Springer.

D'Este, P. (2005). How Do Firms' Knowledge Bases Affect Intra-industry Heterogeneity? An Analysis of the Spanish Pharmaceutical Industry. *Research Policy*, 34(2005): 33-45.

Dosi, G., Lechevalier, S., & Secchi, A. (2010). Introduction: Interfirm Heterogeneity--Nature, Sources and Consequences for Industrial Dynamics. *Industrial and Corporate Change*, 19(6): 1867–1890.

Edquist, C. (2001). *The Systems of Innovation Approach and Innovation Policy: An Account of the State of the Art*. Paper Presented at DRUID Conference, Aalborg, June 12-15.

Evans, D. S. (1987). The Relationship between Firm Growth, Size, and Age: Estimates for 100 Manufacturing Industries. *The Journal of Industrial Economics*, 35(4): 567-581.

Fagiolo, G., & Dosi, G. (2003). Exploitation, Exploration and Innovation in a Model of Endogenous Growth with Locally Interacting Agents. *Structural Change and Economic Dynamics*, 14(3): 237-273.

Fagiolo, G., Dosi, G., & Gabriele, R. (2004). Matching, Bargaining, and Wage Setting in an Evolutionary Model of Labor Market and Output Dynamics. *Advances in Complex Systems*, 7(2): 157-186.

Flanagan, K., Uyarra, E., & Laranja, M. (2011). Reconceptualising the 'Policy Mix' for Innovation. *Research Policy*, 40(5): 702-713.

Frankel, J., & Rose, A. (2002). An Estimate of the Effect of Common Currencies on Trade and Income. *Quarterly Journal of Economics*, 117(2): 409–466.

Freeman, C. (1979). Centrality in Social Networks Conceptual Clarification. *Social Networks*, 1(2): 215-239.

Freeman, C. (1987). *Technology Policy and Economic Performance : Lessons from Japan*. London: Frances Pinter.

Furrer, O., & Thomas, H. (2000). The Rivalry Matrix: Understanding Rivalry and Competitive Dynamics. *European Management Journal*, 18(6): 619-637.

Galbraith, J. K. (1952). *American Capitalism, The Concept of Countervailing Power.* Boston: Houghton Mifflin Company.

Gibrat, R. (1931). *Les Inegalites Economiques, Applications: Aux Inegalites des Richesses, a la Concentration des Entreprises, aux Populations des Ville, aux Statistiques des Familles, etc., d'une Loi Nouvelle, la Loi de l'Effet Proportionnel*. Paris: Librarie du Recueil Sirey

Gilbert, N., & Troitzsch, K. (2005). *Simulation for the Social Scientist*. Oxford: Oxford University Press.

Gulati, R., Khanna, T., & Nohria, N. (1994). Unilateral Commitments and the Importance of Process in Alliances. *Sloan Management Review*, 35(3): 61–69.

Guerzoni, M., Raiteri, E. (2015). Demand-side vs. Supply-side Technology Policies: Hidden Treatment and New Empirical Evidence on the Policy Mix. *Research Policy*, 44 (3): 726-747.

Gunday, G., Ulusoy, G., Kilic, K., & Alpkan, L. (2011). Effects of Innovation Types on Firm Performance. *International Journal of Production Economics*, 133(2): 662-676.

Hamill, L., & Gilbert, N. (2015). *Agent-Based Modelling in Economics*. New York: Wiley.

Heshimati, A., & Lenz-Cesar, F. (2015). Policy Simulation of Firms' Cooperation in

Innovation. *Research Evaluation*, 24 (2015): 293-311.

Hoffman, K. Parejo, M. Bessant, J., & Perren, L. (1998). Small firms, R&D, Technology and Innovation in the UK: A Literature Review. *Technovation*, 18(1): 39-55.

Huff, D. L. (1964). Defining and Estimating a Trading Area. *Journal of Marketing*, 28(3): 34-38.

IEA. (2011). *Interactions of Policies for Renewable Energy and Climate*. Paris: International Energy Agency.

Johnston, E. W., Hicks, D., Nan, N., & Auer, J. C. (2011). Managing the Inclusion Process in Collaborative Governance. *Journal of Public Administration Research and Theory*, 21(4): 699-721.

Jung, J. H., & Hong, J. P. (2015). A Study on the Network Structure of the Supplier-Customer Relations between Flagship and Small Companies. *The Korean Small Business Review*, 37(4): 77-103.

Kim, C-W., & Lee, K. (2003). Innovation, Technological Regimes and Organizational Selection in Industry Evolution: a 'History Friendly Model' of the DRAM Industry, *Industrial and Corporate Change*, 12(6): 1195–1221.

Kim, J. H. (2012). *Interpretation on Polarization between Large Firms and SMEs*. Seoul: KDI Report.

Kim, S. W., & Yang, H. C. (2017). *Cooperative R&D performance and network effect of SMEs*. Sejong: STEPI Report.

Laffont, J-J., & Tirole, J. (1993). *A Theory of Incentives in Procurement and Regulation*. Cambridge MA: MIT Press.

LaRiviere, J. (2014). *Government Subsidies and Incentives for R&D Collaboration*. Working Paper, Retrieved from http://web.utk.edu/~jlarivi1

Lee, G., & Xia, W. (2006). Organizational Size and IT Innovation Adoption: A Meta-Analysis. *Information & Management*, 43(8): 975-985.

Lee, H. S. (2011). *Research on Open Innovation Policy in Connection with Development of Gyeonggi-do Innovation Cluster*. Gyeonggi: GSTEP Report.

Lee, J. (2017, September, 27). Takeover of SME Technology, Report of Damage of 306.4 Billion Won in Recent 5 Years. *The JoongAng Ilbo*. Retrieved from http://news.joins.com/article/21977940

Lee, K. (2009). *An Analysis of the Polarization of Profitability between Large Corporations and Small-and Medium-sized Enterprises(SMEs) and Economic Growth*. Seoul: KIF Report.

Lewis, C. D. (1982). *Industrial and Business Forecasting Methods*. London: Butterworths.

Li, M., Nguyen, B., & Yu, X. (2016). Competition vs. Collaboration in the Generation and Adoption of a Sequence of New Technologies: A Game Theory Approach. *Technology Analysis & Strategic Management*, 28(3): 348-379.

Lundvall, B.-A., & Borrás, S. (2005). *Science, Technology and Innovation Policy.* in Fagerberg, J., Mowery, D.C. and Nelson, R.R. (eds.) The Oxford Handbook of Innovation, Oxford: Oxford University Press.

Maggioni, M., & Uberti, E. (2007): *Inter-Regional Knowledge Flows in Europe: An Econometric Analysis.* In Frenken K (ed.): Applied Evolutionary Economics and Economic Geography, Cheltenham: Edward Elgar.

Majeski, S. J. (1986). Technological Innovation and Cooperation in Arms Races. *International Studies Quarterly*, 30: 175-191.

Malerba, F., Nelson, R., Orsenigo, L., & Winter, S. (1999). 'History-Friendly' Models of Industry Evolution: the Computer Industry, *Industrial and Corporate Change*,

8(1): 3-40.

Malerba, F., & Orsenigo, L. (2002). Innovation and Market Structure in the Dynamics of the Pharmaceutical Industry and Biotechnology: Towards a History-friendly Model, *Industrial and Corporate Change*, 11(4): 667–703.

Malerba, F. (2005). Sectoral Systems of Innovation: A Framework for Linking Innovation to the Knowledge Base, Structure and Dynamics of Sectors. *Economics of Innovation and New Technology*, 14(1-2): 63-82.

Mansfield, E. (1962). Entry, Gibrat's Law, Innovation, and the Growth of Firms. *American Economic Review*, 52(5): 1023-1051.

Martin, S. (2002). Spillovers, Appropriability, and R&D. *Journal of Economics*, 75(1): 1-32.

Massimiliano, G. (2015). *Genetically Modified Seeds, Intellectual Property Protection and the Role of Law.* in Transnational Perspective in Bellantuono, G., & Lara, F. T. (eds.), Law, Development and Innovation. Switzerland: Springer.

McMillan, G. S., Mauri, A. L., & Casey, D. L. (2014), The Scientific Openness Decision Model: "Gaming" the Technological and Scientific Outcomes. *Technological Forecasting and Social Change*, 86: 132-142.

Min, K. (2002). Interaction Effects between Variables in Inducing Foreign Direct Investment. *Korean Public Administration Review*, 36(4): 145-166.

Montobbio, F., & Sterzi, V. (2013). The Globalization of Technology in Emerging Markets: A Gravity Model on the Determinants of International Patent Collaborations. *World Development*, 44(C): 281-299.

Morescalchi, A., Pammolli, F., Penner, O., Peterson, A. M., & Riccaboni, M. (2015). The Evolution of Networks of Innovators within and across Borders: Evidence from Patent Data. *Research Policy*, 44(3): 651-668.

Morrison, M., & Morgan, M. S. (1999). *Models as Mediating Instruments*. In Morgan, M. S., & Morrison, M. (Eds.) Models as Mediators. Perspectives on Natural and Social Science. Cambridge: Cambridge University Press.

Mowery, D. C. (1983). Industrial Research and Firm Size, Survival and Growth in American Manufacturing, 1921~1946: An Assessment. *Journal of Economic History*, 43(4) : 953-980.

MSS. (2018). *Eradication Measures of SMEs Technology Theft*. Daejeon, MSS Report.

Myers N., & Kent, J. (2001). *Perverse Subsidies : How Tax Dollars Can Undercut the Environment and the Economy*. UK: Island Press.

Na, J., Lee, J-D., & Baek, C. (2017). Is the Service Sector Different in Size Heterogeneity?. *Journal of Economic Interaction and Coordination*, 12(1): 95-120.

NARS. (2013). *Policies and Improvement Tasks for Polarization between Large Firms and SMEs: Focusing on Protection of SME Business Area and Fair Trade in Subcontracting*. Seoul: NARS.

Nauwelaers, C., & Wintjes, R. (2008). *Conclusions and Perspectives: Adapting Old Policy Institutions to New Challenges*. in Nauwelaers, C., & Wintjes, R. (Eds.) Innovation Policy in Europe: Measurement and Strategy. Edward Elgar, Cheltenham.

Nelson, R. R., & Winter, S. G. (1982). *An Evolutionary Theory of Economic Change.* Cambridge, Mass.: Belknap Press of Harvard University Press.

Nelson, R. R. (1991). Why Firms Differ, and How Does It Matter?. *Strategic Management Journal*, 12(Winter): 61-74.

Niesten, E., & Jolink, A. (2012). Incentives, Opportunism and Behavioral Uncertainty in Electricity Industries. *Journal of Business Research*, 65(7): 1031-1039.

Noda, T., & Collis, D. J. (2001). The Evolution of Intraindustry Firm Heterogeneity: Insights from a Process Study. *Academy of Management Journal*, 44(4): 897-925.

Nowak, M., & Sigmund, K. (1993). A Strategy of Win-shift, Lose-stay that Outperforms Tit-for-tat in the Prisoners' Dilemma Game. *Nature*, 364: 56-58.

OECD. (2001). *Innovative Networks: Co-operation in National Innovation Systems*, OECD Proceedings, Paris: OECD Publishing.

OECD. (2002). *Dynamising National Innovation Systems*. Paris: OECD Publishing.

Pavitt, K. (1987). The Objectives of Technology Policy. *Science and Public Policy*, 14(4): 182–188.

Penrose, E. (1959). *The Theory of the Growth of the Firm*, New York: Oxford University Press.

Picci, L. (2010). The Internationalization of Inventive Activity: A Gravity Model using Patent Data. *Research Policy*, 39(8): 1070-1081.

Popov, E. V., & Simonova, V. L. (2006). Forms of Opportunism between Principals and Agents. *International Advances in Economic Research*, 12(1): 115-123.

Popp. D. (2006). International Innovation and Diffusion of Air Pollution Control Technologies: The Effects of NOX and SO2 Regulation in the US Japan and Germany. *Journal of Environmental Economics and Management*, 51(1): 46-71.

Porter, M. E. (1980) *Competitive Strategy Techniques for Analyzing Industries and Competitors*. New York: Free Press.

Posner, R. (1971). Taxation by Regulation. *Bell Journal of Economics and Management Science*, 2(1): 22-50.

Power, C. (2009). A Spatial Agent-Based Model of N-Person Prisoner's Dilemma Cooperation in a Socio-Geographic Community. *Journal of Artificial Societies*

and Social Simulation, 12(18).

Rogge, K. S., & Reichardt, K. (2015). *Going Beyond Instrument Interactions: Towards a More Comprehensive Policy Mix Conceptualization for Environmental Technological Change*. SPRU Working Paper Series 2015-12; University of Sussex,

Rogge, K. S., Kern, F., & Howlett, M. (2017). Conceptual and Empirical Advances in Analysing Policy Mixes for Energy Transitions. *Energy Research & Social Sciences*, 33: 1-10.

Sandu, S.& Anghel. I. (2010). The Interaction of Policy-Mix Instruments Conducive to Increasing Investment in Romania. *Curentul Juridic*, 42: 150–162.

Sargent, R. G. (1999). *Verification and Validation of Simulation Models*. In: Farrington, P. A., Nembhard, H. B., Sturrock, D. T., & Evans, G. W. (eds.) Proceedings of the 1999 Winter Simulation Conference, Squaw Peak, Phoenix, 5–8 Dec 1999: 39–48.

Schelling, T. C. (1971). Dynamic Models of Segregation. *The Journal of Mathematical Sociology*, 1: 143-86.

Schelling, T. C. (1978). *Micromotives and Macrobehavior*. New York: Norton.

Scherer, F. M. (1965). Corporate Inventive Output, Profits and Growth, *Journal of Political Economy*, 73(3): 290-297.

Scherngell, T., & Barber, M. (2009). Spatial Interaction Modelling of Cross-Region R&D Collaborations: Empirical Evidence from the 5th EU Framework Programme. *Regional Science*, 88(3): 531-546.

Schumpeter, J. A. (1942). *Socialism, Capitalism and Democracy*. New York: Harper and Brothers.

Schweitzer, F., Behera, L., & Muhlenbein, H. (2002). Evolution of Cooperation in a

Spatial Prisoner's Dilemma. *Advances in Complex Systems*, 5(2&3): 269-299.

Simon, H. (1955). A Behavioral Model of Rational Choice. *The Quarterly Journal of Economics*, 69(1): 99-118.

Simon, H., & Bonnini, C. (1958). The Size Distribution of Business Firms. *American Economic Review*, 48(4): 607–617.

SMBA. (2017). *Announcement of Plan for the Implementation of the SMEs' Technological Competitiveness Enhancement Partnership Policy*. Daejeon, SMBA Report.

STEPI. (2007). *How to Strengthen Industrial Innovation Capability by Inter-firm Cooperation*. Seoul: STEPI Report.

Sutton, J. (1997). Gibrat's Legacy. *Journal of Economic Literature*, 35(1): 40-59.

Suzumura, K. (1992). Cooperative and Noncooperative R&D in an Oligopoly with Spillovers. *The American Economic Review*, 82(5): 1307-1320.

Szilagyi, M. N., & Szilagyi, Z. C. (2002). Non-Trivial Solutions to the N-Person Prisoner's Dilemma. *Systems Research and Behavioral Science*, 19(3): 281-290.

Teece, D. (1986). Profiting from Technological Innovation: Implications for Integration, Collaboration, Licensing, and Public Policy. *Research Policy*, 15(6): 285–305.

Tesfatsion, L. (2006). *Agent-Based Computational Economics: A Constructive Approach to Economic Theory.* in K. Judd and L. Tesfatsion (eds.), Handbook of Computational Economics, Vol. 2: Agent-Based Computational Economics. Amsterdam: North-Holland.

Uyarra, E., & Ramlogan, R. (2012). *The Effects of Cluster Policy on Innovation.* Nesta Working Paper, Retrieved from https://www.nesta.org.uk

Vossen, R.W., 1998. Relative Strengths and Weaknesses of Small Firms in Innovation. *International Small Business Journal*, 16 (3): 88–94.

Waltman, L. (2011). *Computational and Game-Theoretic Approaches for Modeling Bounded Rationality* (Doctoral dissertation). Retrieved from http://www.ludowaltman.nl/

Walton, M. (1997). When Your Partner Fails You.... *Fortune*, May: 87-89.

Wathne, K. H., & Heide, J. B. (2000). Opportunism in Interfirm Relationships: Forms, Outcomes, and Solutions. *Journal of Marketing*, 64(4): 36-51.

Watts, C., & Gilbert, N. (2014) *Simulating Innovation: Computer-based Tools for Rethinking Innovation*. Cheltenham: Edward Elgar Publishing.

Weber, R. A. (2006). Managing Growth to Achieve Coordination in Large Groups. *American Economic Review*, 96(1): 114-126.

Wilensky, U. (1999). *NetLogo*. http://ccl.northwestern.edu/netlogo/. Center for Connected Learning and Computer-Based Modeling, Northwestern University, Evanston, IL.

Wilensky, U. (2002). *NetLogo PD N-Person Iterated model*. http://ccl.northwestern.edu/netlogo/models/PDN-PersonIterated. Center for Connected Learning and Computer-Based Modeling, Northwestern University, Evanston, IL.

Wilensky, U., & Rand, W. (2007). Making Models Match: Replicating an Agent-Based Model. *Journal of Artificial Societies and Social Simulation*, 10(4): 2.

Williamson, O. E. (1975). *Markets and Hierarchies: Analysis and Antitrust Implications*. New York: Free Press.

Williamson, O. E. (1981). The Economics of Organization: The Transaction Cost Approach. *American Journal of Sociology*, 87(3): 548-577.

Williamson, O. E. (1985). *The Economic Institutions of Capitalism*. New York: Free Press.

Windrum, P., Fagiolo, G., & Moneta, A. (2007). Empirical Validation of Agent-Based Models: Alternatives and Prospect. *Journal of Artificial Societies and Social Simulation*, 10(2): 8.

Yamamoto, H., Ishida, K. and Ohta, T. (2004). Modeling Reputation Management System on Online C2C Market. *Computational & Mathematical Organization Theory*, 10(2): 165-178.

Yang, H-L., & Wu, T. C. T. (2008). Knowledge Sharing in an Organization. *Technological Forecasting and Social Change*, 75(2008): 1128-1156.

Yoon, M., & Lee, K. (2009). Agent-based and "History-Friendly" Models for Explaining Industrial Evolution. *Evolutionary and Institutional Economics Review*, 6(1): 45-70.

Yun, J. J., Won, D., & Park, K. (2016). Dynamics from Open Innovation to Evolutionary Change. *Journal of Open Innovation: Technology, Market, and Complexity*, 2(7): 1-22.

Yurtseven, A. E., & Tandoğan, V. S. (2012). Patterns of Innovation and Intra-industry heterogeneity in Turkey. *International Review of Applied Economics*, 26(5): 657-671.

Zlowodzki, M., Poolman, R. W., Kerkhoffs, G. M., Tornetta, P., Bhandari, M., & On behalf of the International Evidence-Based Orthopedic Surgery Working Group (2007). How to Interpret a Meta-analysis and Judge Its Value as a Guide for Clinical Practice. *Acta Orthopaedica*, 78(5): 598-609.

Appendix 2-A. Sensitivity Analysis on Collaborative Innovation

The sensitivity analysis was performed to check the robustness of the model. One of the most popular sensitivity analysis methodologies for assessing robustness in ABM is the one-factor-at-a-time (OFAT) method (Broeke, Voorn, & Ligtenberg, 2016). The OFAT method is a method of analyzing the relationship between one independent variable and a dependent variable according to the change of independent variable. Broeke et al. (2016) called the OFAT method an important methodology for revealing the relationship between valid parameters and outputs.

This study performs an OFAT sensitivity analysis for independent variables R and T, respectively. In all scenarios, 30 iterations are performed. In this study, sensitivity analysis is performed by manipulating the intervals of R and T, respectively. As mentioned in the study design, the minimum value of R in the default payoff is 3, and the maximum value of T is 5. The interval of the payoff in the base model is 2, but this study analyzes the sensitivity of collaborative innovation when the interval is 2, 3, and 4. Each scenario is listed in Table 2.29.

Table 2.29 OFAT Sensitivity Analysis Scenarios

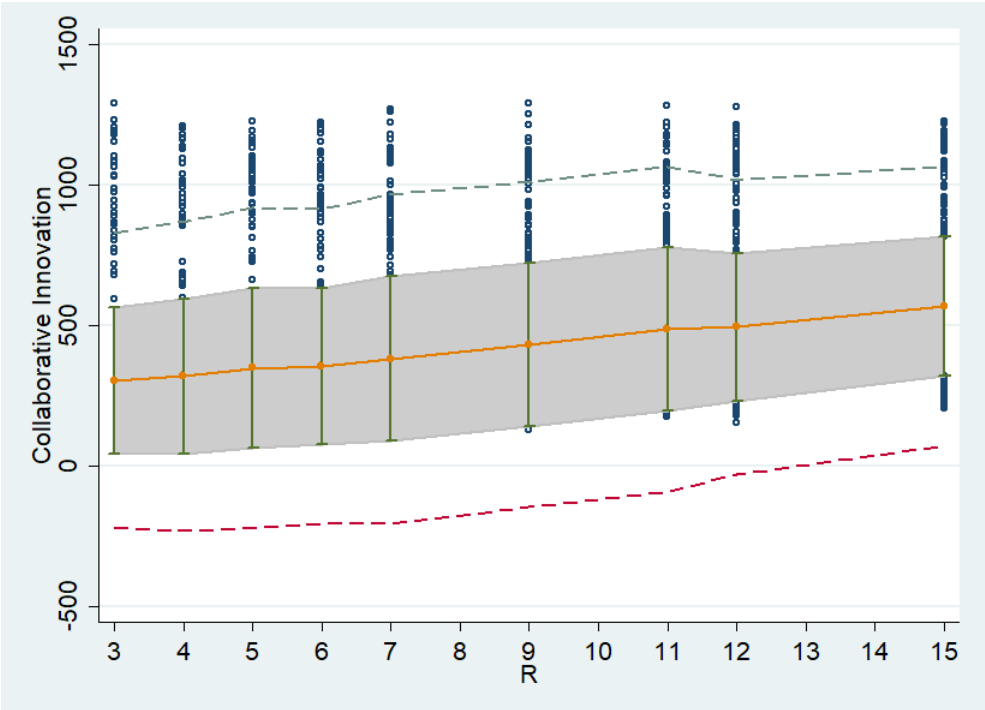
No.	Interval of R	Interval of T	Payoffs by Policy Scenario
1	1	1	R (NI=3, SI=4, MI=5, HI=6) T(NR=5, WR=4, MR=3, SR=2)
2	1	2	R (NI=3, SI=4, MI=5, HI=6) T(NR=5, WR=3, MR=1, SR=-1)
3	1	3	R (NI=3, SI=4, MI=5, HI=6) T(NR=5, WR=2, MR=-1, SR=-4)
4	1	4	R (NI=3, SI=4, MI=5, HI=6) T(NR=5, WR=1, MR=-3, SR=-7)
5	2	1	R (NI=3, SI=5, MI=7, HI=9) T(NR=5, WR=4, MR=3, SR=2)

6	2	2	R (NI=3, SI=5, MI=7, HI=9) T(NR=5, WR=3, MR=1, SR=-1) (Default Payoffs)
7	2	3	R (NI=3, SI=5, MI=7, HI=9) T(NR=5, WR=2, MR=-1, SR=-4)
8	2	4	R (NI=3, SI=5, MI=7, HI=9) T(NR=5, WR=1, MR=-3, SR=-7)
9	3	1	R (NI=3, SI=6, MI=9, HI=12) T(NR=5, WR=4, MR=3, SR=2)
10	3	2	R (NI=3, SI=6, MI=9, HI=12) T(NR=5, WR=3, MR=1, SR=-1)
11	3	3	R (NI=3, SI=6, MI=9, HI=12) T(NR=5, WR=2, MR=-1, SR=-4)
12	3	4	R (NI=3, SI=6, MI=9, HI=12) T(NR=5, WR=1, MR=-3, SR=-7)
13	4	1	R (NI=3, SI=7, MI=11, HI=15) T(NR=5, WR=4, MR=3, SR=2)
14	4	2	R (NI=3, SI=7, MI=11, HI=15) T(NR=5, WR=3, MR=1, SR=-1)
15	4	3	R (NI=3, SI=7, MI=11, HI=15) T(NR=5, WR=2, MR=-1, SR=-4)
16	4	4	R (NI=3, SI=7, MI=11, HI=15) T(NR=5, WR=1, MR=-3, SR=-7)

Note: NI = No Incentives, SI = Small Incentives, MI = Medium Incentives, HI = High Incentives, NR = No Regulations, WR = Weak Regulations, MR = Moderate Regulations, SR = Strong Regulations

Firstly, the results of OFAT sensitivity analysis for R are shown in Figure 2.25.

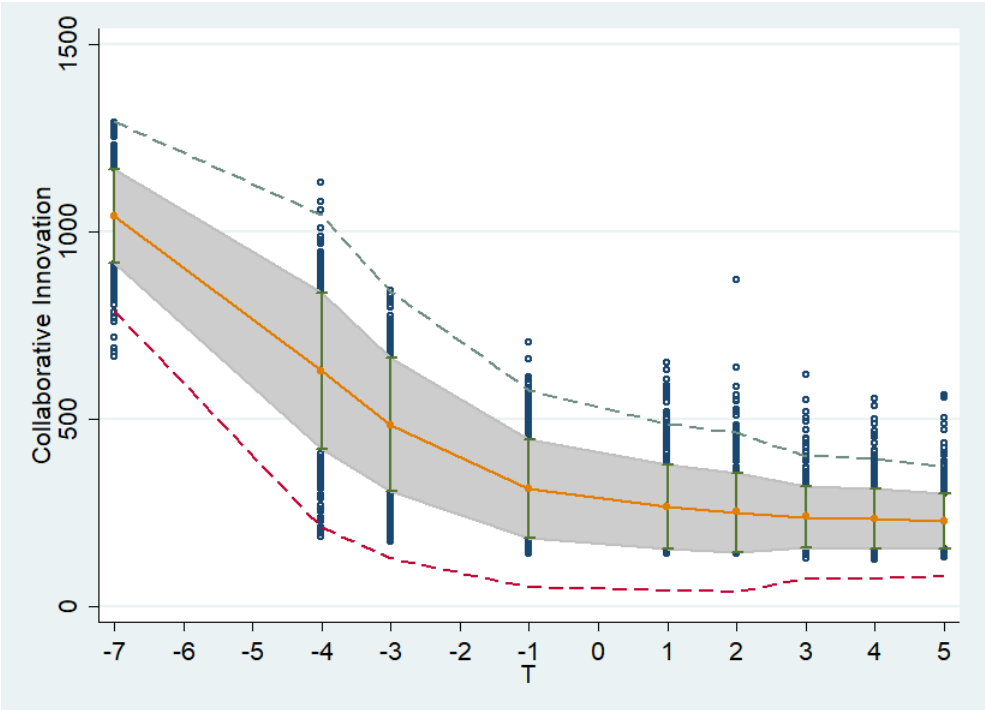
Figure 2.25 Results of Sensitivity Analysis of Collaborative Innovation according to R



As R increases, collaborative innovation increases gradually. The change of collaborative innovation according to the change of R is small. This indicates that collaborative innovation is relatively robust as the R changes. Therefore, it can be interpreted that the robustness of the model to the level of incentives is high.

Next, the OFAT sensitivity analysis results for T are shown in Figure 2.26.

Figure 2.26 Result of Sensitivity Analysis of Collaborative Innovation according to T



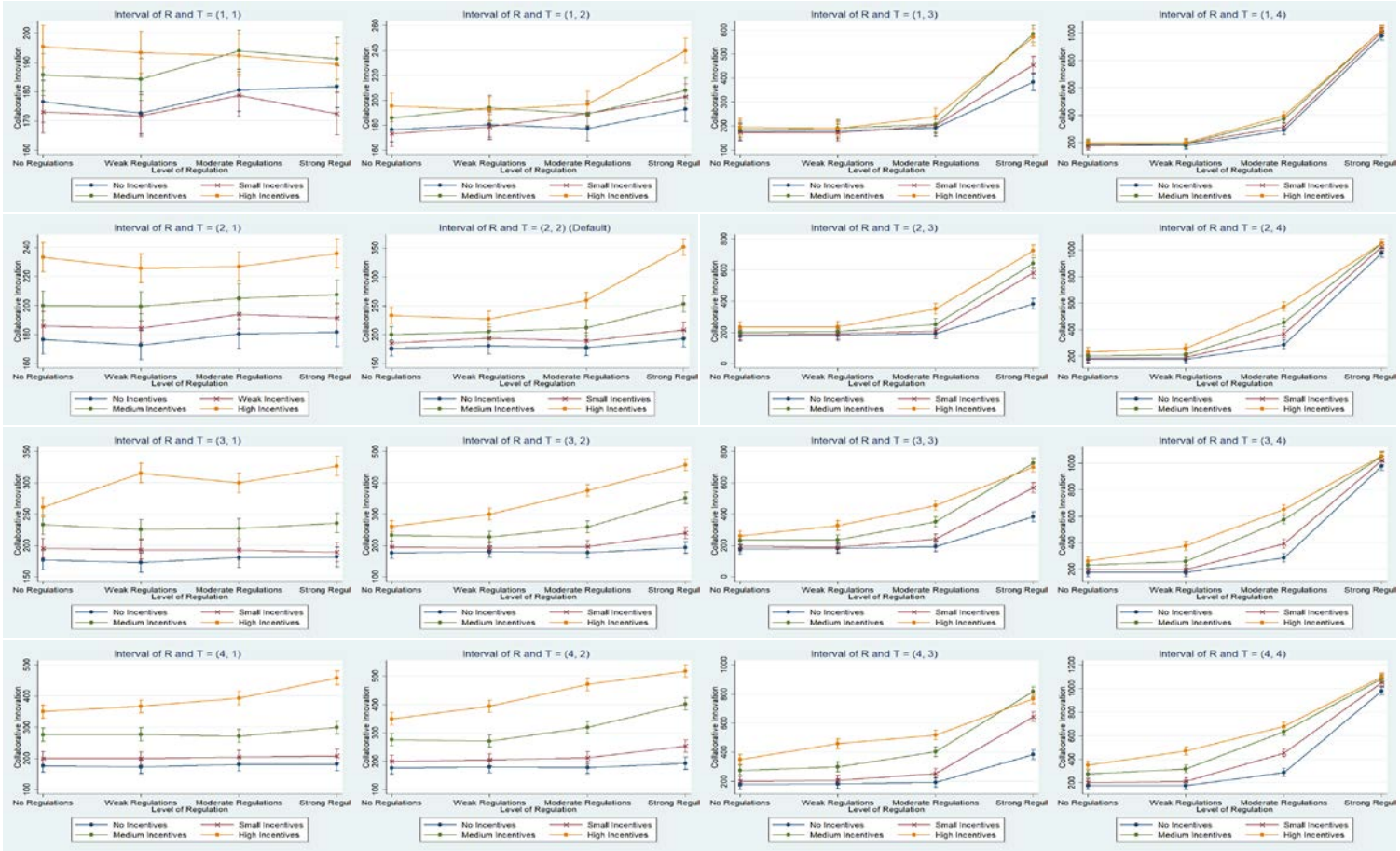
As T decreases, the collaborative innovation gradually increases and then decreases sharply at some point. Collaborative innovation changes dramatically over certain thresholds. This indicates that collaborative innovation is relatively more sensitive to changes in T than R. However when T is higher than -1, it shows a stable pattern at R level. Therefore, it can be interpreted that the model is robust when the level of regulation is low, but the robustness of the model is lowered as the level of regulation increases.

The OFAT sensitivity analysis results show that the model is robust to the interval of R, but the robustness of the model decreases as the interval of T increases. This suggests that the model is sensitive to high levels of regulation. In conclusion, this

model is robust to all incentives and low-level regulations but sensitive to high-level regulations. Therefore, if the level of regulation is increased or the regulation interval is increased, the result of this simulation can be changed.

Although the OFAT method has the advantage of being able to evaluate the robustness of the model, there is a limitation in that the interaction effect cannot be analyzed (Broeke et al., 2016). Since this study analyzesd the interaction effect, it is not enough to perform only the OFAT. Therefore, this study performs a sensitivity analysis on the interaction effect through the same difference test under different payoffs. All scenarios were subjected to 30 iterations. The simulation results for the models in Table 2.29 are shown in Figure 2.27.

Figure 2.27 Result of Sensitivity Analysis



As shown in the OFAT sensitivity analysis results, this model responds sensitively to a certain level of regulation. Therefore, the larger the interval of T, the greater the variation of the simulation results. Sensitivity analysis results show that under all conditions, as T increases, it converges to a similar trajectory. As shown in Figure 2.26, the effect of T on the model increases as the variation of the model increases when T exceeds a certain level, and thus the pattern of all the models tends to be determined by T. On the other hand, even if the interval of R increases, the simulation result does not change much, as the model is robust to all levels of R, as shown in Figure 2.25. Finally, when the interval of T is 1, the payoff of the moderate regulation is equal to the payoff of the weak regulation of the default settings in the base model. Therefore, when the interval of T is 1, the trajectory is enlarged to the mid-point between weak regulation and moderate regulation when the interval of T is 2, and this is why the trajectory is clearly different from other scenarios.

The agents of this model are designed to be very sensitive to the relative size of the payoff of each action. This study suggests that the reason for adopting the Pavlov strategy in the research design section is that, in reality, firms are sensitive to changes in payoffs and modify their behavior. In other words, the model of this study is designed to strategically modify behavior according to changes in payoffs, as in reality. Thus, in the context of this study, a model that is not sensitive to changes in payoff is a weak model of the explanatory power of firms' behavior.

However, it is assumed that a sensitivity analysis of this model may be possible if some assumptions inherent in this model are satisfied. This model makes several assumptions about the level of policy. Also, the default payoff of this model satisfies two fundamental conditions of PD game at the same time. The reason that these assumptions should be satisfied is that agents in this model choose behavior according

to the expected value of the difference in payoff relative to behavior: in other words, agents make unrealistic choices if the assumptions about the level of policy in this model are not satisfied. Therefore, this study attempts to find out whether the results are robust when the payoff is changed under these assumptions.

The strengths of the policies defined in this study are shown in Table 2.30.

Table 2.30 Assumptions Underlying the Policy Instruments

Level of Policy Instrument	Assumptions
Small Incentives	Modified R = Default T
Medium Incentives	Modified R > Default T
High Incentives	Modified R > Default T
Weak Regulations	Default R = Modified T
Moderate Regulations	Default R > Modified T, and Modified T > 0
Strong Regulations	Default R > Modified T, and Modified T < 0

The criterion for distinguishing between moderate and strong regulations in this study is whether the magnitude of punishment is higher than the profit when opportunistic behavior is successful. If the penalty is higher than profit, T is less than zero; otherwise, T is higher than zero. In other words, the strong regulation defined in this study represents a strong punitive damages level that exceeds the magnitude of all direct and indirect profits arising from opportunistic behavior. Also, this study follows the definition of the default payoff of PD game S = 0 in all cases, because it is unrealistic to assume that an agent who has been unilaterally betrayed to its opponent gains a payoff. The payoffs in this study also satisfy the following assumptions (Yamamoto et al., 2004):

$$\begin{cases} \boldsymbol{T > R > P > S} \\ \boldsymbol{2R > T + S} \end{cases}$$

The policy scenarios that satisfy these assumptions are shown in Table 2.31.

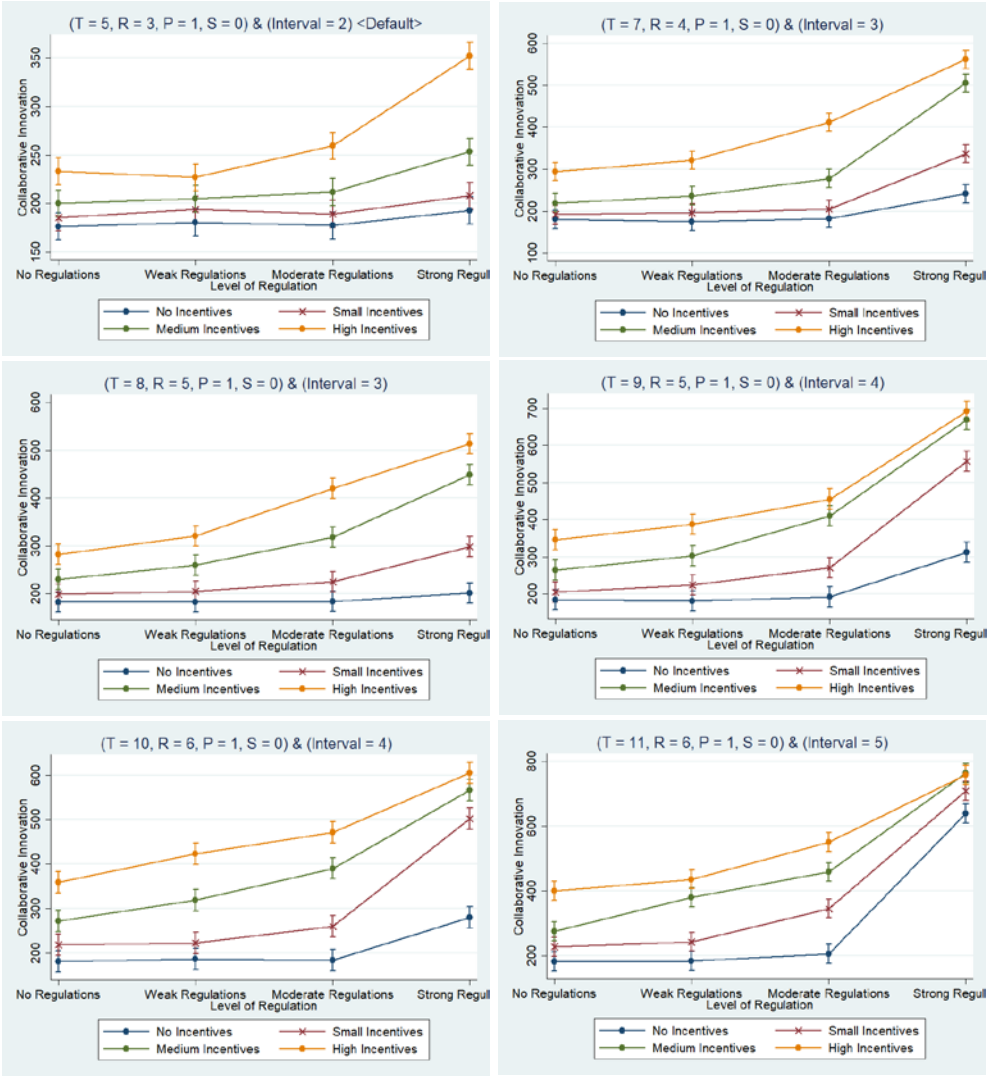
Table 2.31 Modified Models for Sensitivity Analysis (Under the Assumptions)

No.	Default Payoffs	Level of Policy Instrument	Measurement
1	T = 7, R = 4, P = 1, S = 0	No Incentives	R = 4
		Small Incentives	R = 7
		Medium Incentives	R = 10
		High Incentives	R = 13
		No Regulations	T = 7
		Weak Regulations	T = 4
		Moderate Regulations	T = 1
		Strong Regulations	T = -2
2	T = 8, R = 5, P = 1, S = 0	No Incentives	R = 5
		Small Incentives	R = 8
		Medium Incentives	R = 11
		High Incentives	R = 14
		No Regulations	T = 8
		Weak Regulations	T = 5
		Moderate Regulations	T = 2
		Strong Regulations	T = -1
3	T = 9, R = 5, P = 1, S = 0	No Incentives	R = 5
		Small Incentives	R = 9
		Medium Incentives	R = 13
		High Incentives	R = 17
		No Regulations	T = 9
		Weak Regulations	T = 5
		Moderate Regulations	T = 1
		Strong Regulations	T = -3
4	T = 10, R = 6, P = 1, S = 0	No Incentives	R = 6
		Small Incentives	R = 10
		Medium Incentives	R = 14
		High Incentives	R = 18
		No Regulations	T = 10
		Weak Regulations	T = 6
		Moderate Regulations	T = 2
		Strong Regulations	T = -2
5	T = 11, R = 6, P = 1, S = 0	No Incentives	R = 6
		Small Incentives	R = 11

		Medium Incentives	R = 16
		High Incentives	R = 21
		No Regulations	T = 11
		Weak Regulations	T = 6
		Moderate Regulations	T = 1
		Strong Regulations	T = -4

The interval of the payoff according to the policy level is 3 in the first and second models, 4 in the third and fourth models, and 5 in the fifth model. They differ from the base model in that the payoff interval is 2. The above models have very high payoffs of R and T, and real explanatory power is lower than the default payoff matrix of the base model. This study conducts a sensitivity analysis on the collaborative innovation of each model. All models include 16 policy scenarios based on the level of incentives and regulations, and 30 scenarios were applied to all models. The results of the first model are shown in Figure 2.28.

Figure 2.28 Result of Sensitivity Analysis (Under the Assumptions)



The results of the analysis show that the model is robust under the assumptions of policy level and PD game payoff. As the policy interval increases, the relative difference between high incentives and medium incentives is narrowed in strong regulation, but this trend is due to the large fluctuation when T is higher than -1, as shown in the OFAT

sensitivity analysis in Figure 2.26. All analytical results are closer to exponential curves as the level of regulation increases, which is also related to the greater variability when T is higher than -1. However, when the assumptions of this study are met, no significant variation is observed.

In conclusion, the sensitivity analysis results suggest that the model is robust to changes in policy level or default payoff, except when the interval of T increases to an extreme level. The extreme increase in the interval of T means that the level of regulations becomes very strong. However, since the level of regulations on opportunistic behavior by the Korean government is not high enough, it is unrealistic to assume that the interval of T increases to an extreme level. In Korea, the level of regulations has always remained moderate, and the interval of T has been small because the punishment for opportunistic behavior does not exceed the magnitude of profit. Therefore, considering that the interval of T is small in reality, this study can conclude that this model is robust enough.

Chapter 3. [Essay 2] Evolution of the Collaborative Innovation Network in the Korean ICT Industry

3.1 Introduction

Firms can respond to rapidly changing technology needs and reduce the cost of innovation through collaboration (Williamson, 1981). In the 2000s, with the development of ICT, collaborative innovation became increasingly important due to the diversification of the technology demand, such as the convergence of heterogeneous technologies based on ICT. Researchers have emphasized the need to create an open innovation ecosystem for collaborative innovation (Chesbrough, 2003; Lundvall & Borrás, 2005), but the knowledge of the structural characteristics of inter-firm collaborative innovation is very limited. The purpose of this study is to explore the structural characteristics of inter-firm collaborative innovation in the Korean ICT industry from various perspectives.

The aim of this study is summarized as follows. First, it intends to reveal the structural characteristics of the evolution of the inter-firm collaborative innovation network in the Korean ICT industry. Specifically, it seeks to examine the evolution of the network over time using various network indicators, such as centrality. This study also identifies the key agents in the network and the topology of the network. Through this process, the structural evolution of the inter-firm collaborative innovation network of the Korean ICT industry can be explained more analytically.

Second, this study examines the effect of innovation and relational factors on inter-firm homophily and then determines which factors are more effective in homophily. In network studies, homophily has been noted as a macroscopic pattern due to microscopic

interactions between agents (Kegen, 2013). Previous studies have noted that homophily depends on certain characteristics of the firms in the inter-firm collaborative innovation network (Cantner & Graf, 2006).

Firms cooperate strategically with other firms, and discussions about the factors that affect this process have differed between network studies and traditional partner selection studies. The preliminary studies on homophily in collaborative innovation networks from the network perspective have shown that network characteristics, such as relational factors, affect homophily. However, empirical studies on partner selection in collaborative innovation show that innovation factors, including firm characteristics, affect partner selection. Given these arguments, both the relational and the innovation factors need to be considered as important factors affecting the evolution of the collaborative innovation network. In particular, some recent studies have demonstrated that it is important to consider innovation factors and relational factors simultaneously in homophily analysis. This analysis can narrow the gap between the perspectives of the formation of a collaborative innovation network that has been discussed independently in network research and partner selection studies.

It is also possible to infer the openness of a network by identifying the factors that have a more significant effect on the inter-firm homophily among innovation and relational factors. According to resource-based theory, firms engage in collaborative innovation to meet the changing technological demand by supplementing their own innovation resources with those of other firms (Penrose, 1959). However, according to transaction cost theory, firms are expected to carry out collaborative innovation to reduce the costs associated with innovation (Coase, 1937; Williamson, 1981). If the macroscopic pattern of the network is more affected by the technical characteristics, firms can perform collaborative innovation to complement their technological resources.

On the other hand, if the macroscopic pattern of the network is more affected by relational factors, firms rely on "safe choices" to perform collaborative innovation with partners to reduce the potential conflicts and transaction costs. Therefore, this study has significance in that it can infer the level of openness of the innovation ecosystem in the Korean ICT industry.

This study focuses on ICT firms in Korea. The Korean ICT industry is highly innovation intensive, and the R&D expenditure to GDP ratio ranks first among the OECD countries. In addition, Korea has reached the top position in the ICT Development Index (IDI) ranking, which indicates the level of ICT development in a country (ITU, 2016). In the innovation process, firms produce most of the innovations in the industry, and Korean ICT firms also generate most of the innovations in the Korean ICT industry. Therefore, the analysis of Korean ICT firms can not only promote the understanding of the collaborative innovation ecosystem of the Korean ICT industry but can also provide implications for the ICT industry in other countries.

This study consists of five chapters including the introduction. Chapter 2 introduces the previous research on the evolution of the collaborative innovation network, examines the evolution of networks around homophily, identifies the important factors affecting homophily in the collaborative innovation network. Chapter 3 presents the research hypotheses and the research design. Specifically, this study presents the conceptual framework, explains the process of data collection and conversion to network data, introduces the variables, methodology, and estimation strategy, and presents the descriptive statistics. Chapter 4 analyzes the network evolution process through descriptive network analysis and determines which factors affect the macroscopic pattern of homophily in the collaborative innovation network. Finally, Chapter 5 summarizes the conclusions and presents the implications and

limitations of the study.

3.2 Literature Review

3.2.1 Collaborative Innovation from a Network Perspective

Various systems in the world can be seen as networks with complex characteristics (Barabási & Albert, 1999). The link that forms the network plays the role of transferring information between the nodes, and the whole network can be regarded as a large information delivery system. Thus, applied network studies have been conducted in a wide range of disciplines, including inter-neuronal networks, genetic networks, computer communication networks, such as the World Wide Web (WWW), power networks, and social networks that analyze people-to-people relationships.

In the field of social network analysis (SNA), there has been active research on the evolution of collaborative networks, which analyze how collaborations among agents evolved in various networks. These studies have been conducted in a wide range of fields, from collaborative networks in small organizations to inter-firms that form one industry, policy networks surrounding policy issues, and disaster response collaboration networks. For example, Butts, Acton & Marcum (2012) analyzed the evolutionary process of the disaster response collaboration network corresponding to Hurricane Katrina and found out which agents played a major role.

Collaborative innovation networks have been widely accepted as one of the most important topics in the field of innovation research. Researchers have attempted to analyze the evolution of collaborative innovation patterns from a variety of perspectives.

From the very beginning of innovation research, scholars have sought to identify whether certain patterns of evolution are present in industries over time. Evolutionary economists have explored the evolution of innovation patterns in industries from the viewpoint of mark 1 and mark 2 proposed by Schumpeter (Nelson & Winter, 1982).

Also, researchers have attempted to explain the evolution of the industrial structure by analyzing not only innovation but also the pattern of collaborative innovation among firms. For example, Zanfei (1993) analyzed the patterns of collaborative innovation among regional holding firms and independent holding firms in the US telecommunications industry from 1984 to 1990. The results showed that the firms increased the possibility of introducing new technologies through the expansion of international cooperation. In addition, the firms that were constrained by vertical integration found that they partnered more firms as a defense against opportunistic behavior by suppliers. These studies have mainly investigated changes in collaboration over time through changes in transactional relationship data, but, as Barabási and Albert (1999) noted, a large and complex interaction system can best be explained by focusing on the topology of the system. Through this analysis, this study identifies the agents who play a central role in the whole network and explains how the relationship structure has changed around these agents from the macro perspective.

Recent studies mainly explore the evolution of the collaborative innovation network by analyzing the joint patenting network among firms with patent data. Social network analysis is a useful method for explaining network characteristics, and patent network analysis is an important and popular topic in social network analysis (Lee, Lee, & Sohn, 2016). For example, Cantner and Graf (2006) analyzed the evolution of the innovator network in Jena, Germany, using patent data from 1995 to 2001. Lee et al. (2016) used the joint patent data of the US and Korea to illustrate the convergence network of robot technology and identified the determinants of such a convergence network. Guan and Liu (2016) analyzed the evolution of collaborative and knowledge networks in the nano energy field using patent data. These studies analyzed the temporal variation of various network characteristics, including centrality indicators, to capture

the structural changes over time and identify the key agents.

3.2.2 Network-type Technology Development Program for SMEs in Korea

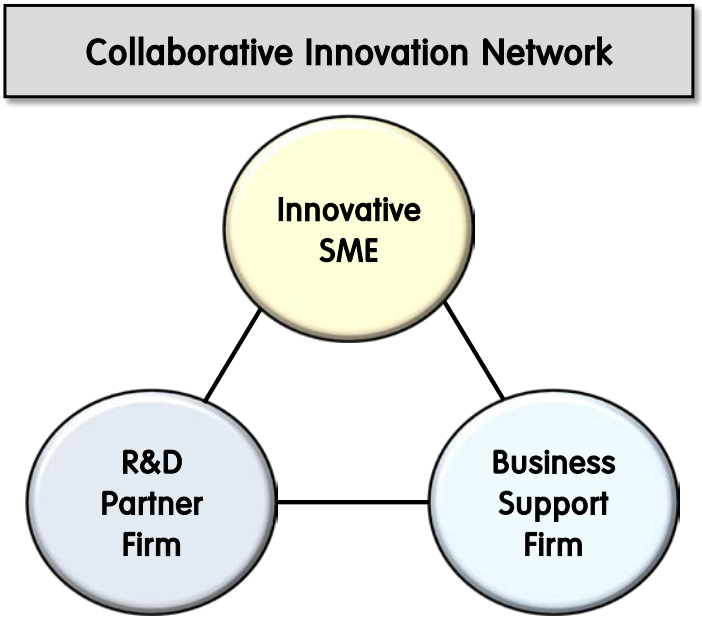
The Korean government has been promoting a network-based collaborative innovation support program to create an open innovation ecosystem and promote a collaborative innovation network. The Network-type Technology Development Program for SMEs is a program that supports technology development and commercialization through horizontal cooperation among SMEs. Participants include innovative SMEs that are technology development entities, SMEs that perform joint technology development, and firms that establish commercialization strategies. These three or more firms construct a network to perform collaborative innovation (SMBA, 2017).

This program is led by the Ministry of SMEs and Startups (MSS) and the Korean Intellectual Property Office (KIPO), which includes an MIS budget of 14.7 billion KRW and KIPO budget of 400 million KRW by 2018. Supported technologies are limited to 12, including AI and big data, intelligent sensors, AR and VR, future cars, smart home, smart factory, safety, bio, energy, embedded software, and equipment (MSS, 2018).

This program consists of network planning support and R&D support. Network planning support is the first step in establishing the technology development plan by upgrading the innovation idea suggested by the innovative SME. The participating firm matches the collaborative innovation partners with the support of the planning and management organization for six months, and the government then supports the patent analysis, technological feasibility evaluation, and technology development strategy.

The structure of the collaborative innovation network supported by this program is shown in Figure 3.1 below.

Figure 3.1 Network diagram of the Network-type Technology Development Program for SMEs (SMBA, 2017)



The network consists of innovative SMEs, R&D partner firms, and business support firms. The number of participating firms is not limited to three, and additional R&D partners are allowed to participate.

Specifically, MSS not only matches the technological collaboration partners of participating firms, but also assists firm analysis, market analysis, technological analysis, intellectual property strategy analysis, economic analysis, R&D strategy, commercialization strategy, and network cooperation agreement. Also, the KIPO supports the establishment of patent strategies for participating firms, such as firm and

market analysis, competitor analysis, core patent strategy, patent securing strategy, network pooling strategy, and presentation of R&D direction (MSS, 2018).

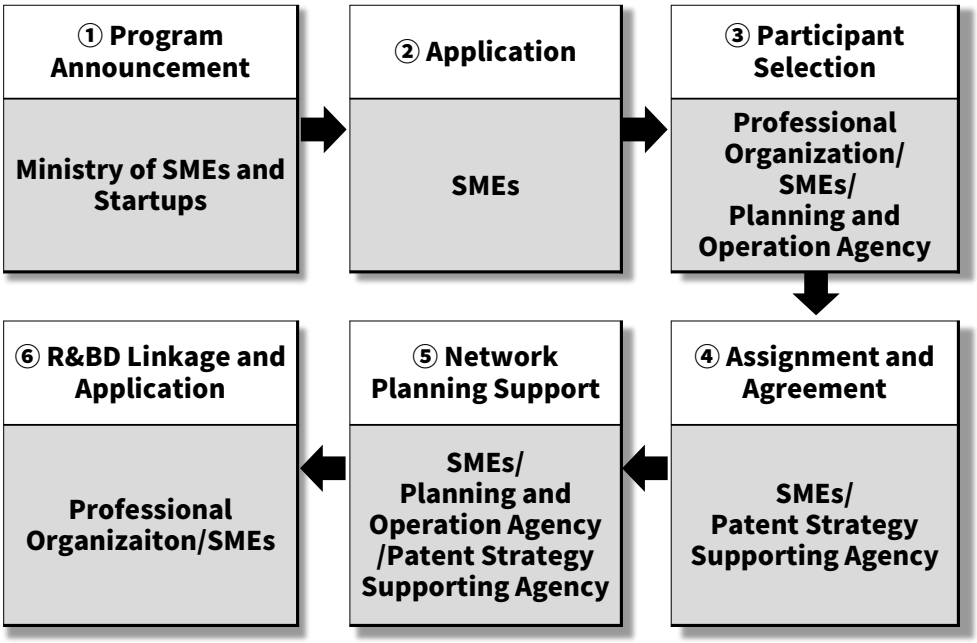
Secondly, the R&D support program selects the best projects through the evaluation of the projects that have completed the network planning support, and subsidizes the technology development for less than 600 million KRW for up to two years. Specifically, it supports design development, IP strategy development, business model development, and performance certification and clinical testing (MSS, 2018). The support period and subsidy limits for each stage are shown in Table 3.1 below.

Table 3.1 Support Period and Limit by Program Level (MSS, 2018)

		Support Period	Support Limit	Budget Configuration	
				Government	Private
Network Planning Support	R&D Planning	Up to 6 months	30 million KRW	Within 100%	None
	R&D Planning + Patent Strategy	Up to 6 months	30million + 80million KRW	Within 100%	None
Technological Development – R&BD		Up to 2 years	600million KRW	Within 65%	35%

Network planning support in this program consists of six steps in total. The propulsion procedure is shown in Figure 3.2 below.

Figure 3.2 Implementation and Evaluation Procedures for Network Planning Support (MSS, 2018)



The selection and evaluation of network planning support is conducted through conformity assessment and face-to-face evaluation. The evaluator may conduct additional field surveys as necessary. In terms of technological development, the R&BD process consists of three stages. The implementation and evaluation procedure is shown in Figure 3.3 below.

Figure 3.3 Implementation and Evaluation Procedures for Technological Development R&BD (MSS, 2018)

This program supports the collaborative innovation of three or more firms in a network form and has the advantage of reducing inefficiency and opportunistic behavior due to role duplication, because it shares the role of technology development and programming in collaborative innovation. Also, the program mainly supports ICT-based innovation technologies because ICT technology has a ripple effect that promotes the development of other technologies.

3.2.3 Homphily in Collaborative Innovation Network

3.2.3.1 Homphily in Collaborative Innovation Network

A variety of explanations are available for network formation and evolution mechanisms. The macroscopic patterns that appear in the relationships between agents are shaped by the interactions between the micro-motives of the agents (Schelling, 1978). Likewise, the various macroscopic patterns that appear in networks can also be explained by the process through which the micro-motives of the agents lead to macroscopic macro-behavior, as Schelling (1978) asserted. For example, when

choosing a collaborative innovation network, firms consider various factors, such as the size and innovation capacity of the other firm, the physical distance between the firms, the expected utility of the cooperation, and the transaction costs incurred in cooperating. As the network is formed by the interaction of agents with various micro-motives, various macroscopic patterns appear. Homophily is one of these macroscopic patterns that have been of interest to researchers.

A pattern of homophily is observed when all network-dependent social agents interact with other agents (McPherson, Smith-Lovin, & Cook, 2001). Homophily, best expressed by the proverbial "Birds of a feather," refers to the principle that contacts among similar agents occur more rapidly than other agents (McPherson et al., 2001). Homophily refers to a phenomenon in which connections between agents with the same characteristics appear in the network. Homophily is a matter of social selection, explaining the phenomenon of more active interaction among similar agents than the dissimilar agents (Kegen, 2013). Homophily tends to accelerate social stratification by giving members of the majority group the opportunity to acquire more social resources (Baron, Davis-Blake, & Bielby, 1986; Kleinbaum, Stuart, & Tushman, 2013). In network research, homophily is defined as a phenomenon in which connections are made among agents with similar characteristics.

Lazarsfeld and Merton (1954) reported that homophily occurs between agents with the same attributes. Ibarra (1992) also stated that agents' limited access to the interaction network is due to homophily based on agent characteristics. That is, homophily affects the network formation between agents with the same characteristics but also restricts the network entry of heterogeneous agents. Since homophily affects network evolution by linking agents under certain conditions, it is necessary to analyze the determinants of homophily to understand the network formation mechanism. In particular, in the

collaborative innovation network, homophily is regarded as important because it simplifies communication among innovators, increases predictability of behavioral characteristics, and increases mutual trust (Kegen, 2013).

Homophily is also observable in a collaborative innovation network. In a complexly connected collaborative innovation network, several simple patterns are found, one of which is the formation of connections between firms with the same characteristics. For example, firms that share common characteristics—such as firms with the same technology portfolio, firms in the same stock market, affiliates in the same group, or firms in the same region—can perform collaborative innovation more frequently. In this case, as pointed out in previous studies, there is a limitation in that collaborative innovation can be restricted to only those groups that share certain attributes (Baron et al., 1986; Kleinbaum et al., 2013). In other words, firms that do not have the typical attributes shared by the agents in the network that lead the collaborative innovation may have trouble entering the collaborative innovation network. Therefore, in the collaborative innovation network, homophily can cause stratification of innovation between firms with common attributes and those without it

In this way, researchers have analyzed various aspects of the 'birds of a feather' phenomenon in collaborative innovation networks. Research on homophily in collaborative innovation networks can be divided into two categories: research at the innovation entity level and research at the innovation output level. In general, the former is divided into individual-level studies, firm-level studies, and regional-level studies (Katz & Martin, 1997; Von Proff & Brenner, 2014). First, studies on homophily in the collaborative innovation network at the individual level have attempted to determine which characteristics of individuals cause homophily in collaborative innovation behavior between scientists and inventors. Cantner and Graf (2006) analyzed the factors

affecting the homophily effect of the collaborative innovation network in Jena, Germany, and found that the effects of public linkages and technological overlap among innovators affected it. Harris, Wong, Thompson, Haire-Joshu, & Hipp (2015) analyzed the factors affecting homophily among scientists at the Washington University Center for Diabetes Translation Research. The results showed that there is homophily among professors in the same discipline in overall collaboration. Second, Casanueva, Castro, & Galan (2013) studied homophily in a collaborative innovation network at the firm level. They analyzed the homophily effect of firms' social network on the innovation network in mature geographic clusters. The results showed that the presence of personal relationships between trust, intra-sector cooperation, and firm bosses in an explicit knowledge network and a tacit knowledge network affected network formation. Third, Von Proff and Brenner (2014) analyzed homophily in a collaborative innovation network at the regional level. They found that geographical proximity is an important factor in the formation of a regional collaborative innovation network in various industries.

In addition, Lee et al. (2016) analyzed homophily in a collaborative innovation network at the level of patents, which are the output of typical innovation. They identified the determinants of the homophily in the US and Korea's robotics patent network. The results showed that the time taken from the application of the centralities of the network, the applicant's nationality, and the patent to the registration affect homophily.

Studies at the innovatior level, such as firms, individuals, and regions, have mainly focused on the characteristics of agents. On the other hand, studies at the innovation output level, such as patents, have used the private or public relations among agents as the main variable. The former tend to appear mainly in the social sciences, such as

economics, business administration, and public policy, and the latter tend to appear mainly in the engineering field, presumably because the focus of research is different in each academic field. Since the initial analysis of innovation economics, including that conducted by Pakes and Griliches (1984), the focus of the research has been the innovation entity. Therefore, the former emphasized the policy significance of promoting innovation through firm support and regulation, and the latter could also be used as a basis for innovation policy on the surface, but its practical purpose seemed to be more focused on mapping the current technology situation analytically.

In conclusion, research at the level of innovator such as firms and individuals focuses on how to promote innovators' innovation activities so that they can provide policy makers with a more direct basis for decision making. In addition, since the most active innovator is firms and most innovation policies target firms, identifying the characteristics of the firm that cause homophily through firm-level research helps to provide a better understanding of the characteristics of the innovation ecosystem in an industry and contributes to deriving appropriate policy recommendations.

3.2.3.2 Determinants of Inter-firm Homophily

Previous studies that have analyzed homophily at the firm level have mainly selected relationship variables as factors affecting homophily, which differs from the existing partner selection literature. Specifically, the classic partner selection literature focuses primarily on firm characteristics when identifying factors that affect the formation of a collaborative innovation network (Becker & Dietz, 2004; Faria, Lima, & Santos, 2010; Hong & Su, 2013; Maggioni, Nosvelli, & Uberti, 2007; Maietta, 2015). Conversely, studies analyzing inter-firm homophily from a network perspective tend to focus on

relational variables such as previous collaborations, private relations among CEOs, and location of firms within the network (Casanueva,et al, 2013).

Previous studies on the determinants of inter-firm homophily have focused primarily on innovation and relational factors. However, there are differences between traditional partner selection studies and network studies in respect of whether or not to focus more on any of the variables.

First, studies on partner selection between firms have presented different results on the effect of technological proximity on collaborative innovation among firms. Mowery, Oxley, & Silverman (1998) analyzed 151 joint ventures, including 292 firms, using the Cooperative Agreements and Technology Indicators (CATI) database and found that a technological overlap facilitated the formation of a joint venture between firms. In contrast, Kim and Song (2007) determined that a technological overlap has no effect on joint patenting among firms through an analysis of the pharmaceutical industry. Cantner and Graf (2006) also analyzed the evolution of collaborative innovation networks with a focus on homophily. They hypothesized that technological proximity would lead to homophily in the innovation network and then conducted an empirical analysis using German patent data. They defined a technological overlap as technology of the same field shared by different innovators and analyzed the effect of a technological overlap on the formation of a collaborative innovation network. The results showed that innovators who have the same technology domain tend to engage in collaborative innovation. Since these studies were conducted at the individual level, it is unclear whether technological proximity also affects inter-firm homophily. However, the results of partner selection and homophily studies can infer that a technological overlap affects the formation of a collaborative innovation network.

Also, previous studies have shown that the economic proximity between firms also

affects partner selection in collaborative innovation networks. Sun and Liu (2016) argued that economic proximity affects network formation in China's inter-regional technology transactions. Economic proximity between firms indicates the similarity between sales and size among firms, and it can be guessed whether they belong to the same stock market and whether they are designated as large firms or SMEs.

Second, relational factors have also been regarded as promoting homophily in a collaborative innovation network. Previous studies have shown that public linkage among firms also affects partner selection in collaborative innovation networks. Public linkage among firms also affects partner selection in collaborative innovation networks (Cantner & Graf, 2006). A typical public relationship among firms is the presence of affiliates belonging to the same group. The decision makers in a group can use collaborative innovation among their affiliates as one of their growth strategies.

Previous studies on inter-firm collaborative innovation have found that regional proximity also affects partner selection among firms. Owen-Smith and Powell (2004) analyzed the collaborative innovation network of biotech firms in Boston, USA, and found that geographical proximity mitigates the effect of network centrality on innovation. Previous research has suggested that regional factors affect the formation and evolution of collaborative innovation networks, which suggests that firms tend to cooperate with one another in the same area or nearby. Cantner and Meder (2008) argued that not only technical but also regional factors affect the formation of a collaborative innovation network. They found that the tendency to engage in collaborative innovation in the region was frequent, especially in Eastern Germany. Broekel and Hartog (2013) conducted an empirical analysis of the structure of the cross-regional collaborative innovation network in the German chemical industry and found that the closer the distance between firms on the dyad level, the higher the tendency to

cooperate. Sun and Liu (2016) concluded that there is a high probability of network formation between agents that are close to each other in inter-regional technology transactions in China.

These previous studies suggest that innovation and relational factors affect homophily in collaborative innovation networks. If so, a question can be raised about which of the two factors has a more significant effect on homophily. This discussion is closely related to the debate between resource-based theory and transaction cost theory of collaborative innovation.

The debate regarding which approaches to resource-based theory and transaction cost theory better explain collaborative innovation has continued in the area of innovation research. According to resource-based theory, firms respond to diversified innovation needs by performing collaborative innovation (Penrose, 1959) in search of a partner with an innovative portfolio that can complement their lack of innovation capacity. According to this approach, firms consider innovative factors as the top priority when selecting partners.

According to transaction cost theory, firms perform collaborative innovation to reduce the cost of innovation (Coase, 1937; Williamson, 1981). In the collaborative innovation process, transaction costs are incurred not only due to the cost of the joint management of intellectual property rights but also due to the partner's opportunistic behavior and potential conflicts. Firms that participate in collaborative innovation as a motivator for cost reduction should consider reducing their transaction costs even when selecting partners. Therefore, they tend to make relatively "safe choices." If collaborative innovation is carried out among the affiliates in the same group, the management cost is reduced according to the group-level decision making and management system, the partner's opportunistic behavior possibility becomes relatively

low, and the possibility of a dispute decreases.

Thus, if the innovation factor has a more significant effect on the inter-firm homophily than the relational factor, it can be interpreted that firms choose a partner with innovation capability as the top priority, which represents the ideal open innovation ecosystem. In this innovative ecosystem, firms with a high level of innovation capacity and with a large number of technology portfolios tend to be preferred over other firms as collaborative innovation partners. Conversely, if the relational factor has a more significant effect on the inter-firm homophily than the innovation factor, it can be interpreted that firms choose partners with transaction cost savings as the top priority, and innovation competency is an ancillary criterion in partner selection. In this environment, the network is relatively closed due to the selection of partners based on existing public relations.

This section reviewed the previous research on the effect of innovation factors and relational factors on inter-firm homophily in a collaborative innovation network. The next section develops some research hypotheses and presents the research design for finding answers to these research hypotheses.

3.3 Research Design

3.3.1 Research Hypotheses

This study suggests some hypotheses about the factors of inter-firm homophily in the collaborative innovation network.

Both innovation and relational factors in collaborative innovation networks can promote inter-firm homophily. Previous studies have shown a tendency to discuss innovation and relational factors separately. Despite the fact that homophily in a collaborative innovation network is a partner selection process, there are two reasons for this difference in interpretation. First, the nature of the data used by each approach is different. Partner selection studies have tended to rely on firm-level panel data sets. Most researchers have not performed this transformation, although additional programming work and effort are required to generate additional relational variables. Also, studies analyzing homophily from the viewpoint of the network have depended on the network analysis program of the patent-level network data in the form of an adjacency matrix and extracted various relational variables, such as reciprocity and centrality. However, these studies have not undertaken the process of collecting additional firm characteristic data and converting them into network data. Second, there is a difference in the previous research on which each study depends. Partner selection studies have depended on traditional innovations while selecting variables, whereas homophily studies have tended to rely primarily on network literature in other areas.

However, some partner selection studies have used relational variables, and some homophily studies have used firm characteristic data. For example, Glückler (2010) conducted an analysis of homophily in a sales partnership network between firms in Germany. The results showed that firm characteristics, such as digital entry and firm

size, as well as relational variables, such as colocation, degree centrality, and multiconnectivity, also affect the formation of alliances between firms.

These studies have indicated that both innovation factors and relational variables are important factors in network formation and that both need to be considered when explaining network evolution. Therefore, innovation factors that include firm characteristics should still be considered in network analysis, as previous research on partner selection has revealed that it is the key element of collaborative innovation.

Similarly, Korean ICT firms can take into consideration the innovation capabilities of their counterparts when exploring collaborative innovation partners, and consider the relationship with their counterparts when considering the costs associated with collaborative innovation. Although the firm mainly considers the other firm's innovation factor when selecting its partner, the relationship factor can be set as a constraint. Similarly, even if the firm mainly considers the other firm's relationship factor, it can choose a firm with a high level of innovation capacity among firms with similar conditions. Therefore, this study hypothesizes that both innovation factors and relational factors promote homophily in a collaborative innovation network.

H1: Innovation factors promote inter-firm homophily in a collaborative innovation network.

H2: Relational factors promote inter-firm homophily in collaborative innovation networks.

The question then arises of which factors, among the relational and innovation factors, have a more significant effect on inter-firm homophily. This study suggests

hypotheses based on the characteristics of collaborative innovation and the perception of collaborative innovation of Korean firms.

Innovation factors affect collaborative innovation, considering that it is a complementary sharing of technology among firms. However, transaction costs associated with collaborative innovation are applied as a constraint to collaborative innovation decision-making. In other words, if the firm perceives the transaction costs associated with collaborative innovation to be higher than the benefits associated with collaborative innovation, firms prefer internal innovation rather than collaborative innovation. Given the nature of the collaborative innovation, the factors that have the most significant effect on inter-firm homophily can be grounded in the firm's perception of the benefits or costs associated with it.

Korean firms are more aware of the disadvantages of managing costs and resource outflows than collaborative innovation offers (Choi & Lee, 2010). The low proportion of Korean firms' participating in collaborative innovation is also because they recognize the costs associated with collaborative innovation more than profit. Therefore, transaction cost can be a significant constraint in the collaborative innovation of Korean firms, and Korean firms may prefer collaborative innovation with firms that have established public relations to reduce the associated transaction cost. In particular, large firms in Korea control their affiliates effectively at the group level, because they have a large share of the group as the majority shareholder and a vertical structure in which group-level decision making has a strong effect on the affiliates.

Innovation in the Korean ICT industry is dominated by some large firms with high market concentration. In addition, as noted above, the innovation activities of these large firms are controlled by top-down decision making at the group level. The main purpose of the diversification of the firm is to reduce the transaction costs due to

outsourcing, so the motivation to resolve the innovation internally is also reflected in diversification (Coase, 1937). Therefore, the group can try to reduce the transaction costs associated with collaborative innovation by controlling the innovation process within the group through the diversification of affiliates. Based on these discussions, this study presents the following hypothesis:

H3: Relational factors have a larger effect on inter-firm homophily in a collaborative innovation network than innovation factors.

3.3.2 Research Design

3.3.2.1 Conceptual Framework

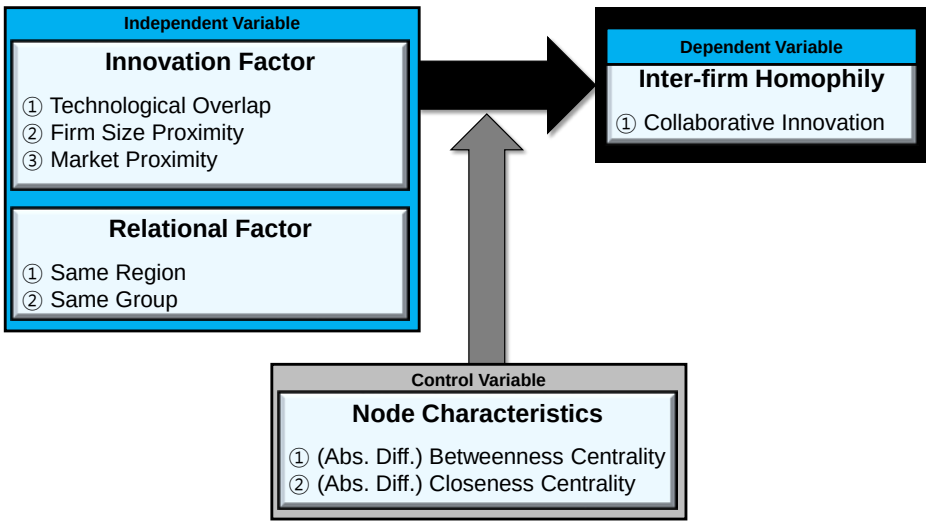
This section presents a conceptual framework based on the discussion in the previous section. The purposes of this study are as follows. First, it explores the evolution and general characteristics of the inter-firm collaborative innovation network in the Korean ICT industry. Second, it examines the effects of innovation and relational factors on inter-firm homophily and then identifies the factors that have a greater effect on homophily. This work not only extends the understanding of the process of forming a collaborative innovation network between Korean ICT firms but also examines the openness of the collaborative innovation ecosystem in the Korean ICT industry.

This study assumes that both innovation factors and relational factors affect homophily in a collaborative innovation network by integrating two research trends: research on partner selection between firms and research on network evolution.

However, it also supposes that there is a difference in the magnitude of the effect of these factors on homophily. Specifically, this study shows that the inter-firm homophily phenomenon in the Korean ICT industry is motivated by "safe choices" to reduce transaction costs rather than the complementary use of innovation capabilities in firms' decision-making process regarding partners. In contrast, resource-based theory explains that firms engage in collaborative innovation based on their motivation to complement their innovation capacity (Penrose, 1959), while transaction cost theory explains that firms carry out collaborative innovation to minimize their transaction costs (Coase, 1937). Therefore, this study argues that transaction cost theory rather than resource-based theory can better explain homophily in the collaborative innovation network of the Korean ICT industry.

In the inter-firm collaborative innovation network in the Korean ICT industry covered in this study, firms consider various factors when selecting innovation partners. When a network is formed by the interaction of multiple micro-motives of agents, a macroscopic pattern of homophily appears. The hypotheses presented in this study are tested through an analysis of the determinants of homophily. The conceptual framework of this study is presented in Figure 3.4 below.

Figure 3.4 The Conceptual Framework of the Study



3.3.2.2 Data Collection

This study builds a firm-level panel data set of patents filed by Korean ICT firms. The ICT firms in this study are 525 firms defined by the KIS-IC. The patent data filed by these firms are collected from the National Digital Science Library (NDSL). The data are from the period 1980 to 2015, when all registered patents were published. The patent data include the application year, firm name, and IPC code.

Additionally, this study collects firm characteristic data from KISVALUE. First, it collects the location information of the firm's head office at the detailed address level and then reclassifies the firms into 17 regions at the city and provincial level.[14] Second, it collects data on whether any individual firms belong to KOSPI, KOSDAQ, or

[14] Seoul Metropolitan City, Incheon, Daejeon, Sejong, Daegu, Ulsan, Busan, Gwangju, Gyeonggi, Gangwon, Chungcheongbuk, Chungcheongnam, Gyeongsangbuk, Gyeongsangnam, Jeonbuk, Jeollanam, and Jeju.

KONEX. Third, this study collects information on whether each firm is classified as a large firm or SME. Fourth, this study collects group names of affiliates to identify whether they belong to the same group. Finally, all the IPC codes of each patent that firms have filed from raw patent data are collected.

The collected data are transformed into a firm-level adjacency matrix for network analysis. Specifically, this study transforms the collaborative innovation network among firms into a weighted adjacency matrix using the raw patent data. The weight is proportional to the number of cumulative collaborations with the other agent.

3.3.2.3 Variables

First, previous studies have produced varying results on the effect of technological proximity on collaborative innovation among firms. Cantner and Graf (2006) defined a technological overlap as technology of the same field common to different innovation entities. Specifically, they measured a technological overlap by determining whether each agent had the same IPC and then analyzed the effect of the technological overlap on the formation of a collaborative innovation network.

Second, the economic proximity among firms affects partner selection in collaborative innovation networks (Sun & Liu, 2016). The economic proximity among firms means the similarity of the sales and size of firms, which can be judged by whether they belong to the same stock market and whether they are designated as large or small firms.

Third, the public linkage among firms also affects partner selection in collaborative innovation networks (Cantner & Graf, 2006). A typical public relationship among firms is the presence of affiliates belonging to the same group.

Fourth, previous studies have suggested that regional proximity affects partner selection (Broekel & Hartog, 2013). They have proposed that regional factors affect the formation and evolution of collaborative innovation networks, and they have argued that there is a tendency to collaborate with firms within the same geographical area or nearby.

Finally, the differences in centrality indicators among firms need to be controlled. This means that the central agent tends to relate to the isolated agents. The centrality indicators include closeness and betweenness centrality. These variables are presented in Table 3.2 below.

Table 3.2 Variables of Analysis by Type

Variable Type		Variable Name	Measurement
Dependent Variable		*Collaborative Innovation*	Number of Joint Patents (Cantner & Graf, 2006).
Independent Variables	**Innovation Factors**	*Technological Overlap*	Number of overlapped IPCs within a patent between two firms (Cantner & Graf, 2006)
		Firm Size Proximity	Whether each firm is classified as a Large firm or a SME
		Market Proximity	(Same stock market = 1, else = 0)
	Relational Factors	*Same Region*	(Same region = 1, else = 0)
		Same Group	(Same Group = 1, else = 0)
Control Variables	**Relational Factors**	*Betweenness Centrality*	The absolute difference of betweenness centrality between two agents
		Closeness Centrality	The absolute difference of closeness centrality between two agents

The variables used in this study form an adjacency matrix with 525 rows and columns. The descriptive statistics for the observations in the matrix corresponding to each variable are shown in Table 3.3 below.

Table 3.3 Descriptive Statistics of the Network Variables

Variable	Obs.[1)]	Mean	Std. Dev.	Min.	Max.
Dependent Variable					
Collaborative Innovation	275,625	0.00210	0.21828	0	60
Independent Variable					
Technological Overlap	275,625	0.86889	8.68539	0	1943
Firm Size Proximity	275,625	0.57040	0.49502	0	1
Market Proximity	275,625	0.62743	0.48349	0	1
Same Region	275,625	0.29694	0.45691	0	1
Same Group	275,625	0.00094	0.03070	0	1
Control Variable					
Betweenness Centrality	275,625	14.01523	90.81037	0	1009.167
Closeness Centrality	275,625	0.08654	0.19697	0	1

Note: 1) The number of nodes in the adjacency matrix with 525 rows and columns.

Since all the variables form the adjacency matrix, the observed value of each variable is 275,625, which is the square of 525. The summary statistic of the collaborative innovation variable, which is a dependent variable in this study, indicates that a firm performed an average of 0.002 collaborative innovations with 524 other firms. Collaborative innovation between 2 firms was performed up to 60 times. Given that the standard deviation is much larger than the average, it is evident that collaborative innovation is performed only among a small number of firms.

Looking at the technological overlap variable, one firm shares 0.87 patent IPCs on average with other firms and shares a maximum of 1943 patent IPCs. The reason for the large size of the maximum value is that a plurality of IPCs can exist in 1 patent and a firm performs many independent innovations and accumulates its own technical capability. The remaining independent variables are dummy variables with a maximum value of 1. The average of firm size proximity and market proximity is higher than 0.5, but the average of the same region and the same group is lower than 0.5.

3.3.2.4 Methodology and Estimation Strategy

Estimating network dyadic data using OLS violates the assumption that all observations are independent and identically distributed (iid). Observations in the network are interconnected. For example, $y_{i,j}$ and $y_{i,k}$ are not independent of each other because i is overlapped. Since the observations of the same row or column in dyadic data have a positive correlation with each other, estimating them using OLS can result in too small of a standard error and a more optimistic p-value than the actual one (Simpson, 2001). Therefore, there is a problem of autocorrelation when analyzing dyadic data using OLS.

To solve this problem, Krackhardt (1988) proposed the quadratic assignment procedure (QAP). QAP is an alternative estimation method based on a simulation which is known to be robust against multicollinearity and autocorrelation (Dekker, Krackhardt & Snijders, 2007). If the independence assumption is not satisfied, the rows and columns of the dependent variable matrix are randomly permuted and regression analysis is performed using the independent variable matrix (Simpson, 2001). This random permutation is repeated several times to derive the distribution of regression

coefficients based on the results of regression analysis. Since there are too many possible permutations, random samples of these permutations are used to generate the reference distribution (Cantner & Graf, 2006; Hubert, 1987). Based on the distribution of the regression coefficients, the probability of the regression coefficients between the dependent variable and the independent variable matrix is estimated. The structural representation of the network variables are presented as below (Cantner & Graf, 2006).

$$\mathrm{Y} = \begin{bmatrix} 0 & y_{1,2} & \cdots & y_{1,n-1} & y_{1,n} \\ y_{2,1} & 0 & & y_{1,n-1} & y_{2,2} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ y_{n,1} & y_{n,2} & \cdots & y_{n,n-1} & 0 \end{bmatrix}$$

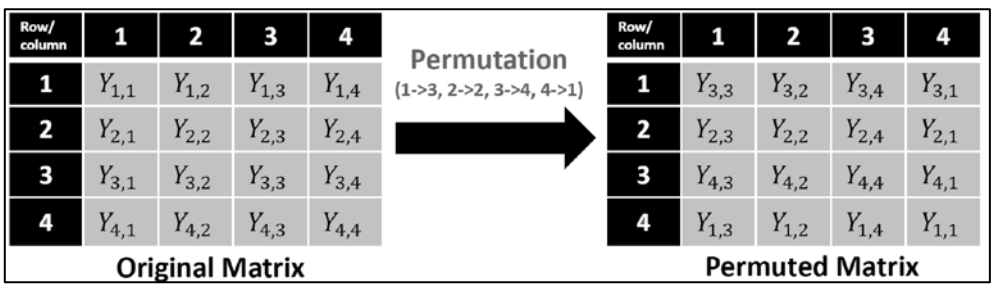
$$\mathrm{X} = \begin{bmatrix} 0 & x_{1,2} & \cdots & x_{1,n-1} & x_{1,n} \\ x_{2,1} & 0 & & x_{1,n-1} & x_{2,2} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ x_{n,1} & x_{n,2} & \cdots & x_{n,n-1} & 0 \end{bmatrix}$$

In an undirected network, the observations in the above adjacency matrix are transformed into the generalized specification as follows:

$$y_{ij} = \alpha + \beta x_{ij} + \varepsilon_{ij}$$

In the above equation, y_{ij} presents the network corresponding to the dependent variable and x_{ij} presents the network corresponding to the independent variable. After estimating the above equation as OLS, the study returns to the first step and performs random permutation on the rows and columns of the dependent variable. An example of random permutation is presented in Figure 3.5 (Simpson, 2001).

Figure 3.5 An Example of Random Permutation (Retrieved from Simpson, 2001)



Next, this study transforms the adjacency matrices back into vectors, converts them into a generalized form, and then performs a regression analysis. It repeats this process about 2,000 times and uses the estimates to derive the distribution of the regression coefficients. The specification of the regression model is as follows:

$$
\begin{aligned}
&CollaborativeInnovation_{ij} \\
&\quad = \alpha + \beta_1 TechOverlap_{ij} + \beta_2 SubTechOverlap_{ij} \\
&\quad + \beta_3 FirmSizeProximity_{ij} + \beta_4 MarketProximity_{ij} \\
&\quad + \beta_5 SameRegion_{ij} + \beta_6 SameGroup_{ij} \\
&\quad + \beta_7 ClosenessCentrality_{ij} + \beta_8 BetweennessCentrality + \varepsilon_{ij}
\end{aligned}
$$

If the dependent variable is continuous data or count data, QAP regression should be performed, but exponential random graph model (ERGM) analysis should be performed when the dependent variable is binary data (Carley, Pfeffer, Reminga, Storrick, & Columbus, 2013). Since the dependent variable matrix is a weighted network consisting of count data, this study conducts QAP regression analysis.

When the size of the network is too large, that is, when the number of nodes is too large, a large network problem occurs (Borgatti, Everett, & Johnson, 2013). Borgatti et al. (2013) summarized the large network problem as space, time, and usability, where space represents computer memory, time represents execution time, and usability represents usefulness of results. That is, in a network with a considerable number of nodes, the memory required for network operation increases exponentially, which is very time-consuming to analyze with general computing power. Also, when analyzing a large network, the R-squared value of the QAP regression analysis is estimated to be very low, thus reducing the overall explanatory power of the analysis result. Borgatti et al. (2013) propose a method to remove unconnected nodes or less weighted edges to reduce the size of this large network problem. When this is not possible, they suggest selecting sample networks on a large network.

3.4 Results

3.4.1 Descriptive Network Analysis

Before conducting the network regression analysis, this study examines the changes in network characteristics and their implications with descriptive statistics. Descriptive network analysis has the advantage of capturing the structure and structural evolution among agents that regression or empirical case studies cannot capture (Topper & Carley, 1999). This study explores 1) the changes in network characteristics, 2) the key agents by period, and 3) the characteristics of network topology through a descriptive network analysis.

3.4.1.1 Network Characteristics

This study explores how the characteristics of the collaborative innovation network between Korean ICT firms from 1980 to 2015 changed. Changes in these network characteristics can be captured using standard social network measures (Topper & Carley, 1999). Topper and Carley (1999) presented the number of nodes, number of isolates, density, connectivity, graph efficiency, and betweenness centrality as standard social network measures available at the descriptive network analysis stage. This study explores how the number of firms, number of connected firms, network density, mean degree, mean betweenness centrality, and mean closeness centrality have changed over time, using the same or similar measures to those presented.

To explore the changes in the network for each regime, the time of observation is set to the last year of each regime, which is the year of the presidential election, except for 2015. This interval setting enables the study to identify how the collaborative innovation network has changed as the regime has changed.

Therefore, this study analyzes the change in the network at seven points: 1987, 1992, 1997, 2002, 2007, 2012, and 2015. To increase the visibility, the top five groups with the highest innovation performances are presented in different colors. The highest innovation performances are for the Samsung Group followed by KT, LG, Dongbu, and SK. In addition, the size of the nodes in this study is shown to increase in proportion to the degree. Changes in the network by the regime are presented in Figure 3.6 below.

Figure 3.6 Evolution of the Inter-firm Collaborative Innovation Network in the Korean ICT Industry

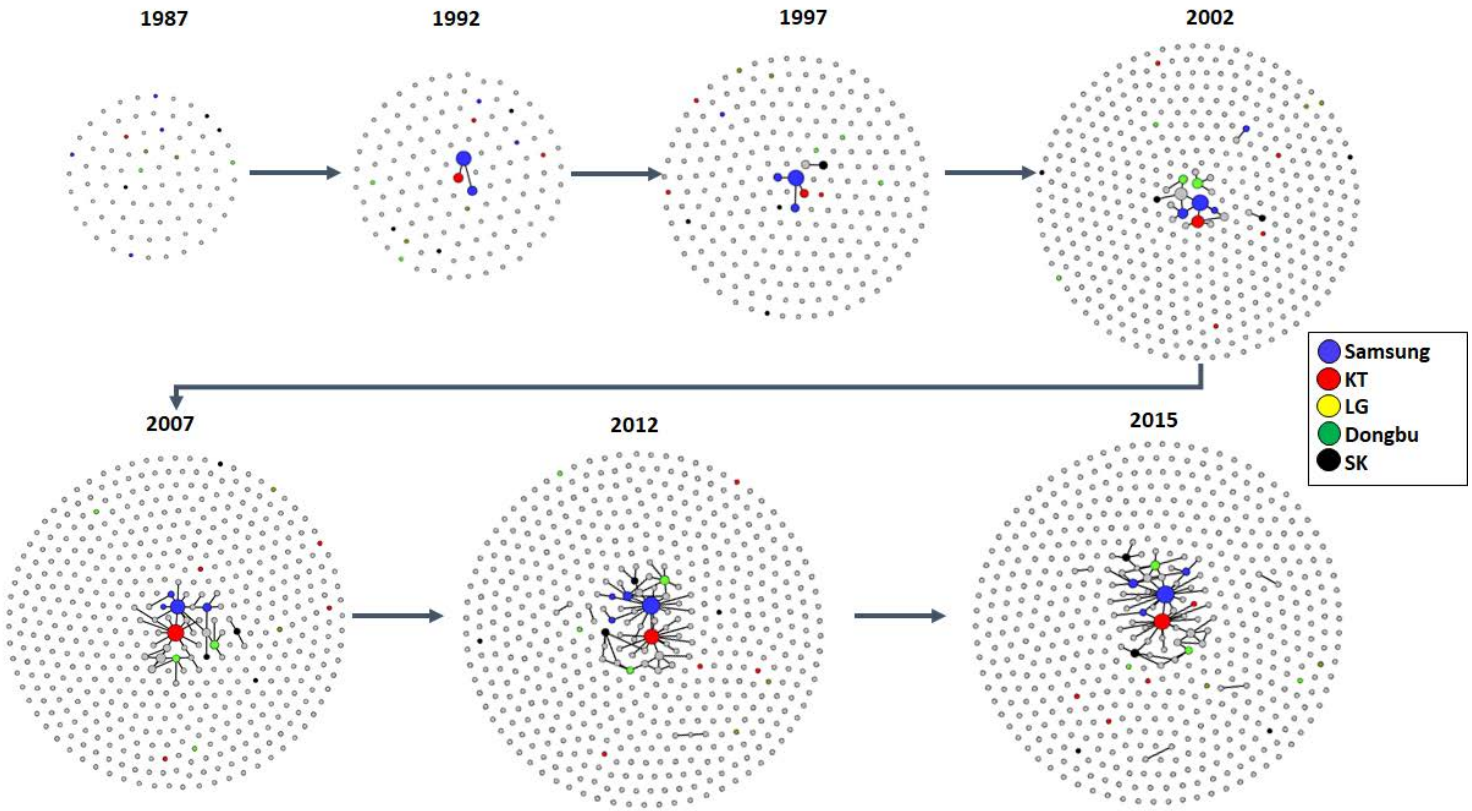


Figure 3.6 shows some of the characteristics of the network change. First, the collaborative innovation network between Korean ICT firms is a low-density network. The ratio of unconnected nodes among all the nodes is high, indicating that inter-firm collaborative innovation in the Korean ICT industry is not well activated.

Second, inter-firm collaborative innovation in the Korean ICT industry is dominated by a small number of large firm affiliates with high innovation performance. Figure 3.6 shows that the collaborative innovation from the blue node representing the Samsung group affiliate and the red node representing KT appeared in 1992 and that the collaborative innovation network has evolved around these two entities. In the network, at the beginning of 2015, large firm subsidiaries with high innovation performance formed hubs, and other firms were located on the edge. This means that large firm affiliates with high innovation performance were in a leading position in the collaborative innovation network, while the remaining firms performed collaborative innovation by joining the existing cooperative relationship network formed by large firms. Exceptionally, it is also observed that some firms formed a one-to-one network independently, but they did not form a separate cluster.

Third, the collaborative innovation network between Korean ICT firms expanded significantly over a certain period. During the period from 1997 to 2002, a large number of ICT firms were established, and LG Group affiliates and other firms joined the collaborative innovation network. During the period from 2002 to 2007, Samsung affiliates and KT began to form the hub of the current network. In summary, the number of nodes expanded during the Kim Dae-jung administration, and since the Roh Moo-hyun Government has begun to participate in various firms in the network, the network has become complicated.

This study explores the changes in five network measures over time to investigate the change in the network more specifically. The changes in each measure are shown in Table 3.4 below.

Table 3.4 Network Characteristics

Year	Firms (Linked)	Density (Edges)	Mean Degree	Betweenness Centrality	Closeness Centrality
1987	81 (0)	0.0000000 (0)	0.00000	0.000000	0.00000
1992	123 (3)	0.0002665 (2)	0.03252	0.000000	0.01897
1997	232 (6)	0.0001493 (4)	0.03448	0.000000	0.02069
2002	432 (21)	0.0002041 (19)	0.08796	0.004167	0.02835
2007	486 (41)	0.0003564 (42)	0.17284	0.007393	0.03153
2012	515 (57)	0.0004684 (62)	0.24078	0.007508	0.04194
2015	525 (64)	0.0005089 (70)	0.26667	0.008411	0.04758

The number of ICT firms in Korea has increased steadily, reaching 525 in 2015, 6.5 times more than in 1987. Between 1997 and 2002, 200 firms, 38% of all firms, were established. The number of linked firms shows the highest net increase between 2002 and 2007. As of 2015, 64 firms, about 12% of all firms, are participating in collaborative innovation. The proportion of firms participating in collaborative innovation has been increasing steadily, but the increase has been gradual since 2007.

The network density has grown moderately since 1992, but it remains low. This indicates that the network is sparse rather than dense. In a sparse network, only a small number of nodes are connected to each other. In this network, only a few firms

can form a collaborative innovation network. The total number of edges shows the highest net increase between 2002 and 2007. This means that the most new collaborative innovation partnerships were formed during this period.

The change in the mean degree shows that the average number of connections of firms has been steadily increasing. This represents the average number of collaborative innovation partners in firms. In other words, as of 2015, the average number of collaborative innovation partners in Korea's ICT firms is 0.27.

The mean betweenness centrality increased sharply from 1997 to 2007. High mean betweenness centrality suggests that the network is a centralized system (Topper & Carley, 1999). Therefore, the rapid centralization of the collaborative innovation network from 1997 to 2007 can be seen. This means that the central agents have begun to act as hubs in the network in earnest from this period, and the network has begun to be formed around a few hubs.

The mean closeness centrality is 0.04 as of 2015, which is relatively low. The mean closeness centrality is also used to determine whether the network is a centralized system as well as the mean betweenness centrality. However, closeness centrality differs from betweenness centrality in that it defines the network in consideration of the path distance including the indirect connection between the nodes. Therefore, when the indirect connection is included, the network can be regarded as maintaining the form of a sparse network.

To sum up, the collaborative innovation network between Korean ICT firms has a low-density network, which means that the proportion of firms participating in collaborative innovation is not high. Collaborative innovation is dominated by a handful of firms, which act as hubs within the network. The questions arise of who

the firms that are leading the collaborative innovation are, what their position is in the network, and which characteristics they have. This study conducts a second descriptive network analysis to find answers to these questions.

3.4.1.2 Identifying the Key Agents

This study identifies key agents at each point in the collaborative innovation network. Therefore, it presents the five firms with the highest degree by seven points in 1987, 1992, 1997, 2002, 2007, 2012, and 2015 and explores the network characteristics of these firms. As firms with higher degrees have many connections with other firms, they can be interpreted as firms that actively participate in collaborative innovation. Specifically, this study examines the degree, weighted degree, betweenness centrality, and closeness centrality of the major agents.

First, this study analyzes the distribution of the major agents in the collaborative innovation network. The linked firms in 2015 are shown in Figure 3.7.

Figure 3.7 Linked Firms in 2015

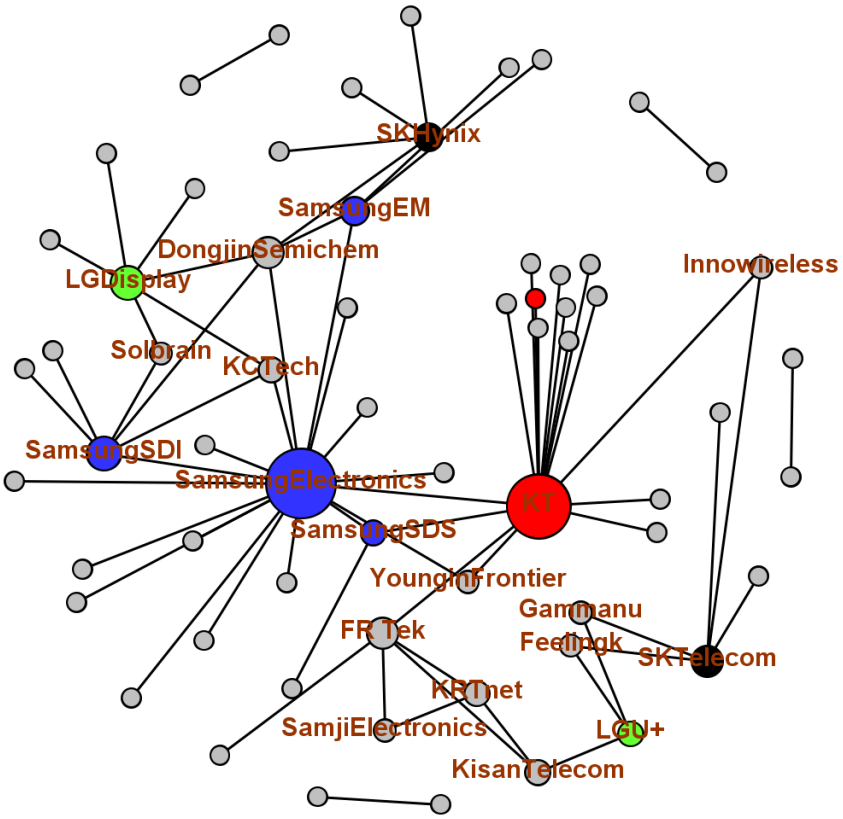


Figure 3.7 shows that Samsung Electronics and KT form a hub in a collaborative innovation network. Large firms, as well as SMEs, appear to join the collaborative innovation network. Therefore, it seems that the major agents in the network are not limited to large firms. Most firms, except SMEs with some one-to-one cooperation, belong to the giant component, and mainly SMEs are connected to the large firm at the center. This means that large firms are in a more important position than SMEs in the whole collaborative innovation network.

Samsung Electronics, which acts as a hub in the network, is directly connected to KT as well as being connected through Samsung SDS and Youngin Frontier. Firms that are connected to Samsung Electronics act as intermediary hubs for firms that actively participate in innovation. These include large firms, SMEs, and medium-sized firms, and they actively participate in collaborative innovation with a variety of partners. On the other hand, many firms are directly connected to KT, most of which are small and medium-sized firms, and the connection structure is straightforward compared with Samsung Electronics.

This is because the technology portfolio of Samsung Electronics is more complicated than that of KT and its investment in innovation is much higher than that of KT. In particular, unlike KT, Samsung Electronics conducts R&D on semiconductors, so it appears to have diversified collaborative innovation relationships with semiconductor firms. Therefore, the complexity of its collaborative innovation structure seems to be greater than that of KT.

The remaining large firms are mainly located at the edge of the network and are connected to SMEs. Figure 3.7 shows that there are few connections between large firms and large firm–SME connections.

This study selects the key agents at a certain time in the collaborative innovation network to examine them more specifically. The list of key agents by time is presented in Table 3.5 below.

Table 3.5 Key Agents in the Collaborative Innovation Network

Year	Firm	Degree (Weighted)	Betweenness Centrality	Closeness Centrality
1987	(None)	--	--	--
1992	Samsung Electronics	2 (3)	1.0000	1.00000

	KT	1 (2)	0.0000	0.66667
	Samsung SDI	1 (1)	0.0000	0.66667
1997	Samsung Electronics	3 (15)	3.0000	1.00000
	KT	1 (11)	0.0000	0.60000
	Samsung EM	1 (3)	0.0000	0.60000
	SK Telecom	1 (1)	0.0000	1.00000
	Fine Digital	1 (1)	0.0000	1.00000
	Samsung SDI	1 (1)	0.0000	0.60000
2002	Samsung Electronics	6 (31)	45.0000	0.63158
	KT	4 (24)	21.0000	0.48000
	Dongjin Semichem	4 (5)	29.0000	0.54546
	LG U+	3 (8)	3.0000	1.00000
	Samsung SDI	3 (4)	11.0000	0.50000
2007	KT	12 (48)	414.0000	0.47297
	Samsung Electronics	10 (112)	387.0000	0.46667
	FR Tek	5 (8)	204.0000	0.37234
	Samsung SDI	4 (26)	67.0000	0.35354
	LG Display	4 (25)	99.0000	0.28226
	Dongjin Semichem	4 (25)	154.0000	0.36458
2012	Samsung Electronics	17 (157)	893.3333	0.49505
	KT	14 (51)	775.6667	0.46729
	LG Display	6 (35)	147.8333	0.29240
	Samsung SDI	6 (33)	138.8333	0.37037
	FR Tek	5 (8)	216.6667	0.34722
2015	Samsung Electronics	18 (169)	1009.1670	0.48673
	KT	16 (53)	939.0000	0.46610
	Samsung SDI	6 (42)	152.2661	0.36424
	LG Display	6 (35)	164.6667	0.29255
	Dongjin Semichem	5 (30)	304.5000	0.38194
	FR Tek	5 (8)	239.0000	0.34375
	SK Telecom	5 (7)	198.5000	0.26961

Firms with a high degree are "mass collaborators" (Butts, Acton, & Marcum, 2012). Cooperating with new partners always involves coordination costs, so these mass collaborators face pressure to organize interaction with other partners (Butts et

al., 2012; Williamson, 1975). The list of top firms in order of degree shows the key agents over time. In 1987 no firms were involved in inter-firm collaborative innovation, but in 1992 Samsung Electronics, KT, and Samsung SDI participated. Since then, Samsung Electronics and KT have widened the degree gap with other firms and played the role of a mass collaborator in collaborative innovation. Samsung SDI has a high weighted degree, while the lower degree is due to its cooperation with existing partners rather than new partners.

Firms with a high degree may have a high degree of betweenness centrality and closeness centrality, but this is not necessarily the case. Betweenness centrality measures the degree to which a node is located between other nodes in the network. Organizations with a high degree of betweenness centrality play a key role in information and resource sharing (Butts et al., 2012). A firm with high betweenness centrality in a collaborative innovation network is in a position to complement its technical resources with firms that lack the information or technical resources needed for innovation. Therefore, it can be interpreted that there is a great capacity to use internal innovation resources complementarily with external partners.

Closeness centrality is measured as the shortest path distance between two nodes. The shorter the path distance is, the higher the closeness centrality is. Organizations with high closeness centrality can acquire new information more quickly than others and establish "information centers" within the network (Butts et al., 2012).

According to Table 3.5, firms with a higher degree have higher betweenness centrality and closeness centrality. Exceptionally, Dongjin Semichem and FR Tek show higher betweenness centrality than other large firms, except for Samsung

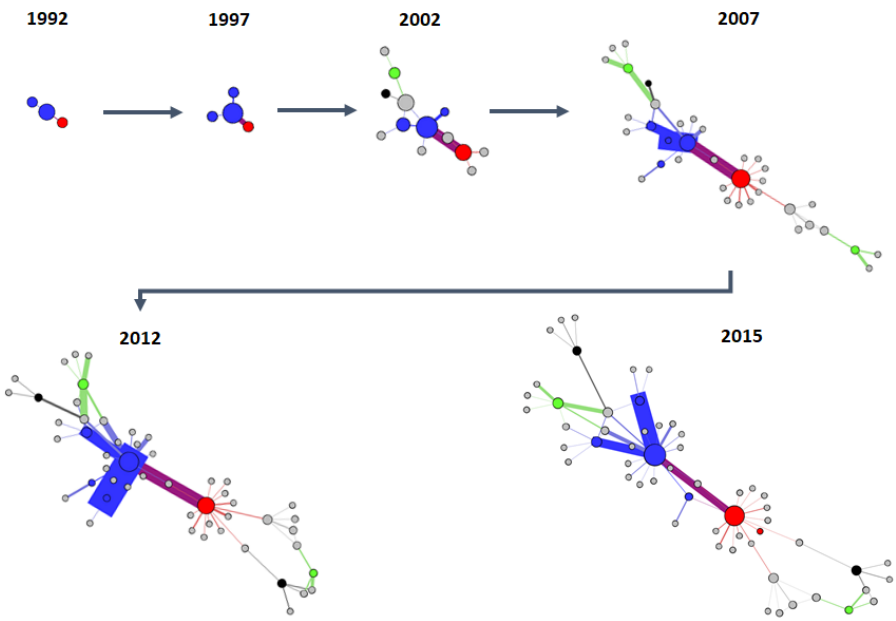
Electronics and KT. This indicates that it is in a position to share its technical resources with other firms and that it is highly competent in using internal innovation resources complementarily with external partners. This implies that SMEs play an important role in collaborative innovation rather than the collaborative innovation network between Korean firms and ICT firms.

The next section defines the topology of the giant components that are formed by the key agents discussed in this section and performs a third descriptive network analysis to analyze what these topologies typically have.

3.4.1.3 Network Topology

Third, this study examines the characteristics of the topology of the collaborative innovation network. Specifically, it investigates the giant component composed of interconnected firms to examine the characteristics of the topology. The topology change in the giant component over time is shown in Figure 3.8 below.

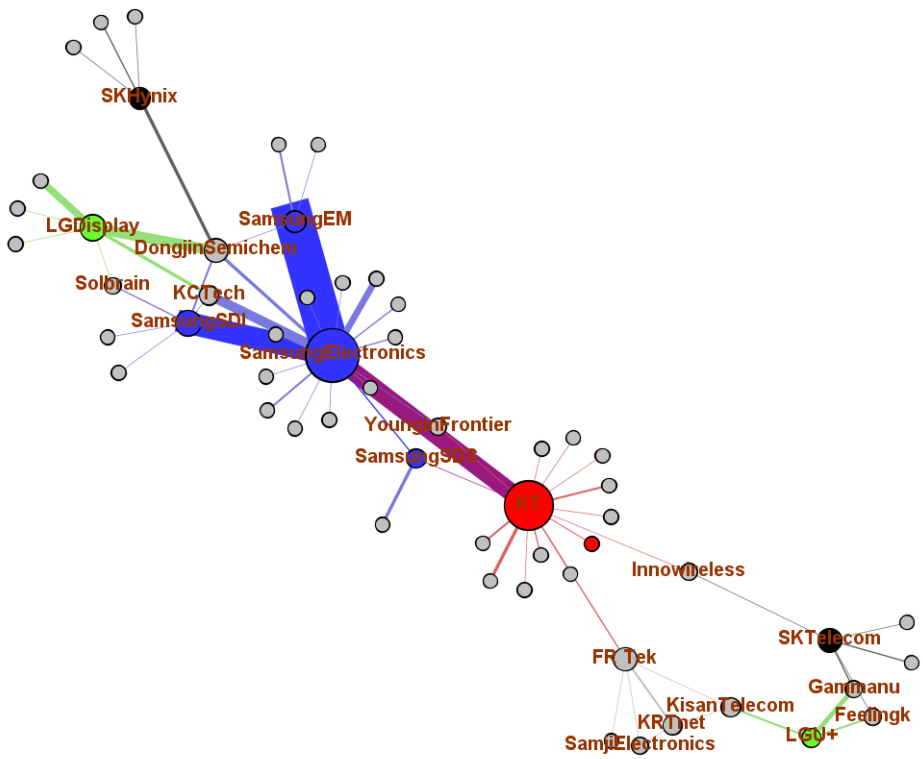
Figure 3.8 Evolution of the Giant Component (Topology)



The thickness of the edge increases proportionally to the weight, and the weight is determined by the number of collaborative innovations between the two firms. The bold edge indicates that the number of collaborative innovations between the two firms is relatively high. According to Fig. 2.4, Samsung affiliates and KT were linked to Samsung Electronics until 1997, but in 2002 collaborative innovation between Samsung Electronics and KT increased and KT formed a hub of the network with Samsung Electronics. Samsung affiliates have also begun to engage in collaborative innovation with SMEs. In 2007 a network similar to the current one emerged with Samsung Electronics and KT as hubs. The giant component in 2015 is presented in

Figure 3.9.

Figure 3.9 Giant Component in 2015



Samsung Electronics and KT are the hubs within the giant component. Samsung Electronics, Samsung Electro-Mechanics, Samsung SDI, KC Tech, and Dongjin Semichem are connected to each other. KT extends the branch through FR Tek and Innowireless. Furthermore, both Samsung Electronics and KT are directly connected

with SMEs. The edges connecting Samsung Electronics with Samsung Electro-Mechanics, Samsung Electronics, and Samsung SDI and Samsung Electronics with KT are bigger than the other edges, indicating that the collaborative innovation among these firms is relatively active.

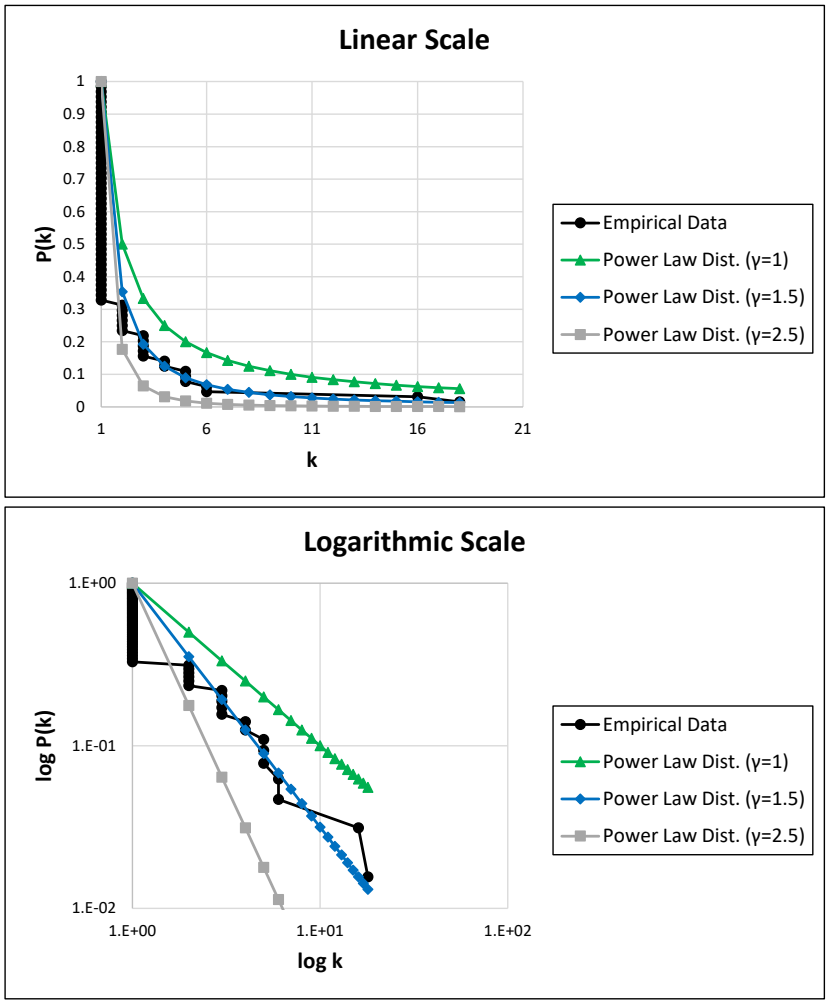
The network looks like a typical scale-free network. A scale-free network is a network in which the distribution of degree k is in the form of a power law function (Watts & Strogatz, 1998).

$$P(k) \sim k^{-\gamma}$$

where k is the degree and P (k) is the probability that the nodes will have k connections. That is, in a scale-free network, the probability that internal nodes will have k connections is given by the γ power of k. For example, the probability of a node having one connection is close to 1, which means that the probability of having two or more connections decreases drastically.

To discriminate more analytically whether the degree distribution of the giant component follows the power law distribution, this study compares the giant component of the collaborative innovation network and the various power law distributions according to the γ values on a linear scale and a logarithm scale. These comparisons are shown in Figure 3.10.

Figure 3.10 Degree Distribution of Giant Component



The comparison on the linear scale shows that the network has a long tail distribution close to the power law distribution. In addition, the degree distribution of the network is on the logarithmic scale, which is not perfect but looks like a straight line. Specifically, it is evident that the degree distribution is similar to the scale-free network following the power law distribution with $\gamma = 1.5$. A network with

$\gamma > 2$ is a sparse scale-free network, while a network with $\gamma \leq 2$ is a dense scale-free network (Genio, Gross, & Bassler, 2011). Therefore, the collaborative innovation network between Korean ICT firms is close to a sparse scale-free network.

This scale-free network is described as being generated according to the preferential attachment process due to the preference among agents (Price, 1976). Therefore, considering the preferential attachment process, it can be interpreted that the Korean ICT network is formed based on the preference of other firms about Samsung Electronics and KT, which are hub firms, and expanded with the preference for firms that have collaborative innovation with them. In other words, Samsung Electronics and KT had higher levels of technological competitiveness than other firms, and firms that collaborated with them also increased their innovation capacity, which made them a preferred partner.

3.4.2 Network Regression Analysis

This study examines the correlation between networks corresponding to each variable through QAP correlation analysis before performing regression analysis. The QAP correlation analysis is performed for all the nodes and linked nodes to respond to the potential large-network problems. The results of the QAP correlation analysis for all the nodes are shown in Table 3.6, and the results of the QAP correlation analysis for the linked nodes are shown in Table 3.7. The correlation coefficient of each analysis is estimated through 5,000 iterations of a random permutation.

The correlation analysis results presented in Table 3.6 show that the independent

and control variables in the whole network have weak or moderate correlations with each other. The correlation coefficient between betweenness centrality and closeness centrality is 0.233, and all the others have a correlation coefficient that is less than 0.3 or not significant. Therefore, it is judged that there is no multicollinearity problem in the regression model for all the nodes.

Additionally, the correlation analysis results presented in Table 3.7 show that there is a weak or moderate correlation between the independent and the control variables in the connected network. The correlation coefficient between firm size proximity and market proximity is the highest at 0.308. All of the other variables show a correlation coefficient that is less than 0.3 or not significant. Therefore, the regression model for the linked nodes is also considered to have no multicollinearity problem.

Table 3.6 QAP Correlation Coefficients between Independent Variables (All Nodes)

	Collab. Inno. (Dependent)	Tech. Overlap	Firm Size Proximity	Market Proximity	Same Region	Same Group	Closeness Centrality	Betweenness Centrality
Collab. Inno.(Dependent) (P-value)	1							
Tech. Overlap (P-value)	0.597*** (0.000)	1						
Firm Size Proximity (P-value)	0.002 (0.298)	0.006 (0.238)	1					
Market Proximity (P-value)	0.001 (0.484)	0.007 (0.322)	0.084*** (0.000)	1				
Same Region (P-value)	-0.003 (0.231)	-0.006 (0.223)	0.011 (0.158)	0.035* (0.032)	1			
Same Group (P-value)	-0.000 (0.936)	-0.003 (0.180)	0.011** (0.001)	0.002 (0.291)	0.019*** (0.000)	1		
Closeness Centrality (P-value)	0.001 (0.305)	0.063** (0.005)	0.008 (0.381)	0.012 (0.391)	0.008 (0.356)	0.002 (0.302)	1	
Betweenness Centrality (P-value)	0.058** (0.001)	0.208*** (0.000)	0.000 (0.507)	0.031 (0.231)	-0.010 (0.323)	0.000 (0.337)	0.233** (0.002)	1

Note: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

Table 3.7 QAP Correlation Coefficients between Independent Variables (Linked Nodes)

	Collab. Inno. (Dependent)	Tech. Overlap	Firm Size Proximity	Market Proximity	Same Region	Same Group	Closeness Centrality	Betweenness Centrality
Collab. Inno.(Dependent) (P-value)	1							
Tech. Overlap (P-value)	0.769*** (0.000)	1						
Firm Size Proximity (P-value)	0.036 (0.078)	0.039 (0.106)	1					
Market Proximity (P-value)	-0.007 (0.369)	-0.020 (0.392)	0.308*** (0.000)	1				
Same Region (P-value)	0.051* (0.042)	0.058 (0.076)	0.017 (0.223)	-0.050 (0.193)	1			
Same Group (P-value)	0.356*** (0.000)	0.291*** (0.000)	0.049 (0.055)	0.020 (0.297)	0.024 (0.202)	1		
Closeness Centrality (P-value)	-0.031 (0.123)	-0.021 (0.478)	0.026 (0.277)	-0.076** (0.002)	0.047 (0.237)	-0.043* (0.032)	1	
Betweenness Centrality (P-value)	0.159 (0.018)	0.235** (0.001)	-0.116** (0.002)	-0.307 (0.170)	0.080 (0.122)	0.078* (0.019)	-0.018 (0.640)	1

Note: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

This study performs QAP regression to investigate the effect of innovation and relational factors on firm homophily. First, it conducts a regression analysis for all the nodes and then a regression analysis for the linked nodes. A total of 2,000 random permutations are performed for each model.

First, the results of the QAP regression for all the nodes are shown in Table 3.8 below. Since the p-value for the regression model is statistically significant at the 99.9% level, this model is statistically significant, and the R-squared model has relatively low explanatory power of about 0.36.

Table 3.8 QAP Regression (All Nodes)

Variable		Un-stdized. Coefficient	Stdized. Coefficient	Std. Error	P-value
Independent Variables					
Innovation Factors	Technological Overlap	0.01537***	0.61138***	0.00050	0.00050
	Firm Size Proximity	-0.00064	-0.00145	0.00153	0.34383
	Market Proximity	-0.00046	-0.00102	0.00231	0.44428
Relational Factors	Same Region	0.00028	0.00058	0.00167	0.43728
	Same Group	0.00317	0.00045	0.01419	0.25137
Control Variables					
Closeness Centrality (Abs. Diff.)		-0.00015***	0.02325***	0.00002	0.00050
Betweenness Centrality (Abs. Diff.)		-0.02578***	0.06331***	0.00661	0.00550
Intercept		-0.00634***	0.00000***	0.00000	0.00000
Nodes		525			
Permutations		2,000			
R-squared		0.36106			
Adj. R-squared		0.36104			
P-value		0.00050***			

Note: * p<0.05; ** p<0.01; *** p<0.001

The QAP regression results for all the nodes indicate that the independent variables have little or no effect on inter-firm homophily. Technological overlap is the only statistically significant positive effect of homophily. However, unlike previous studies, such as that by Cantner and Graf (2006), the coefficient estimated by this analysis is 0.015, and the magnitude of the effect is relatively small. The remaining variables are small in the magnitude of the estimated effect and statistically insignificant, with all of the relational factors appearing to be ineffective.

There are two possibilities for the cause of these estimation results. First, there may be little or no actual effect. Second, the coefficients may be underestimated due to the large-network problem (Borgatti, Everett, & Johnson, 2013). Only about 12% of all the firms in the Korean ICT industry participate in collaborative innovation, and most firms do not consider collaborative innovation as a strategic option or innovate at all. These firms can offset the effects of firms' characteristics on homophily. Therefore, previous studies have also analyzed only linked firms (Cantner & Graf, 2006) rather than firms as a whole. They have also recommended analyzing only linked firms to reduce the large-network problem (Borgatti et al., 2013). Therefore, this study assumes that a large-network problem is involved in the estimation result and additionally performs a QAP regression for linked firms to reduce this large-network problem.

The results of the QAP regression for linked firms are shown in Table 3.9 below. Since the p-value for the regression model is statistically significant at the 99.9% level, this model is statistically significant.

Table 3.9 QAP Regression (Linked Nodes)

Variable	Un-stdized.	Stdized.	Std.	P-value

		Coefficient	Coefficient	Error	
Independent Variables					
Innovation Factors	Technological Overlap	0.02394***	0.73312***	0.00074	0.00050
	Firm Size Proximity	-0.00117	-0.00420	0.05404	0.47926
	Market Proximity	-0.01306	-0.00352	0.06673	0.44678
Relational Factors	Same Region	0.02640	0.00700	0.05923	0.33283
	Same Group	3.36666**	0.14394**	0.39690	0.00150
Control Variables					
Closeness Centrality (Abs. Diff.)		-0.07205	-0.07205	0.11104	0.23238
Betweenness Centrality (Abs. Diff.)		-0.00021	-0.00021	0.00016	0.08246
Intercept		-0.03631***	-0.03631***	0.00000	0.00000
Nodes		64			
Permutations		2,000			
R-squared		0.61183			
Adj. R-squared		0.61115			
P-value		0.00050***			

Note: * p<0.05; ** p<0.01; *** p<0.001

The QAP regression results for linked firms show some differences from the QAP regression results for all the nodes. First, the model's R-squared is about 0.61, showing better explanatory power than the regression for all the nodes. This change in explanatory power indicates that the large-network problem has been successfully reduced through this second analysis. Second, the magnitude of all the effects of the independent variables is estimated to be larger. In particular, the size of the same group's estimate increases by a factor of 100, and the estimate of the technological overlap increases about twice. Third, the effect of the independent variables on the dependent variables differs from the first analysis.

The results of this analysis show that, among all the factors, the technological

overlap variable has the greatest effect on inter-firm homophily. In other words, the effect of homophily among firms with the same technology portfolio is most significant. When the standardized coefficients of technological overlap and same group are compared, it is estimated that the effect size of technological overlap is about five times larger than that of affiliates in the same group. These results show that there is a substantial homophily effect in partnership for collaborative innovation between firms holding the same technology portfolio in the inter-ICT firm collaborative innovation network.

If the effect size of a relational factor such as the same group is relatively large, firms conclude that minimizing the potential cost of various types of conflict in collaborative innovation is the top priority. However, this analysis shows that the effect of innovative factors such as technological overlap is substantial, indicating that Korean ICT firms have a similar innovation capacity in collaborative innovation. Collaborative innovation between firms with the same technology portfolio means that firms prefer a firm with sufficient technology capability in the same business area when selecting partners for collaborative innovation. If the firm builds a sufficient technology portfolio, it can be interpreted that it participates in the collaborative innovation according to the partner search mechanism based on the resource of the firm's technology portfolio. This is consistent with the argument presented by the resource-based theory on collaborative innovation.

However, the unstandardized coefficient of the same group variable makes it possible to infer that group-level decision-making is also taking place in the collaborative innovation ecosystem. The results show that collaborative innovation among affiliates in the same group is conducted about 3.4 times more than non-collaborative innovation. Although technological overlap has a greater effect on

homophily than same group, it can be interpreted that group-level decision-making has a preference for a 'safe choice' to minimize the possibility of disputes or transaction costs in collaborative innovation.

Through descriptive network analysis, this study assumes that the collaborative innovation ecosystem has become active in the Korean ICT industry since 2002. The collaborative innovation network in the Korean ICT industry is a scale-free network, which means a network formed by preferential attachment (Price, 1976). Firms interact according to preferences for various factors. Regression analysis reveals that these preferences are most evident in the technology portfolio (unveiled). Therefore, the results of this analysis show that Korean ICT firms in the ecosystem select innovative partners in the direction of complementary utilization of technology capacity by finding a firm with a sufficient technology portfolio in the same business area rather than reducing the transaction cost of the partner search. In conclusion, the collaborative innovation ecosystem among Korean ICT firms is relatively open.

The results of this study suggest that the greater the technological overlap, the easier the inter-firm collaborative innovation. The more firms build their technology portfolios, the easier it is for them to enter the collaborative innovation network. Therefore, the government can encourage participation in collaborative innovation by supporting the establishment of a technology portfolio to promote the participation of SMEs in collaborative innovation. The Korean government has been supporting SME technology development through collaborative innovation through a network-type technology development program for SMEs. As an SME’s technology capabilities are strengthened by the SME technology development support program and its technology portfolio increases, its position as a collaborative innovation partner in the market also improves. Therefore, this policy approach is reasonable in that SMEs accumulate their

technological competence and induce other firms in the market to be recognized as collaborative innovation partners.

However, this policy only supports collaborative innovation between SMEs, which limits the scope of technology development of participating firms. Descriptive analysis results show that the collaborative innovation networks in the ICT industry in Korea are centered on large firms, and SMEs participate in collaborative innovation networks according to their technological preferences. Therefore, for SMEs to participate in collaborative innovation networks, it is necessary to develop technologies in areas similar to the technology portfolios of large firms that play an essential role in collaborative innovation. For this, it is more effective to support technology development through collaborative innovation between SMEs, along with technology development through collaborative innovation between SMEs and large firms. Large firms have much broader technology portfolios than SMEs and have higher technical capabilities. Therefore, SMEs are more likely to develop technologies that are similar to the technology portfolios of existing large firms in collaborative innovation with large firms rather than in collaborative innovation between SMEs.

In summary, the homophily in the collaborative innovation of Korean ICT firms show that collaborative innovation is most actively carried out among firms with the same technology portfolio. Therefore, it can be interpreted that Korean ICT firms are choosing innovative partners to find a firm with a sufficient technology portfolio in the same business area and complimentary use of technological capacity. Given that homophily accounts for about 60 percent of total connections, inter-firm collaborative innovation in the Korean ICT industry is relatively open. Therefore, the government can help SMEs to build their technology portfolio through technology development support and so promote participation in collaborative innovation. The current policy

limits the scope of technology development support to collaborative innovation among SMEs, but this restricts the scope of technology development of SMEs. Thus, the government can extend the scope of technology development support to collaborative innovation between large firms and SMEs so that SMEs can access large firms' preferred technology portfolios. This allows the government to increase SME preference as a co-operative partner in the market, and the collaborative innovation network to be entered more effectively.

3.5 Conclusions

This study shows that a macroscopic pattern of homophily occurs when a network is formed by the interaction of various micro-motives of agents. This study then suggests that both innovation and network factors can affect inter-firm homophily in a collaborative innovation network by examining the prior research on firm selection and network evolution. Based on these arguments, this study suggests that collaborative innovation in the Korean ICT industry should be evaluated for openness by comparing the effects of innovation and relational factors on inter-firm homophily. This study constructs a firm-level panel data set including firm characteristics, patent information, and collaborative innovation records and then transforms it into a firm-level adjacency matrix and performs QAP regression, a network regression analysis. This study analyzes both all nodes and linked nodes to reduce the potential large-network problem (Borgatti et al., 2013). In addition, the descriptive network analysis is performed separately to investigate the characteristics of network evolution that can be overlooked in regression analysis. Specifically, this study explores the network characteristics and identifies the key actors and the network topology through descriptive network analysis.

The new findings from the descriptive network analysis can be summarized as follows. First, the collaborative innovation network between Korean ICT firms is a low-density sparse network with a low percentage of firms participating in collaborative innovation. Collaborative innovation networks between Korean ICT firms expanded significantly over a certain period. The number of nodes expanded during the Kim Dae-jung Government, and the networks became more complicated as various firms joined the network in the Roh Moo-hyun Government. Second, Samsung Electronics and KT are hubs in the network and have been the central collaborators of the network formation, as they show a high degree of mass collaboration. Some SMEs show greater

betweenness centrality than Samsung Electronics and KT. This means that SMEs have a greater capacity to utilize their technical resources complementarily with other firms. Therefore, SMEs play an important role in collaborative innovation rather than the collaborative innovation network between Korean firms and ICT firms. Third, this study finds that the collaborative innovation network between Korean ICT firms is in the form of a sparse scale-free network to examine the characteristics of the topology. Scale-free networks are formed according to the preferential attachment mechanism. Therefore, the Korean ICT network has been formed based on the preference of other firms for Samsung Electronics and KT, which are hub firms, and it has been expanded with the preference for firms that have collaborative innovation with them.

Next, the results of network regression analysis show that the technological overlay variable has the greatest effect on the inter-firm homophily. This indicates that collaborative innovation between firms holding the same technology portfolio is active. The results of this study show that the effect size of technological overlap is about five times bigger than that of affiliates in the same group, so the effect of the innovation factor is much larger than that of the relational factor. Given that this homophily accounts for about 60 percent of the total connections, the results of this study suggest that Korean ICT firms are choosing innovative partners with sufficient technology portfolios in the same business area for complementary use of technology competencies. Therefore, it can be interpreted that the inter-firm collaborative innovation in the Korean ICT industry is relatively open.

The results of this study can contribute to the theoretical development of the firms' partner selection and corporate alliance research. Specifically, this study can contribute to firms' decision-making mechanism in firm-to-firm interaction, including partner selection. The result that inter-firm homophily is more affected by the innovation factor

than by the relational factor suggests that if the firm builds a sufficient technology portfolio, it participates in collaborative innovation according to the partner's search mechanism in the market. This is consistent with the argument presented by the resource-based theory of collaborative innovation. Therefore, the results of this study show that the explanatory power of the resource-based theory is greater in the debate between resource-based theory and transaction cost theory in relation to collaborative innovation. This implies that the market mechanism based on the skills of the firm in the selection of collaborative innovation partners works. However, the unstandardized coefficient of the same group variable makes it possible to infer that group-level decision-making is also taking place in the collaborative innovation ecosystem. Although technological overlap has a greater effect on homophily than same group, it can be interpreted that the so-called ‘safe choice’ of group-level decision-making is also made to minimize the possibility of disputes or transaction costs in collaborative innovation.

This study is also significant in that it attempts to integrate network selection studies with a focus primarily on relational factors and partner selection studies that are primarily focused on innovation factors. In particular, this study contributes to the research design of the field by controlling the absolute values of the differences between the centrality measures in the network for all firms of the individual firms to control the interaction between heterogeneous agents. In addition, it shows that the inter-firm collaborative innovation network is a scale-free network, so it can contribute to network research that collects examples of scale-free networks.

This study can contribute to the government policy to create an open innovation ecosystem. Firms tend to interact with firms with similar characteristics, and policymakers have the advantage of simplifying intervention by promoting these

characteristics. The homophily network connection pattern improves predictability by simplifying firms' behavioral characteristics (Kegen, 2013). Therefore, government intervention can be simplified, and it is relatively easy for firms to predict their behavior accordingly. To facilitate inter-firm collaborative innovation by promoting specific factors, market-based instruments such as incentives have the advantage of being more effective than regulations (Costantini et al., 2016; Popp, 2006).

The results of this study show that the more firms build up their technology portfolios, the easier it is to enter the collaborative innovation network. Therefore, the government can encourage participation in collaborative innovation by supporting the establishment of a technology portfolio to promote the participation of SMEs in collaborative innovation. The Korean government's network-type technology development program for SMEs supports subsidies for technology development through collaborative innovation between SMEs. As a result of the collaborative innovation between SMEs, SMEs' accumulated technology portfolios and their technological capabilities are strengthened, and they will more and more become collaborative innovation partners in the market. Therefore, the network-type technology development program for SMEs is reasonable in that it accumulates SMEs' technological competence and induces them to be recognized as collaborative innovation partners by other firms in the market.

Since the collaborative innovation between SMEs has been very limited in the collaborative innovation network in the Korean ICT industry, this approach can be justified in terms of facilitating collaborative innovation between SMEs.[15] However, from the viewpoint of accumulation of technology capability, limiting the scope of program support to collaborative innovation between SMEs is limited. The

[15] See Appendix 3B.

collaborative innovation network in the Korean ICT industry is centered on large firms, and SMEs participate in collaborative innovation networks according to their technological preferences. Therefore, for SMEs to participate in collaborative innovation networks, it is necessary to develop technologies in areas similar to the technology portfolios of large firms, which are in a central position in the collaborative innovation network. To this end, it may be more effective to extend the scope of program support to include both collaborative innovation between SMEs and collaborative innovation between large firms and SMEs.

For example, governments can match large firms to SMEs seeking technology development through collaborative innovation and can subsidize R&D grants for them. Considering that large firms have a much broader technology portfolio than SMEs and have higher technological competency, SMEs are likely to develop technologies in areas similar to large firms' technology portfolios through collaborative innovation with large firms. SMEs with a large number of technology portfolios of this type are more likely to participate in existing collaborative innovation networks. Therefore, the government needs to extend the scope of the technology development program to include both collaborative innovation between large firms and SMEs and collaborative innovation among SMEs.

Also, the distribution of technological overlap between firms shows that the technological overlap between large firms and SMEs is greater than the technological overlap among large firms.[16] This is in contrast to the collaborative innovation between large firms and SMEs, which is about 2.7 times larger than the collaborative innovation among large firms. These differences imply that SMEs may have non-innovation factors that do not enter the collaborative innovation network sufficiently, despite the

[16] See Appendix 3A.

technological potential of SMEs to participate in existing collaborative innovation networks centered on large firms. Therefore, the government needs to determine the factors that limit SMEs' collaborative innovation and seek ways to mitigate them.

Large firms tend to choose other affiliates in the same group when choosing a collaborative innovation partner. The results of this study show that the collaborative innovation among affiliates of the same group is conducted about 3.4 times more than non-collaborative innovation. Also, in terms of collaborative innovation among large firms, collaborative innovation among the group affiliates accounted for 194, comprising 47 percent of the total collaborative innovation among large firms.[17] This is very high considering that collaborative innovation between the large firm and the SME comprises 4 percent of the total collaborative innovation between large firms and SMEs. This shows that large firms in the central position of collaborative innovation networks tend to make 'safe choices' when performing collaborative innovation with partners capable of top-down control at the group level in order to reduce the various transaction costs associated with collaborative innovation. This pattern implies that large firms perform collaborative innovation in the form of internal innovation at the group level.

Thus, governments can implement policies that encourage large firms to engage in collaborative innovation with other firms outside the same group of affiliates. For example, governments can run programs that match innovative SMEs with high technological potential to large firms, or enhance dispute resolution capabilities to reduce the transaction costs associated with collaborative innovation.

[17] See Appendix 3B.

Bibliography

Baron, J. N., Davis-Blake, A., & Bielby, W. T. (1986). The Structure of Opportunity: How Promotion Ladders Vary within and among Organizations. *Administrative Science Quarterly*, 31(2): 248–273.

Barabási, A-L., & Albert, R. (1999). Emergence of Scaling in Random Networks, *Science*, 286(5439): 509-512.

Becker, W., & Dietz, J. (2004). R&D Cooperation and Innovation Activities of Firms—Evidence for the German Manufacturing Industry. *Research Policy*, 33(2): 209-223.

Borgatti, S. P., Everett, M. G., & Johnson, J. C. (2013). *Analyzing Social Networks*. Thousand Oaks, CA: Sage.

Broekel, T., & Hartog, M. (2013). *Determinants of Cross-Regional R&D Collaboration Networks: An Application of Exponential Random Graph Models*. In T. Scherngell (Ed.), The Geography of Networks and R&D Collaborations (pp. 49–70). Springer International Publishing.

Butts, C. T., Acton, R. M., & Marcum, C. S. (2012). Interorganizational Collaboration in the Hurricane Katrina Response. *Journal of Social Structure*, 13: 1-36.

Cantner, U., & Graf, H. (2006). The Network of Innovators in Jena: An Application of Social Network Analysis, *Research Policy*, 35 (4), 463–480.

Cantner, U., & Meder, A. (2008). *Regional and Technological Effects of Cooperation Behavior*, Jena Economic Research Paper, Friedrich-Schiller-University Jena, Max-Planck-Institute of Economics.

Carley, K. M., Pfeffer, J., Reminga, J., Storrick, J., & Columbus, D. (2013). *ORA User's*

Guide 2013. Technical Report CMU-ISR-13-108, Carnegie Mellon University, School of Computer Science, Institute for Software Research, Pittsburgh, PA.

Casanueva C., Castro, I., & Galan, J. L. (2013). Informational Networks and Innovation in Mature Industrial Clusters. *Journal of Business Research*, 66(5): 603 - 613.

Chesbrough, H. W. (2003). *Open Innovation: The New Imperative for Creating and Profiting from Technology*. Boston, Mass: Harvard Business School Press.

Coase, R. H. (1937). The Nature of the Firm. *Economica*, 4(16): 386–405.

Costantini, V., Crespi, F., & Palma, A. (2015). *Characterizing the Policy Mix and Its Impact on Eco-Innovation in Energy-Efficient Technologies.* SEEDS Working Paper.

Choi, H. P, & Lee, J. H. (2010). An Analysis of the Factors that Influence the Choice of R&D Collaboration : Evidence from Korean Manufacturing Companies. *Journal of Technology Innovation*, 18(1): 153–175.

Dekker, D., Krackhardt, D., & Snijders, T. A. B. (2007). Sensitivity of MRQAP Tests to Collinearity and Autocorrelation Conditions. *Psychometrika*. 72(4): 563–581.

Faria, P., Lima, F., & Santos, R. (2010). Cooperation in Innovation Activities: The Importance of Partners. *Research Policy*, 39(8): 1082-1092.

Genio, C. I. D., Gross, T., & Bassler, K. E. (2011). All Scale-Free Networks are Sparse. *Physics Review Letters*, 107: 178701.

Glückler, J. (2010). *The Evolution of a Strategic Alliance Network: Exploring the Case of Stock Photography*, in R. Boschma and R. Martin (eds) Handbook of Evolutionary Economic Geography, Cheltenham: Edward Elgar, 298–315.

Guan, J., & Liu, N. (2016). Exploitative and Exploratory Innovations in Knowledge Network and Collaboration Network: A Patent Analysis in the Technological Field of Nano-Energy, *Research Policy,* 2016: 45(1): 97-112.

Harris, J. K., Wong, R., Thompson, K., Haire-Joshu, D., & Hipp, J. A. (2015). Networks of Collaboration among Scientists in a Center for Diabetes Translation Research. *PLoS ONE*, 10(8): e0136457.

Hong, W., & Su, Y-S. (2013). The Effect of Institutional Proximity in Non-Local University-Industry Collaborations: An Analysis Based on Chinese Patent Data. *Research Policy*, 42(2): 454-464.

Hubert, L. J. (1987). *Assignment Methods in Combinatorial Data Analysis*. New York and Basel: Marcel Dekker.

Ibarra, H. (1992). Homophily and Differential Returns: Sex Differences in Network Structure and Access in an Advertising Firm. *Administrative Science Quarterly*, 37(3): 422-447.

ITU. (2016). *Measuring the Information Society Report 2016*, Geneva: ITU Report.

Katz, J. S., & Martin, B. R. (1997). What is Research Collaboration?. *Research Policy*, 26(1): 1–18.

Kegen, N. V. (2013). Science Networks in Cutting-edge Research Institutions: Gender Homophily and Embeddedness in Formal and Informal Networks. *Procedia—Social and Behavior Sciences*, 79(2013) :62–81.

Kim, C., & Song, J. (2007). Creating New Technology through Alliances: An Empirical Investigation of Joint Patents. *Technovation*, 27(8): 461-470.

Kleinbaum, A. M., Stuart, T. E., & Tushman, M. L. (2013). Discretion within Constraint: Homophily and Structure in a Formal Organization. *Organization Science*, 24(5): 1316-1336.

Krackhardt, D. (1988). Predicting with Networks: Nonparametric Multiple Regression Analysis of Dyadic Data. *Social Networks*, 10: 359-381.

Lazarsfeld, P. F., & Merton, R. K. (1954). *Friendship as a Social Process: A Substantive*

and Methodological Analysis. In Freedom and Control in Modern Society (ed.). M Berger, New York: Van Nostrand.

Lee, W. J., Lee, W. K., & Sohn, S. Y. (2016). Patent Network Analysis and Quadratic Assignment Procedures to Identify the Convergence of Robot Technologies. *PLoS ONE*, 11(10): e0165091.

Lundvall, B.-A., & Borrás, S. (2005). *Science, Technology and Innovation Policy.* in Fagerberg, J., Mowery, D.C. and Nelson, R.R. (eds.) The Oxford Handbook of Innovation, Oxford: Oxford University Press.

Maggioni, M., Nosvelli, M., & Uberti, E. (2007). Space versus Networks in the Geography of Innovation: A European Analysis. *Papers in Regional Scienc*e, 86(3): 471–493.

Maietta, O. W. (2015) Determinants of University–Firm R&D Collaboration and Its Effect on Innovation: A Perspective from a Low-Tech Industry. *Research Policy*, 44(7): 1341–1359.

McPherson, M., Smith-Lovin, L., & Cook, J. M. (2001). Birds of a Feather: Homophily in Social Networks. *Annual Review of Sociology*, 27, 415–444.

Mowery, D. C., Oxley, J. E., & Silverman, B. (1998). Technological Overlap and Interfirm Cooperation: Implications for the Resource-Based View of the Firm, *Research Policy*, 27(5): 507-523.

MSS. (2018). *Announcement of Network-type Technology Development Program for SMEs*. Daejeon, MSS Report.

Nelson, R. R., & Winter, S. G. (1982). *An Evolutionary Theory of Economic Change.* Cambridge, Mass.: Belknap Press of Harvard University Press.

Owen-Smith, J., & Powell, W. (2004). Knowledge Networks as Channels and Conduits: The Effects of Spillovers in the Boston Biotechnology Community.

Organization. Science. 15 (1): 5–21.

Pakes, A., & Griliches, Z. (1984). *Patents and R&D at the Firm Level: A First Look*. In Griliches, Z., editor, R&D, Patents, and Productivity, Chicago: University of Chicago Press.

Penrose, E. (1959). *The Theory of the Growth of the Firm*, New York: Oxford University Press.

Popp. D. (2006). International Innovation and Diffusion of Air Pollution Control Technologies: The Effects of NOX and SO2 Regulation in the US Japan and Germany. *Journal of Environmental Economics and Management*, 51(1): 46-71.

Price, D. J. (1976). A General Theory of Bibliometric and Other Cumulative Advantage Processes. *Journal of the American Society for Information Science*, 27(5-6): 292-306.

Schelling, T. C. (1978). *Micromotives and Macrobehavior*. New York: Norton.

Simpson, W. B. (2001). *QAP: The Quadratic Assignment Procedure*. Paper Presented at the North American STATA Users' Group Meeting, Retrieved from http://fmwww.bc.edu/RePEc/nasug2001/simpson.pdf

SMBA. (2017). *A Guide to the Network-type Technology Development Program for SMEs*. Daejeon, SMBA Report.

Sun, Y., & Liu, K. (2016). Proximity Effect, Preferential Attachment and Path Dependence in Inter-Regional Network: A Case of China's Technology Transaction. *Scientometrics* 108 (1), 201–220.

Topper, C. M., & Carley, K. M. (1999). A Structural Perspective on the Emergence of Network Organizations. *Journal of Mathematical Sociology*, 24(1): 67–96.

Von Proff, S., & Brenner, T. (2014). The Dynamics of Intern-Regional Collaboration: An Analysis of Co-Patenting. *Annals of Regional Science*, 52(1): 41-64.

Watts, D. J., & Strogatz, H. (1998). Collective Dynamics of Small-World. *Nature*, 393: 440-442.

Williamson, O. E. (1975). *Markets and Hierarchies, Analysis and Antitrust Implications: A Study in the Economics of Internal Organizations*. New York: Free Press.

Williamson, O. E. (1981). The Economics of Organization: The Transaction Cost Approach. *American Journal of Sociology*, 87(3): 548-577.

Zanfei, A. (1993). Patterns of Collaborative Innovation in the US Telecommunications Industry after Divestiture. *Research Policy*, 22(4): 309-325.

Appendix 3-A. Technological Overlap and Same Group Affiliates

Table 3.10 Descriptive Statistics of Technological Overlap and Same Group Affiliates

Variable	Obs.[1)]	Mean	St. Dev.	Sum	Min.	Max.
Technological Overlap						
Large Firms - SMEs	275,625	0.4051	2.6741	111,662	0	60
Large Firms - Large Firms	275,625	0.2849	8.2318	78,514	0	1943
SMEs - SMEs	275,625	0.1789	1.0003	49,312	0	37
Total	275,625	0.8689	8.6854	239,488	0	1943
Same Group Affiliates						
Large Firms - SMEs	275,625	0.0002	0.0154	66	0	1
Large Firms - Large Firms	275,625	0.0005	0.0207	118	0	1
SMEs - SMEs	275,625	0.0003	0.0166	76	0	1
Total	275,625	0.0009	0.0307	260	0	1

Note: 1) The number of nodes in the adjacency matrix with 525 rows and columns. 2) The observations include 164 large firms and 361 SMEs.

Appendix 3-B. Inter-firm Collaborative Innovation

Table 3.11 Descriptive Statistics of Inter-firm Collaborative Innovation

Variable		Obs.[1)]	Mean	St. Dev.	Sum	Min.	Max.
Collaborative Innovation							
Large Firms – SMEs		275,625	0.00054	0.04603	148	0	11
Large Firms - Large Firms		275,625	0.00149	0.21311	410	0	60
SMEs - SMEs		275,625	0.00007	0.01077	20	0	3
	Collaborative Innovation among Same Group Affiliates						
	Large Firms - SMEs	275,625	0.00002	0.00602	6	0	2
	Large Firms - Large Firms	275,625	0.00070	0.18587	194	0	60
	SMEs - SMEs	275,625	0.00001	0.00269	2	0	1
	Total	275,625	0.00073	0.18598	202	0	60
	Collaborative Innovation among Others						
	Large Firms - SMEs	275,625	0.00052	0.04563	142	0	11
	Large Firms - Large Firms	275,625	0.00078	0.10425	216	0	28
	SMEs - SMEs	275,625	0.00007	0.01043	18	0	3
	Total	275,625	0.00136	0.11428	376	0	28
Total		275,625	0.00210	0.21828	578	0	60

Note: 1) The number of nodes in the adjacency matrix with 525 rows and columns. 2) The observations include 164 large firms and 361 SMEs.

Chapter 4. [Essay 3] Effect of Collaborative Innovation on Technological Convergence

4.1 Introduction

ICT-based technological convergence has rapidly progressed in recent years and is changing the paradigm of modern industry. Therefore, the importance of collaborative innovation is emphasized more than ever as an instrument to promote convergence. The firm determines the innovation performance of a country as the most important innovation entity, and the government invests heavily every year in promoting the innovation activities of firms.

Since the implementation of the policy to promote technological convergence at the national level, governments have maintained an approach to promote technological convergence by fostering the collaborative innovation of firms. Firms collaborate with outside innovation agents to complement their lack of internal innovation capabilities or to reduce the costs and risks associated with innovation processes (Penrose, 1959; Williamson, 1981). It is also known that firms can increase their innovation performance by participating in collaborative innovation. Therefore, various countries have been implementing policies to promote the participation of firms' collaborative innovation, and the Korean government has also been making efforts to promote open innovation environment and promote collaborative innovation. However, the critical approaches to the arguments underlying these policy instruments are limited, and insufficient empirical studies have been conducted. The analysis of the causal relationship between firms' collaborative innovation activity and convergence technology allows the evaluation of the rationality of the argument embedded in the

policy instruments and enables a more effective innovation policy design. This analysis can also contribute to maximizing the positive external effects of ICT-based technological convergence on the economy and society.

The purpose of this study can be summarized in two ways. First, it intends to investigate the effect of various types of collaborative innovation on the technological convergence of ICT firms. In the 2010s, technological convergence has been regarded as a key factor in innovation-driven growth. Governments have implemented policies to promote technological convergence to preempt new technologies and maximize the economic ripple effects in the international technology competition. Recently, ICT-based technological convergence represented by IOT and AI has been extended to the entire technology field, changing the paradigm of the industry and exerting a powerful impact on the economy. Thus, many countries have implemented policies to promote ICT-based technological convergence. The Korean Government has also been making strategic investments since late 2000 to promote ICT-based technological convergence. Although the core of the technological convergence promotion policy is the implementation of collaborative innovation through the creation of an open innovation environment (Lee & Sung, 2009), there is only little empirical evidence on the effect of ICT firms' collaborative innovation on technological convergence. Therefore, identifying the effects of the collaborative innovation of ICT firms on technological convergence makes it possible to judge whether the policy direction focusing on collaborative innovation is reasonable. Previous studies have discussed the relationship between collaborative innovation and technological convergence at the conceptual or correlation level. They have also involved limitations in that they have not taken into account the differential effect of various types of innovation on ICT-based technological convergence. Therefore, it is necessary to analyze the differential effect of the

collaborative innovation type of ICT firms on ICT-based technological convergence based on the consideration of the potential endogeneity problem. In this way, the theoretical discussion on the relationship between collaborative innovation and technological convergence discussed at the level of correlation can be developed one step further from a causal point of view.

Second, this study attempts to find out which types of collaborative innovation promote the most technological convergence. This analysis can redesign the incentive system to increase firms' participation in the most effective innovation types, thereby preventing inefficient investment of government budgets and improving policy efficiency.

This study analyzes Korean ICT firms. The time range of this study is set from 1980 to 2015 due to the availability of patent data and the time lag from patent application to disclosure. Korea has had one of the most developed ICT infrastructures in the world due to its intensive investment in the ICT industry since the end of the 1990s and has always maintained the highest level of international ICT development indicators (ITU, 2016). Furthermore, the Korean ICT industry has a high level of technology and R&D investment internationally, including a large number of global firms in semiconductors and telecommunication. Therefore, as Korea has the highest level of ICT development in the world, the analysis of Korea's ICT firms provides policy implications not only for Korea but also for other countries.

This study consists of five chapters including the introduction. Chapter 2 examines the technological convergence policy of some developed countries and reviews the argument of policy instruments of promoting technological convergence by advocating collaborative innovation centered on Korea. This study reviews the previous studies on the relationship between collaborative innovation and technological convergence and

then presents the limitations of these studies. Chapter 3 presents the research hypotheses and the research design. Specifically, this study provides the conceptual framework of the study, explains the data collection process, introduces the variables, methodology, and estimation strategy, and presents the descriptive statistics. Chapter 4 presents the results of the analysis and empirically tests the research problems presented in this study. Finally, Chapter 5 summarizes the conclusions and presents the implications and limitations of the study.

4.2 Literature Review

4.2.1 Background: Technological Convergence Policy in Korea

Technological convergence creates new markets through the synergistic combination of different technologies and provides technical and economic benefits for the industry as a whole (Nordmann, 2004). Recently, technological convergence has been regarded as a key factor in innovation-driven growth. Therefore, governments have been implementing policies to promote technological convergence to obtain new technologies in the technological competition between countries and maximize the impact on the economy.

A national-level technological convergence policy was introduced by the US Government in 2001, and other governments have also followed this approach. First, the US Government has been implementing technological convergence policies since 2001 under the supervision of the National Research Foundation (NSF), National Institutes of Health (NIH), and Department of Commerce. Specifically, the US Government has supported the R&D infrastructure, a cooperation network between firms, and human resource development. Second, European countries are pursuing convergence strategies within the EU Framework Program (FP). The EU's seventh FP included strengthening multilateral cooperation, identifying creative ideas, enhancing researcher liquidity, and strengthening European collaborative research capabilities (Cho, Yang, Suh, & Jeon, 2015). Third, in contrast to the US and Europe, Japan is promoting the link between science and technology policies and investing in each department and province instead of the central government. The Japanese Government has made efforts to establish horizontal relationships between innovation actors and to promote collaborative innovation, assuming that the hierarchial relationship between

science, education, and government systems are obstacles to the development of convergence technologies (KISTEP, 2007).

The Korean Government has also implemented policies to promote technological convergence at the national level. In 2007, the "Basic Policy for National Convergence Technology Development" was established; in 2008, the "National Master Plan for Convergence Technology" was established; and in 2014, the "Convergence Technology Development Strategy for the Creative Economy" was established. The policy of promoting technological convergence in Korea has been carried out in such a way that various ministries support research specializing in individual fields. The six major strategies of the "National Master Plan for Convergence Technology" are to secure the source convergence technology early, cultivate experts in creative convergence technology, find new convergence industries, strengthen support, advance industries based on convergence technology, and include cooperative systems (Cho et al., 2015).

The program that is common to the technological convergence policy of each country is the promotion of technological convergence through the activation of collaborative innovation. Governments have maintained an approach to creating open innovation ecosystems and activating collaborative innovation to promote technological convergence from the initial stages of the technological convergence policy.

The Korean Government has also been trying to foster collaborative innovation since the early days of promoting technological convergence. Specifically, it established the "National Master Plan for Convergence Technology" in 2008 and has been promoting technological convergence through collaborative innovation since 2009 under the supervision of the Small and Medium Business Administration (SMBA). In 2009, the Korean Government implemented the "Cooperative Technology

Development Project" (linked project), and it has been carrying out the "Convergence Technology Development Project" since 2011 and the "Convergence Technology Development Project for SMEs" since 2014. The size of the Convergence Technology Development Project for SMEs is 135 billion won, with an annual average of 16.9 billion won, and the total number of projects is 784 (Cho et al., 2015).

Among these projects, the Convergence Technology Development Project for SMEs, which is still underway, specifies the development of convergence technology through the activation of open R&D and collaborative innovation in the outline of the project. The scale of support for this project was 32.9 billion won in 2016 and included 133 projects. The contents of the project are composed of two stages. The partnership between technical subjects is supported through development directions and methods, technical feasibility, and feasibility evaluation of research projects, and R&D subsidies are supported in the stage of collaborative innovation. Although only firms can apply for this project, collaborative innovation partners range from firms and universities to government-funded research institutes (SMBA, 2016). In this project, firms can choose to cooperate with various innovation entities, such as firms, universities, and the GRI considering the characteristics of innovation.

Researchers have argued that the Korean Government should focus more on activating open innovation among various policy instruments to promote technological convergence. In particular, some researchers believe that it is necessary to reinforce collaborative innovation in IT and BT (Cho et al., 2015). The logic that collaborative innovation promotes technological convergence can be explained by the resource-based theory of innovation, according to which firms complement their lacking innovation capabilities by working with other firms to meet diversified technology needs. Therefore, to meet the demand for convergence technology, firms perform collaborative

innovation with firms that have the technological capabilities that they lack. For this reason, many countries have implemented policies to create a collaborative innovation ecosystem and activate collaborative innovation to promote technological convergence.[18]

The collaborative innovation activation policy, such as Korea's Convergence Technology Development Project for SMEs, has been carried out continuously since the early days of the technological convergence policy. However, most of the existing literature has focused only on the scope or long-term direction of technological convergence promotion rather than on the adequacy of the policy instruments. This study starts from two issues regarding the adequacy of the policy instrument.

First, there is limited empirical evidence that collaborative innovation promotes technological convergence, despite the fact that the technological convergence policy has been implemented according to a theoretical discussion based on resource-based theory. It is therefore unclear whether the activation of collaborative innovation is a suitable policy instrument for promoting technological convergence.

Second, the Convergence Technology Development Project for SMEs in Korea does not make a difference in the budget allocation or the amount of the subsidy at the stage of application depending on the type of collaborative innovation partner of the participating firms. However, firm–university, firm–GRI, and inter-firm collaborative innovation may have different effects on technological convergence, and certain types of collaborative innovation may not affect technological convergence. Thus, setting the same amount of subsidy regardless of the collaborative innovation type is like giving equal incentives to policy instruments with different effects. These incentive systems are inefficient. Given that the purpose of these incentive systems are to create a

[18] Resource-based theory is described in more detail in the next section.

collaborative innovation ecosystem in the long term, it is necessary to target the focus of the policy to the most effective collaboration type. Therefore, to reduce the inefficiency, it is necessary to give more incentives to the type of collaborative innovation that has the greatest effect on technological convergence. To develop an effective incentive system, it is necessary to identify which collaborative innovation types promote technological convergence the most.

Based on the above discussion, this study examines whether firms' collaborative innovation promotes technological convergence and explores which types of collaborative innovation promote technological convergence the most. For this purpose, it examines collaborative innovation and technological convergence, reviews the previous studies on the relationship between collaborative innovation and technological convergence, and presents research hypotheses.

4.2.2 Collaborative Innovation and Technological Convergence

4.2.2.1 Collaborative Innovation

With the recent development of technology and the rapid progress of convergence between different technologies, it has become difficult for firms to meet various demands in the market due to internal innovation; therefore, the importance of collaborative innovation is increasing. Firms usually perform innovation activities based on internal innovation resources, but they also collaborate strategically with external innovation entities. The theoretical framework that explains the collaborative innovation of firms can be divided into resource-based theory and transaction-cost theory.

First, the resource-based approach defines firms as a collection of resources, and the performance of individual firms is considered to be determined by the internal resources rather than external environments (Penrose, 1959). Thus, firms have to compensate for their lack of competence to secure a competitive advantage in the industry by cooperating with other firms (Prahalad & Hamel, 1990). Teece (1986) suggested that firms complement the assets and capabilities needed for innovation through collaboration. Firms prefer internal innovation for their core competencies, but, as uncertainties in the market environment increase, they prefer to receive resources from outside the firm (Aldrich & Pfeffer, 1976). Cooperation is essential to access external resources (Barney, 1999). To sum up, resource-based theory explains that firms use cooperative strategies to utilize external resources through alliances with other firms to ensure their survival and competitive advantage.

Second, the transaction cost approach suggests that firms that rely solely on internal transactions experience a loss of earnings and that firms interact with external firms to survive (Coase, 1937). When performing R&D, firms prefer collaborative R&D when the cost of collaborative R&D with external firms is less than the cost of internal R&D (Williamson, 1981). When collaborative innovation, a joint venture, or outsourcing is more cost effective than internal innovation, firms collaborate strategically.

Although the above two theories are mainly examples of collaborative innovation between firms, there are various types of collaborative innovation, such as firm–university, firm–government-affiliated research institute, and industry–academic collaboration. Tether (2002) analyzed the collaborative innovation patterns among firms in the UK and found that collaborative innovation is determined by various factors, such as the type of partner or skill level.

Previous studies that have explored the effect of firms' collaborative innovation on innovation performance have analyzed the effect of firms' joint patenting on the patent performance. They have shown that firms' collaborative innovation has a positive effect on patents. For example, Briggs and Wade (2014) found that joint patenting improves the quality of innovation using patent data from the EPO (European Patent Office) from 1978 to 2009 included in the OECD REGPAT database. Hottenrott and Bento (2012) determined that collaborative innovation between firms increases the number of patents and improves their quality. They argued that firms protect their intellectual property rights and strategically build a patent portfolio through collaborative innovation.

It is known that collaborative innovation not only enhances the innovation performance of the industry but also has a significant impact on other industries and economies. Thus, although collaborative innovation is a voluntary strategic action of firms, governments have used various policy instruments to promote collaborative innovation to maximize the impact of collaborative innovation on the industry. With the creation of new markets due to ICT-based technological convergence and rapid changes in the technological environment, ICT firms participate in collaborative innovation to reduce their innovation costs and meet diversified technology needs.

4.2.2.2 Technological Convergence

The term technological convergence was first proposed by Rosenberg (1963) and has been defined as a communal technological innovation that takes place in the process of various industries resolving their technical problems. Kodama (1991) presented the term technology fusion, which refers to the transformation of core technologies. Pennings and Puranam (2001) distinguished technological convergence from

technology fusion. They argued that technology fusion is simply a combination of existing technologies and that technological convergence not only is a combination of existing technologies but also aims to create innovations that did not exist previously. The National Science Foundation (NSF) and the Department of Commerce (DOC) (2002) have also identified converging technologies as four technologies: nanotechnology (NT), biotechnology (BT), information technology (IT), and cognitive technology. They have been defined as a synergistic combination between advanced technologies. To sum up these arguments, technological convergence can be defined as a combination of different technologies used to solve a problem.

Curran and Leker (2011) distinguished convergence into science convergence, technology convergence, market convergence, and industry convergence. Technology convergence is a combination of technologies with different uses that occur from science convergence. Technological convergence, combined with market convergence, ultimately leads to industry convergence (Curran & Leker, 2011). According to this view, technological convergence arises from the transfer of scientific achievements to the industry, which makes the boundaries between the industries obscure with product or service innovation. Therefore, technological convergence is considered to arise from the transfer of accumulated knowledge to the industry as science advances.

Among the four convergence categories classified by the NSF and DOC (2002), ICT-based technological convergence has the advantage that it has a greater impact than other forms of technology-based convergence, and is easy to commercialize and thus stimulates economic stimulation (Suh, Hwang, Kim, Kim, & Oh, 2015). According to Lee, Kim, & Zo (2017), ICT-based technological convergence creates new products and services that have not existed before, changes the existing market structures, creates new markets, and promotes innovation activities in other technology areas.

Suh et al. (2015) pointed out that ICT-based convergence has the most diverse convergence characteristics compared to other technology-based convergence, involving the convergence of products, services, and industries. The characteristics of ICT-based technological convergence are due to the features of the ICT industry. ICT is regarded as general purpose technology (GTP), which fuses with all industries for a long time to make the production process more efficient and promotes innovation in other industries. To summarize, the ICT industry is important because it promotes innovation in entire industries according to the characteristics of general technology, and the convergence of the ICT industry positively affects the national economy. Due to these advantages, countries including the US, Japan, and EU countries, are implementing policies to promote ICT-based technological convergence. The Korean government is also implementing various policies, such as establishing the Industrial Convergence Promotion Act in 2011 and setting the "IT convergence strategy 2013-17" in 2012 to promote ICT-based technological convergence. Also, the Korean government has designated ICT convergence-related new technology as one of its five major national strategic technologies[19] and has made intensive investment after specifying the activation of R&D in basic science and convergent technology as one of the five major investment projects.

4.2.3 Effect of Collaborative Innovation on Technological Convergence

Technological convergence blurs the boundaries between traditional technology fields.

[19] SW / Internet, Strengthening ICT innovation capability based on C-P-N-D, Cultural / tourism content modernization, Smart / Transportation logistics system construction, Advancement of main export industry.

Therefore, innovations that occur in a convergence environment inevitably require technological competence in various fields. Van Tulder and Junne (1988) argued that technological convergence allows firms to use a variety of strategies to implement innovations in an environment in which the technology boundaries are ambiguous and that a cooperative strategy is also one of these strategies. Firms have limitations in innovation based on convergence technology, which depends solely on internal resources. Therefore, firms can overcome the limitation of R&D costs and the shortening of product life cycles through cooperation with another firm rather than internal firm innovation (Rikkiev & Makinen, 2013).

Researchers have pointed out that the empirical studies on the relationship between collaborative innovation and technological convergence are insufficient. Duysters and Hagedoorn (1998) point out that empirical research has not been conducted sufficiently, compared to the conceptual discussion that has taken place on the effects of collaboration or strategic alliances among firms on technological convergence. Previous studies that have explored the relationship between collaborative innovation and technological convergence have mainly focused on adding statistical data to conceptual discussions (Borés, Saurina, & Torres, 2003), performing descriptive analysis based on the collected data (Lee, Lee, Song, & Kim. 2017), or analyzing differences between collaborative and non-collaborative studies (Lee & Zo, 2013). However, it is difficult to deduce the effects of collaborative innovation on technological convergence from these results. Therefore, some researchers have attempted to analyze the effect of collaborative innovation on technological convergence.

Duysters and Hagedoorn (1998) found that the relationship between firm alliances and technological convergence is unclear as a result of analyzing ICT firms using patent

data from the European Patent Office (EPO) and strategic technology alliance data between firms. In their analysis of computer and semiconductor firms, the correlation between strategic alliances and technological convergence was not significant, and only a few telecommunications firms reported that a strategic alliance was less likely to promote technological convergence.

Jeong, Lee, Kim, Oh, & Kwak (2012) explored how convergent technologies are most likely to appear in various collaboration types using Korean patent data. They found that the frequency of applications for technologically convergent patents was the highest in firm-university collaboration. On the other hand, the production of technologically convergent patents is rather reduced in the case of collaborations between firm-Government-funded Research Institute (GRI) and firm-university-GRI. These studies are meaningful in that they explore what type of collaboration promotes the production of convergent technology. However, they only used collaboration types as an independent variable and did not control other factors that affect the production of convergent technology, since they used patents as a unit of analysis. In conclusion, these studies have limitations in predicting causality because they have potential endogeneity problems.

Jeong (2014) also used Korean patent data to explore whether collaborative innovation affects the production of convergent technologies. The results of the analysis using the probit model show that collaboration types that include firms or GRIs reduce the production of convergent technologies, but that collaboration that includes universities increases the production of convergent technologies. He controlled for industry-specific differences by adding seven industry-type dummy variables to the model of Jeong et al. (2012), but he still did not control key variables that affect the production of convergent technology.

Lee et al. (2017) analyzed the effect of collaborative R&D projects on ICT-based technological convergence using Korean patent data. The results of the analysis show inter-firm collaboration involving large firms and collaboration with GRIs promotes ICT-based technological convergence, while collaboration with SMEs has a negative effect on ICT-based technological convergence. They controlled for government subsidies, private funding, the duration of R&D projects, as well as for firm size, one of the main factors of innovation, by adding the dummy variables of the SMEs and the large firms to the model. Of course, their research is improved compared to previous studies in that they controlled for the third factor, which affects innovation. However, since they do not consider a time variable, they could not control for the possibility of bias of cross-sectional analysis in innovative research, as Griliches (1990) mentioned. Also, they did not control for the unobservable factors and there was no consideration of simultaneity, so there is a limit to discuss causal relationships strictly.

The limitations of previous studies can be summarized in two ways. First, firms determine both collaboration and the type of innovation, which means that there may be a third factor that affects both collaboration and technological convergence. Therefore, it is necessary to control for factors that affect innovation. When using cross-sectional data, the correlation between innovation factors and innovation can be seriously overestimated, compared to using time-series data (Griliches, 1990). It is also necessary to build a panel dataset to control for unobservable factors that affect both collaborative innovation and technological convergence. However, since previous studies do not control for factors that affect technological convergence, they have the possibility of omitted variable bias

Secondly, while the previous studies designed the research on the assumption that collaborative innovation of firms affects technological convergence, there is also the

possibility that the technological convergence may affect the collaborative innovation of firms. In other words, firms can strategically determine the type of collaboration in advance to produce technologically convergent patents. Therefore, the existence of endogeneity from the simultaneity should be checked and controlled for properly.

In conclusion, this study examines the effects of collaborative innovation on technological convergence. The next section offers some research hypotheses and presents the research design for finding answers to these research hypotheses.

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4.3 Research Design

4.3.1 Research Hypotheses

The purpose of this study is to explore the effect of collaborative innovation on technological convergence. Therefore, this study presents the following hypotheses.

Firstly, according to the resource-based theory, firms collaborate with other firms to use their complementary innovation capabilities. As the demand for technology in the market diversifies, the firm works with other firms with technology it does not itself have to meet its technology demand. Firms can choose collaborative innovation with other firms to reduce the time and cost of developing heterogeneous technologies. Collaborative innovation between firms with different technologies increases the probability of combining heterogeneous technologies, which can lead to technological convergence.

The ICT industry is one of the most innovative industries, characterized by high R&D intensity and a rapid innovation cycle. Also, due to the characteristics of ICT technology as a general purpose technology, the demand for convergent technology in the market is mostly centered on ICT technology. Given the characteristics of the ICT industry, ICT firms are sensitive to changes in technology demand in the market and are particularly sensitive to changes in demand for convergent technology. Given the high sensitivity and high degree of R&D intensity, ICT firms can have a higher incentive to develop convergent technology than firms in other industries. Therefore, considering the characteristics of the ICT industry, which is highly sensitive to technology changes and high demand for convergent technology, the collaborative innovation activities of ICT firms can have a positive impact on technological convergence. In other words, ICT firms can produce convergent technology by

strategically cooperating with other firms to meet the demand for convergent technology in the market and gain an advantage in the innovation competition. The research hypothesis based on the above discussion is presented below.

H1: The collaborative innovation of ICT firms has a positive effect on technological convergence.

Secondly, the question of what type of collaborative innovation has the greatest effect on technological convergence can be raised. In the previous studies, the direction and magnitude of the effect of each type of collaborative innovation on technological convergence has differed. Therefore, there is a limit to the knowledge regarding the type of collaborative innovation that can best promote technological convergence based on these studies. For example, one study has suggested that collaborative innovation involving firms or GRIs has a negative effect on technological convergence (Jeong, 2014), but other studies have shown that collaborative innovation involving large firms or GRIs has a positive effect on technological convergence (Lee, Lee, Song, & Kim, 2017). However, as mentioned above, previous studies suffer from limitations in that they cannot sufficiently remove endogenous production due to data or methodological limitations. Therefore, this study relies on a theoretical discussion regarding which type of collaborative innovation has the greatest effect on the promotion of technological convergence. This study suggests a hypothesis concerning the types of collaborative innovation that promote technological convergence the most using theoretical arguments about the motivation for collaborative innovation.

According to transaction cost theory, firms prefer innovations that are performed solely within the firm but abandon outsourcing or collaborative innovation if the cost of innovation is greater than its rewards (Williamson, 1981). Therefore, collaborative

innovation motivated by the need to reduce transaction costs may lead to a reduction of the cost of innovation, but it is inevitably difficult to see that it can lead to the convergence of heterogeneous technologies. SMEs that do not have sufficient funds for innovation facilities, manpower, and innovation are less innovative than large firms that can easily finance capital for innovation (Nelson & Winter, 1982; Schumpeter, 1942). Therefore, these SMEs lease personnel and innovation facilities from other innovators for a limited period to obtain the benefits of innovation. One example of this form of collaborative innovation is innovation that includes a GRI. The Korean Government has supported innovation facilities, manpower, and knowledge through the GRI for firms that do not have their own innovation capabilities. Given that the GRI has been used as a policy instrument to support firms' lack of innovation capability, firm–GRI collaborative innovation can be seen as a result of the incentive to reduce the innovation costs of firms with insufficient innovation capacity rather than the convergence of heterogeneous technologies to meet the diversified technology demand of the market. Therefore, it can be assumed that firm–GRI collaborative innovation has less of an effect on technological convergence than other types of collaborative innovation.

The role of lending the resources needed for innovation to the firms lacking innovation capacity is being carried out by the GRI as well as by universities. However, while the innovation of the GRI is directly controlled by the government, universities are more autonomous than the GRI in selecting innovation subjects, because they are indirectly controlled through incentives such as research funding. However, even though universities are guaranteed greater autonomy than the GRI, it is difficult to say that they are as sensitive to changes in the technology demand in the market as firms. Therefore, it can be assumed that universities as collaborative innovation partners are positioned between the firms and the GRI.

Firms that fail to meet the technology demand lose their competitiveness. Thus, a firm can perform collaborative innovation with other firms that have other technologies to reduce the time required for innovation and to respond to the market demand. In innovation-intensive industries, such as the ICT industry, innovation is related to the growth of the firm, so having an advantage in innovation competitiveness is also important to the survival of the firm. Thus, it can be assumed that the frequency of collaborative innovation to respond instantly to diversified technology needs in the market may be higher in inter-firm collaborative innovation than in other types of collaborative innovation. Therefore, this study suggests that collaborative innovation among firms has the most significant effect on technological convergence.

H2: Inter-firm collaborative innovation has a greater positive effect on technological convergence than other types of collaborative innovation.

4.3.2 Research Design

4.3.2.1 Conceptual Framework

This section presents a conceptual framework based on the discussions in the previous chapter. This study is based on the fact that policy instruments such as the Korean Government's Convergence Technology Development Project for SMEs are grounded on the argument that encourages the collaborative innovation of firms to promote technological convergence. Although the approach based on this argument has been implemented from the early stage of the technological convergence policy at the national level, the critical verification of the rationality of the policy instruments is not

sufficient. Therefore, this study empirically tests whether the collaborative innovation of firms promotes technological convergence.

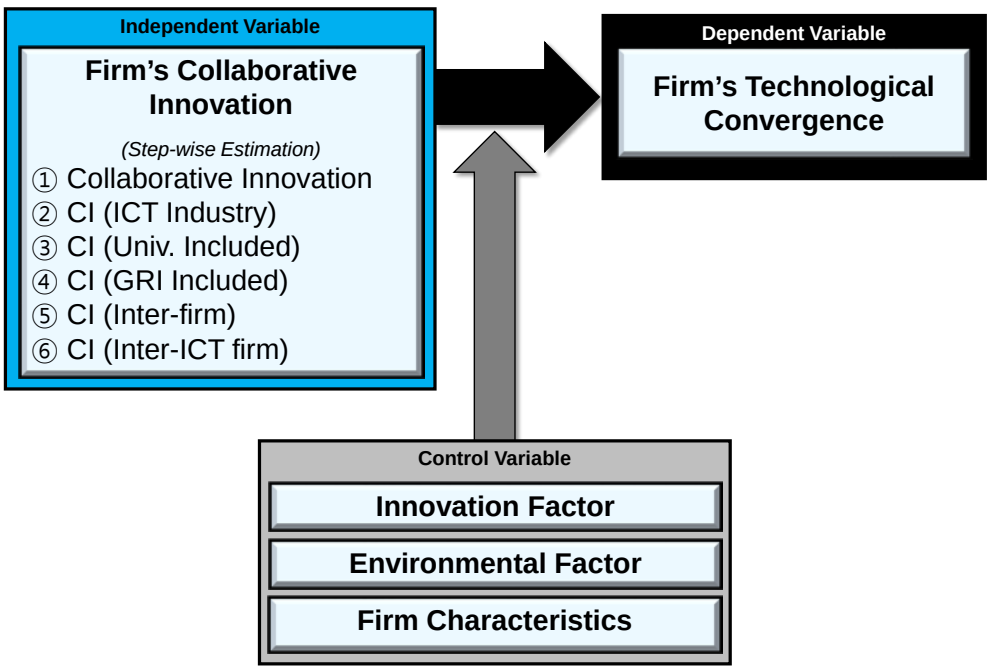
The purposes of this study are as follows. First, it analyzes whether the collaborative innovation of ICT firms has a positive effect on technological convergence. This analysis makes it possible to evaluate whether the government's approach to promoting technological convergence through the activation of collaborative innovation between firms is reasonable. If firms' collaborative innovation has a positive effect on technological convergence, the government can increase the output of technological convergence in the industry in a way that promotes firms' collaborative innovation. Second, this study seeks the answer to the question of which type of collaborative innovation is most likely to promote technological convergence. By identifying the types of collaborative innovation that are the most effective in promoting technological convergence, it is possible to show that government policies should give higher incentives to any type of collaborative innovation and thereby contribute to the establishment of a more effective incentive system. If the incentive system is designed to offer more incentives to the type of collaborative innovation that best facilitates technological convergence, policies can be implemented more effectively than the existing policy, which does not differentiate the budget allocation or the amount of support depending on the type of collaborative innovation partner in the application stage.

This section identifies the possibility of bias associated with the endogeneity and potential simultaneity due to omitted and irrelevant variables and presents a research design to minimize the possibility of these biases. First, previous studies have not adequately controlled the third variables affecting technological convergence. Second, cross-sectional data in innovation studies can be highly overestimated in the statistical

analysis compared with time-series data (Griliches, 1990). This indicates that the effect of unobserved factors on innovation is significant and should be analyzed through firm-level panel data. Third, previous studies have assumed that firms' collaborative innovation affects technological convergence, but, on the contrary, firms' technological convergence may affect collaborative innovation. In this case, the estimates are biased due to the simultaneity, and it is difficult to estimate the net effect. Therefore, this study integrates patent data and firm data to construct a firm-level panel data set, controls various factors affecting innovation, and performs a verification process to confirm the existence of endogeneity due to simultaneity. Through this process, this study overcomes the limitations of the previous studies and suggests improved estimates.

This study suggests that collaborative innovativeness facilitates technological convergence and that inter-firm collaborative innovation has a greater positive effect on technological convergence than other types of collaborative innovation from previous studies and theoretical discussions. The conceptual framework of this study for demonstrating these hypotheses is presented in Figure 4.1.

Figure 4.1 Conceptual Framework of the Study



This study addresses one independent estimation model for one independent variable to compare the effects of each type of collaborative innovation on technological convergence. Thus, it compares the effects of each independent variable by performing a step-wise estimation with six regression models for six independent variables.

4.3.2.2 Data Collection

This study constructs a firm-level panel dataset by collecting patent data and firm data to identify the factors affecting collaborative innovation and to estimate the effect of collaborative innovation on technological convergence. Patent data have been widely used as a proxy for innovation in innovation research (Pakes & Griliches, 1984). In

innovation research, time-invariant unobserved factors have been regarded as disturbing the relationship between explanatory variables and innovation.[20] Therefore, this study collects time series patent data, merges them with firm data, and converts them into firm-level panel data based on the applicant and filing year. Specifically, this study collects patent and firm data from Korean ICT firms and construct unbalanced panel data from 1980 to 2015.

This study limits the scope of Korean ICT firms to those defined by KIS-IC and makes the whole population a subject of analysis. KIS-IC, based on the classification system of GICS, is a classification system developed and introduced in 1999 by S&P and MSC to classify various firms in the world, all industries in Korea are divided into 10 sectors, 23 industry groups, 29 industries, and 122 sub-industries.

This study collects patent data filed with the Korean Intellectual Property Office (KIPO) from 1980 to 2015. The patents disclosed in the Korean Intellectual Property Office include those filed from 1980 to May 2017 at the time of the analysis in mid-2017. However, not all patents are published simultaneously with the application. Therefore, the patent applications filed by mid-2017 cannot fully reflect the patent applications filed in 2016 and 2017 (Kim & Youn, 2009). Patents registered with the Korean Intellectual Property Office will automatically be disclosed when 18 months have elapsed since the filing date. Therefore, all patent information filed 18 months before the current date is disclosed. Therefore, this study analyzes patents registered until December 2015 by applying the time difference of 18 months. Consequently, it collects patent data filed from 1980 to 2015 based on the patent filing date. In this case,

[20] Griliches (1990) reported that the correlation coefficient was 0.9 when cross-sectional data were used for the correlation between R&D and innovation but that the correlation coefficient was 0.3 when the analysis used time-series data. Therefore, there is a limit to the ability to estimate the effect of innovation with cross-sectional data.

525 firms, excluding ICT firms established after 2016, are analyzed.

This study restricts domestic patents to collection subjects. This restriction is intended to prevent the possibility of overestimation due to the ability to register the same patent in several countries.[21] Patent data filed by these firms are collected from the National Digital Science Library (NDSL).[22] To collect all the patent data filed by Korean ICT firms, this study collects data by specifying 525 firm names in the applicant part of the patent search formula. In the case of a firm that has changed its name, the past name is also included.[23]

This study collects a total of 230,388 patent data. The collected patent data includes information such as patent name, patent number, filing date, registration date, publication date, applicant information, and International Patent Classification (IPC) code.

The collected patent data is converted to the firm level to enable regression analysis. After assigning a unique id to each firm, the firm data is constructed by adding the year data to each patent using the year information in the patent application number. This data is then matched with firm data. When matching data, firms that have never filed a patent are also included in the dataset in order to eliminate the possibility of selection bias. The panel data include a total of 9,882 firm-level observations from 1980 to 2015.

The firm data is collected from KIS-Value. However, since the R&D expenditure

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[21] Since patents that are filed and registered in certain countries are only valid within the country concerned, patents are often filed in many countries at the same time. Therefore, in the case of not limiting the boundaries of patents to domestic countries, even though an overseas application is not always made through a separate cooperation act, one cooperation can be duplicated as two or more cooperations.

[22] (http://www.ndsl.kr/)

[23] For example, POSCO ICT was formerly POSDATA, and LG U + was a merger of LG Dacom and LG Powercomm. LG Display was formerly LG Philips Display, Kakao was a merger of Daum Communications and Kakao, and SK Hynix was formerly Hynix Semiconductor. Many firms have changed their names for various reasons, such as M&As and restructuring.

data collected by KIS-Value have many missing values, additional R&D expenditure data is collected from the annual business reports published by Data Analysis, Retrieval and Transfer system (DART), an electronic disclosure system of the Financial Supervisory Service (FSS). The DART has been open to business reports from 1999 to the present, and I collect the R&D expenditure data specified in the annual business report of 525 ICT firms in the system to minimize the missing values.

4.3.2.3 Variables

The purpose of the study is to examine whether the collaborative innovation of ICT firms affects technological convergence. Therefore, this analysis uses technological convergence as a dependent variable, collaborative innovation and various types of collaborative innovation as independent variables, and uses innovation factors, firm characteristics, and environmental factors as control variables.

(1) Dependent Variable

The dependent variable is measured as the number of technologically convergent patents registered by ICT firms. In general, technological convergence is measured using patent data. In this analysis, technological convergence patents are measured based on co-classification using the patent's IPC code (Curran & Leker, 2011). If the IPC codes of a particular patent belong to different technological sectors, the patent is considered to be a technologically convergent patent. I determine whether each patent is technologically convergent and then match it with the firm data, as in the first analysis. Specifically, this analysis classifies the IPC code of each patent by sector according to the IPC-Technology Concordance Table in World Intellectual Property Indicators 2016

published by World Intellectual Property Organization (WIPO) (2016). This classification is shown in Table 4.1.

Table 4.1 IPC-Technology Concordance Table (WIPO, 2016)

Field No.	Sector	Field	IPC Code
1	Electrical engineering	Electrical machinery, apparatus, energy	F21H%, F21K%, F21L%, F21S%, F21V%, F21W%, F21Y%, H01B%, H01C%, H01F%, H01G%, H01H%, H01J%, H01K%, H01M%, H01R%, H01T%, H02B%, H02G%, H02H%, H02J%, H02K%, H02M%, H02N%, H02P%, H02S%, H05B%, H05C%, H05F%, H99Z%
2		Audio-visual technology	G09F%, G09G%, G11B%, H04N 3%, H04N 5%, H04N 7%, H04N 9%, H04N 11%, H04N 13%, H04N 15%, H04N 17%, H04N 19%, H04N 101%, H04R%, H04S%, H05K%
3		Telecommunications	G08C%, H01P%, H01Q%, H04B%, H04H%, H04J%, H04K%, H04M%, H04N 1%, H04Q%
4		Digital communication	H04L%, H04N 21%, H04W%
5		Basic communication processes	H03B%, H03C%, H03D%, H03F%, H03G%, H03H%, H03J%, H03K%, H03L%, H03M%
6		Computer technology	G06C%, G06D%, G06E%, G06F%, G06G%, G06J%, G06K%, G06M%, G06N%, G06T%, G10L%, G11C%
7		IT methods for management	G06Q%
8		Semiconductors	H01L%
9	Instruments	Optics	G02B%, G02C%, G02F%, G03B%, G03C%, G03D%, G03F%, G03G%, G03H%, H01S%
10		Measurement	G01B%, G01C%, G01D%, G01F%, G01G%, G01H%, G01J%, G01K%, G01L%, G01M%, G01N 1%, G01N 3%, G01N 5%, G01N 7%, G01N 9%, G01N 11%, G01N 13%, G01N 15%, G01N 17%, G01N 19%, G01N 21%, G01N 22%, G01N 23%, G01N 24%, G01N 25%, G01N 27%, G01N 29%, G01N 30%, G01N 31%, G01N 35%, G01N 37%, G01P%, G01Q%, G01R%, G01S%, G01V%, G01W%, G04B%, G04C%, G04D%, G04F%, G04G%, G04R%, G12B%, G99Z%
11		Analysis of biological materials	G01N 33%,
12		Control	G05B%, G05D%,G05F%, G07B%, G07C%, G07D%, G07F%,G07G%, G08B%, G08G%, G09B%, G09C%, G09D%
13		Medical technology	A61B%, A61C%, A61D%, A61F%, A61G%, A61H%, A61J%, A61L%, A61M%, A61N%, H05G%

14	Chemistry	Organic fine chemistry	A61K 8%, A61Q%, C07B%, C07C%, C07D%, C07F%, C07H%, C07J%, C40B%
15		Biotechnology	C07G%, C07K%, C12M%, C12N%, C12P%, C12Q%, C12R%, C12S%
16		Pharmaceuticals	A61K 6%, A61K 9%, A61K 31%, A61K 33%, A61K 35%, A61K 36%, A61K 38%, A61K 39%, A61K 41%, A61K 45%, A61K 47%, A61K 48%, A61K 49%, A61K 50%, A61K 51%, A61K 101%, A61K 103%, A61K 125%, A61K 127%, A61K 129%, A61K 131%, A61K 133%, A61K 135%, A61P%
17		Macromolecular chemistry, polymers	C08B%, C08C%, C08F%, C08G%, C08H%, C08K%, C08L%
18		Food chemistry	A01H%, A21D%, A23B%, A23C%, A23D%, A23F%, A23G%, A23J%, A23K%, A23L%, C12C%, C12F%, C12G%, C12H%, C12J%, C13B 10%, C13B 20%, C13B 30%, C13B 35%, C13B 40%, C13B 50%, C13B 99%, C13D%, C13F%, C13J%, C13K%
19		Basic materials chemistry	A01N%, A01P%, C05B%, C05C%, C05D%, C05F%, C05G%, C06B%, C06C%, C06D%, C06F%, C09B%, C09C%, C09D%, C09F%, C09G%, C09H%, C09J%, C09K%, C10B%, C10C%, C10F%, C10G%, C10H%, C10J%, C10K%, C10L%, C10M%, C10N%, C11B%, C11C%, C11D%, C99Z%
20		Materials, metallurgy	B22C%, B22D%, B22F%, C01B%, C01C%, C01D%, C01F%, C01G%, C03C%, C04B%, C21B%, C21C%, C21D%, C22B%, C22C%, C22F%
21		Surface technology, coating	B05C%, B05D%, B32B%, C23C%, C23D%, C23F%, C23G%, C25B%, C25C%, C25D%, C25F%, C30B%
22		Micro-structural and nano-technology	B81B% B81C%, B82B%, B82Y%
23		Chemical engineering	B01B%, B01D 1%, B01D 3%, B01D 5%, B01D 7%, B01D 8%, B01D 9%, B01D 11%, B01D 12%, B01D 15%, B01D 17%, B01D 19%, B01D 21%, B01D 24%, B01D 25%, B01D 27%, B01D 29%, B01D 33%, B01D 35%, B01D 36%, B01D 37%, B01D 39%, B01D 41%, B01D 43%, B01D 57%, B01D 59%, B01D 61%, B01D 63%, B01D 65%, B01D 67%, B01D 69%, B01D 71%, B01F%, B01J%, B01L%, B02C%, B03B%, B03C%, B03D%, B04B%, B04C%, B05B%, B06B%, B07B%, B07C%, B08B%, C14C%, D06B%, D06C%, D06L%, F25J%, F26B%, H05H%
24		Environmental technology	A62C%, B01D 45%, B01D 46%, B01D 47%, B01D 49%, B01D 50%, B01D 51%, B01D 52%, B01D 53%, B09B%, B09C%, B65F%, C02F%, E01F 8%, F01N%, F23G%, F23J%, G01T%
25	Mechanical engineering	Handling	B25J%, B65B%, B65C%, B65D%, B65G%, B65H%, B66B%, B66C%, B66D%, B66F%, B67B%, B67C%, B67D%

26		Machine tools	A62D%, B21B%, B21C%, B21D%, B21F%, B21G%, B21H%, B21J%, B21K%, B21L%, B23B%, B23C%, B23D%, B23F%, B23G%, B23H%, B23K%, B23P%, B23Q%, B24B%, B24C%, B24D%, B25B%, B25C%, B25D%, B25F%, B25G%, B25H%, B26B%, B26D%, B26F%, B27B%, B27C%, B27D%, B27F%, B27G%, B27H%, B27J%, B27K%, B27L%, B27M%, B27N%, B30B%
27		Engines, pumps, turbines	F01B%, F01C%, F01D%, F01K%, F01L%, F01M%, F01P%, F02B%, F02C%, F02D%, F02F%, F02G%, F02K%, F02M%, F02N%, F02P%, F03B%, F03C%, F03D%, F03G%, F03H%, F04B%, F04C%, F04D%, F04F%, F23R%, F99Z%, G21B%, G21C%, G21D%, G21F%, G21G%, G21H%, G21J%, G21K%
28		Textile and paper machines	A41H%, A43D%, A46D%, B31B%, B31C%, B31D%, B31F%, B41B%, B41C%, B41D%, B41F%, B41G%, B41J%, B41K%, B41L%, B41M%, B41N%, C14B%, D01B%, D01C%, D01D%, D01F%, D01G%, D01H%, D02G%, D02H%, D02J%, D03C%, D03D%, D03J%, D04B%, D04C%, D04G%, D04H%, D05B%, D05C%, D06G%, D06H%, D06J%, D06M%, D06P%, D06Q%, D21B%, D21C%, D21D%, D21F%, D21G%, D21H%, D21J%, D99Z%
29		Other special machines	A01B%, A01C%, A01D%, A01F%, A01G%, A01J%, A01K%, A01L%, A01M%, A21B%, A21C%, A22B%, A22C%, A23N%, A23P%, B02B%, B28B%, B28C%, B28D%, B29B%, B29C%, B29D%, B29K%, B29L%, B33Y%, B99Z%, C03B%, C08J%, C12L%, C13B 5%, C13B 15%, C13B 25%, C13B 45%, C13C%, C13G%, C13H%, F41A%, F41B%, F41C%, F41F%, F41G%, F41H%, F41J%, F42B%, F42C%, F42D%
30		Thermal processes and apparatus	F22B%, F22D%, F22G%, F23B%, F23C%, F23D%, F23H%, F23K%, F23L%, F23M%, F23N%, F23Q%, F24B%, F24C%, F24D%, F24F%, F24H%, F24J%, F25B%, F25C%, F27B%, F27D%, F28B%, F28C%, F28D%, F28F%, F28G%
31		Mechanical elements	F15B%, F15C%, F15D%, F16B%, F16C%, F16D%, F16F%, F16G%, F16H%, F16J%, F16K%, F16L%, F16M%, F16N%, F16P%, F16S%, F16T%, F17B%, F17C%, F17D%, G05G
32		Transport	B60B%, B60C%, B60D%, B60F%, B60G%, B60H%, B60J%, B60K%, B60L%, B60M%, B60N%, B60P%, B60Q%, B60R%, B60S%, B60T%, B60V%, B60W%, B61B%, B61C%, B61D%, B61F%, B61G%, B61H%, B61J%, B61K%, B61L%, B62B%, B62C%, B62D%, B62H%, B62J%, B62K%, B62L%, B62M%, B63B%, B63C%, B63G%, B63H%, B63J%, B64B%, B64C%, B64D%, B64F%, B64G%
33	Other fields	Furniture, games	A47B%, A47C%, A47D%, A47F%, A47G%, A47H%, A47J%, A47K%, A47L%, A63B%, A63C%, A63D%, A63F%, A63G%, A63H%, A63J%, A63K%

34		Other consumer goods	A24B%, A24C%, A24D%, A24F%, A41B%, A41C%, A41D%, A41F%, A41G%, A42B%, A42C%, A43B%, A43C%, A44B%, A44C%, A45B%, A45C%, A45D%, A45F%, A46B%, A62B%, A99Z%, B42B%, B42C%, B42D%, B42F%, B43K%, B43L%, B43M%, B44B%, B44C%, B44D%, B44F%, B68B%, B68C%, B68F%, B68G%, D04D%, D06F%, D06N%, D07B%, F25D%, G10B%, G10C%, G10D%, G10F%, G10G%, G10H%, G10K%
35		Civil engineering	E01B%, E01C%, E01D%, E01F 1%, E01F 3%, E01F 5%, E01F 7%, E01F 9%, E01F 11%, E01F 13%, E01F 15%, E01H%, E02B%, E02C%, E02D%, E02F%, E03B%, E03C%, E03D%, E03F%, E04B%, E04C%, E04D%, E04F%, E04G%, E04H%, E05B%, E05C%, E05D%, E05F%, E05G%, E06B%, E06C%, E21B%, E21C%, E21D%, E21F%, E99Z%

(2) Independent Variables

Collaborative innovation and various types of collaborative innovation of ICT firms, which are independent variables of this study, are measured by the number of joint patents registered by ICT firms (Cantner & Graf, 2006; Guan & Liu, 2016; Inoue & Liu, 2015; Maggioni, Nosvelli, & Uberti, 2007). Previous innovation studies have used patents filed by firms as a proxy for innovation (Bernstein, 2015; Briggs & Wade, 2014; Crepon, Duguet, & Mairesse, 1998; Griliches, 1990; Guan & Liu, 2016). This study measures the types of detailed collaborative innovation as ICT industry only, Univ. included, GRI included, Firms only, and ICT firms only. Specifically, these variables are measured by joint patents except non-ICT firms, joint patents involving universities, joint patents involving GRIs, joint patents with other firms, and joint patents with other ICT firms. This study defines a joint patent as a patent with two or more legal entities like a firm. In this study, patents co-filed with both firms and individuals are not regarded as joint patents because most of the individuals are employees or representatives belonging to the firm.[24]

[24] For example, a patent jointly filed by Samsung Electronics and former Samsung Electronics

(3) Control Variables

This study controls the variables that are considered to affect the relationship between collaborative innovation and technological convergence. This study uses a firm's innovation factors as a control variable. Specifically, I divide innovation factors into R&D expenditure, firm size, and firm productivity. The log value is applied to each independent variable.

First, this study uses firm size as a control variable that affects the patent performance. Since the Schumpeterian hypothesis on the relationship between firm size and innovation, many researchers have argued that firm size affects patent performance. In addition, firm size has been extensively used as an independent or controlled variable in innovation research. The firm size is measured by the logarithm of the number of workers. Previous studies have measured firm size as a logarithm of the number of workers (Faria, Lima, & Santos, 2010; Hall & Ziedonis, 2001).

Second, this study uses the R&D expenditure presented in the classical patent production function as a control variable that affects the patent performance, and converts the annual R&D expenditure of each firm into the unit of 1 million won and converts it into a log value. These measurements were used by Hausman, Hall, & Griliches (1984). The innovation activity of a firm is represented by a patent application, and many innovation studies have suggested that R&D expenditure has a positive effect on a firm's patent performance. The most classical model of patent production is the knowledge production function proposed by Pakes and Griliches (1984), which involved a knowledge production function based on the Cobb-Douglas production function. They used the patent as a proxy for knowledge. According to the knowledge

president Jong-Yong Yun is not considered as a joint patent.

production function, factors that affect the patent performance of individual firms can be classified into R&D investment and other innovation factors, time, and characteristics of individual firms (Pakes & Griliches, 1984). Knowledge production functions developed by subsequent studies such as those by Griliches (1990) and Crepon et al. (1998) also have a form of patent production function because they use patents as surrogate variables of knowledge. These studies claim that R&D investment is a major factor in patent performance.

Third, this study uses firm productivity as a control variable. recent studies on innovation factors have revealed that productivity of firms represented by capital intensity affects patent performance. Hall and Ziedonis (2001) have empirically demonstrated the effect of capital intensity on patent applications of semiconductor firms. They hypothesize that capital intensity affects firms' patent behavior and empirically analyze firm and patent data. As a result, they found that capital intensity is a major factor in promoting innovation in semiconductor manufacturers (Hall & Ziedonis, 2001). Subsequent studies have also shown that capital intensity affects firms' patent performance. Through analyzing firms and patents in the US software sector, Bessen and Hunt (2007) found that the magnitude and direction of the effect of capital intensity on a firm's patent performance are similar to that of Hall and Ziedonis (2001). By analyzing Belgian firms, Czarnitzki, Kraft, & Thorwarth (2009) found that capital-intensive firms rely more on technology and tend to retain their intellectual property rights through patent applications. Firm productivity is measured by capital intensity as proposed by Hall and Ziedonis (2001). In this study, the annual capital intensity of each firm is converted into the unit of 1 million won and measured by the log value. Previous studies have also used log values of capital intensity as independent variables (Bessen & Hunt, 2007; Czarnitzki et al., 2009; Hall & Ziedonis, 2001).

Also, this study controls for group affiliates, firm age, large firms, IPO status, and year. Hong and Su (2013) found that there is a positive correlation between firm age and collaborative innovation. IPO status should be controlled in this study because it is an endogenous variable that affects innovation. Bernstein (2015) found that IPO is an endogenous variable affecting innovation represented by patent achievement. Table 4.2 summarizes the variables of this study.

Table 4.2 Variables of Analysis by Type

Variable Type	Variable Name	Measurement
Dependent Variable	*Technological Convergence*	Number of technologically convergent patents applied by each firm; The technologically convergent patents are measured based on the co-classification using the IPC classification (Curran & Leker, 2011); The IPC classification is based on the IPC-Technology Concordance Table by WIPO (WIPO, 2016)
Independent Variables	*Collaborative Innovation*	Number of total joint patents applied for by each firm (Cantner & Graf, 2006; Guan & Liu, 2016; Inoue & Liu, 2015; Maggioni et al., 2007)
	Collaborative Innovation (ICT Industry Only)	Number of joint patents (except non-ICT firms) applied for by each firm
	Collaborative Innovation (Univ. included)	Number of joint patents (Univ. included) applied for by each firm
	Collaborative Innovation (GRI included)	Number of joint patents (GRI included) applied for by each firm

	Collaborative Innovation (Inter-firm)	Number of joint patents (Firms Only) applied for by each firm
	Collaborative Innovation (Inter-ICT firm)	Number of joint patents (ICT Firms Only) applied for by each firm
Control Variables	*Ln (Firm Size)*	Ln (Number of total workers) (Faria et al., 2010; Hall & Ziedonis, 2001)
	Ln (R&D Expenditure)	Ln (R&D expenditure, million KRW) (Hausman et al., 1984)
	Ln (Productivity)	Ln (Capital intensity, million KRW) (Bessen & Hunt, 2007; Czarnitzki et al., 2009; Hall & Ziedonis, 2001)
	Group Dummy	(Unaffiliated = 0, Group affiliated = 1)
	Firm Age	Firm age, yearly
	Large Firms Dummy	(SMEs = 0, Large firms = 1)
	IPO Dummy	(Unlisted = 0, Listed = 1)
	Year	Year (1980~2015)

4.3.2.4 Methodology and Estimation Strategy

Technological convergence, a dependent variable of this analysis, is measured by the number of patents. The number of patents is count data because it is 0 or a positive integer. In general, the count data is estimated by the Poisson model, which assumes a distribution of mean and variance equal to each other. However, the patent data used in this study have characteristics of over-dispersion because the variance is larger than the mean. Estimates are inconsistent when estimating data with over-dispersion by the Poisson model (Hilbe, 2011). Since the number of technologically convergent patents is the count data with over-dispersion, this study uses the negative binomial model, which alleviates the assumption underlying the Poisson model. Additionally, the LR test is performed to determine whether the Poisson model or the negative binomial model is appropriate.

The potential problem of endogeneity must be considered to estimate causality. First, since the firm is the subject of decision making, the same firm decides both collaborative innovation and technological convergence. Therefore, third variables affecting these two variables should be controlled. Since the data used in this study is firm-level panel data, the panel negative binomial model is used. When using panel data, the estimation model includes the heterogeneity of individual firms. Adding fixed or random effects to the model also has the advantage of controlling for time-invariant unobserved variables. This study might intuitively use the fixed effects model because the whole population is analyzed, but some observations are excluded because of the missing values in the analysis. Therefore, this study estimates the fixed effect model and the random effect model, respectively, and then determines which model is more appropriate through the Hausman test.

Second, it is known that collaborative innovation affects technological

convergence, but there is also the possibility that technological convergence may affect collaborative innovation. In this case, an endogeneity problem arises due to simultaneity, and it is necessary to estimate using an instrumental variable.

In summary, the omitted variable bias can be minimized by using appropriate control variables and a fixed or a random effect, but in the case of simultaneity bias, an instrumental variable should be utilized. This study uses the IV Poisson model as an instrumental variable estimation method. Yamamura (2013) notes that when analyzing count data with over-dispersion, the IV negative binomial model has not yet been developed and the IV Poisson model should be used. Specifically, this study uses the IV Poisson GMM model proposed by Mullahy (1997).

Therefore, this study first determines whether there is an endogeneity problem due to simultaneity in the independent variables. The test for endogeneity is performed through the Hausman test on the Poisson and IV Poisson GMM estimates. If the test statistic is statistically significant, the independent variable is considered to have an endogeneity problem due to simultaneity. If there is an endogeneity problem, the IV Poisson GMM estimation result is adopted. Otherwise, the panel negative binomial estimation result is adopted. The lagged value of each independent variable is used as an instrumental variable in estimating IV Poisson GMM model.

First, the specification of the panel negative binomial model is as follows.

$$\begin{aligned} TechConv_{it} = \alpha + \beta_1 X_{it} + \beta_2 Ln(FirmSize)_{it} + \beta_3 Ln(R\&D\_Exp.)_{it} \\ + \beta_4 Ln(Productivity)_{it} + \beta_5 Group_{it} + \beta_6 FirmAge_{it} \\ + \beta_7 LargeFirms_{it} + \beta_8 IPO_{it} + \beta_9 Year + \delta_i + \varepsilon_{it} \end{aligned}$$

(X_{it} = Collaborative Innovation, CI(ICT Industry Only), CI(Univ. Included), CI(GRI Included), CI(Firms Only), CI(ICT Firms Only))

(t = 1980, 1981, … , 2015)

(i = 1, 2, … , 525)

Second, the specification of IV Poisson GMM model for endogenous variable X_{it} is as follows.

$$TechConv_{it} = exp(\alpha + \beta_1 X_{it} + \beta_2 Ln(FirmSize)_{it} + \beta_3 Ln(R\&D\_Exp.)_{it} + \beta_4 Ln(Productivity)_{it} + \beta_5 Group_{it} + \beta_6 FirmAge_{it} + \beta_7 LargeFirms_{it} + \beta_8 IPO_{it} + \beta_9 Year) + \varepsilon_{it}$$

And the moment condition where Z_{it} presents instrumental variable is

$$E[TechConv_{it} - exp(\alpha + \beta_1 X_{it} + \beta_2 Ln(FirmSize)_{it} + \beta_3 Ln(R\&D\_Exp.)_{it} + \beta_4 Ln(Productivity)_{it} + \beta_5 Group_{it} + \beta_6 FirmAge_{it} + \beta_7 LargeFirms_{it} + \beta_8 IPO_{it} + \beta_9 Year)|X_{it}, Z_{it}] = 0$$

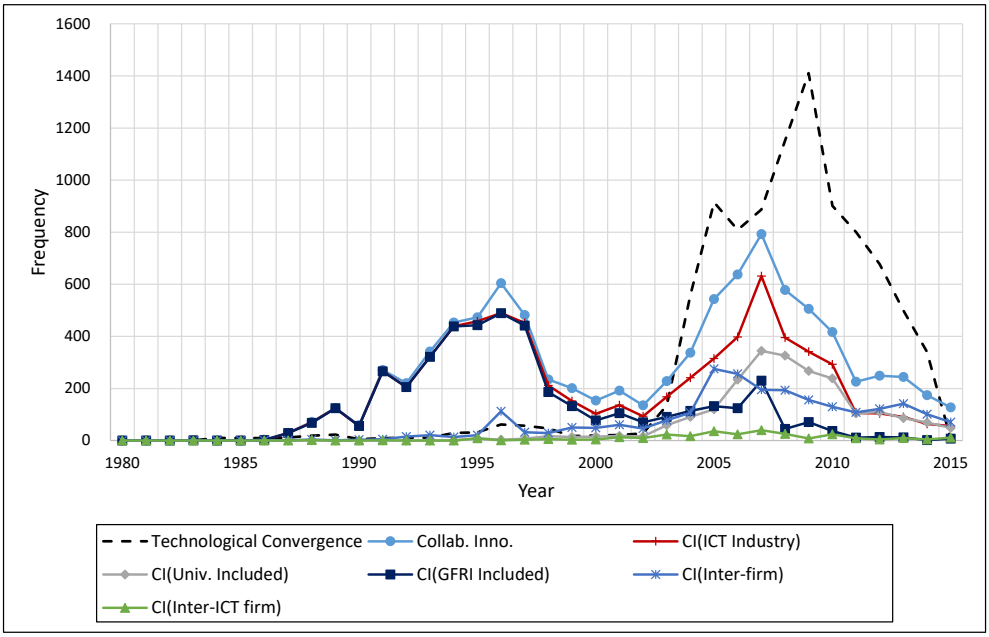
Balsmeier, Buchwald, & Stiebale (2013) suggests that additional test can be performed on the linear 2SLS model to ensure the robustness of the IV estimator when estimating the IV Poisson GMM model. This study performs a weak IV test on the linear 2SLS model for the robustness check on the IV estimator.

4.3.2.5 Descriptive Statistics

This study examines the structure of the data and its implications with descriptive statistics before conducting a regression analysis. First, it examines the overall

collaborative innovation of ICT firms from 1980 to 2015 and the time-dependent trajectories of collaborative innovation and technological convergence for each type. Technological convergence, a dependent variable, the overall collaborative innovation, an independent variable, and the time-dependent changes in each type of collaborative innovation are shown in Figure 4.2 below.

Figure 4.2 Collaborative Innovation and Technological Convergence by Year



Technological convergence increased slightly at the end of the 1990s but remained steady decrease until the early 2000s. Since 2003, technological convergence has increased significantly, peaking in 2009 and then declining, reaching a shallow level in 2015.[25]

[25] This trajectory relates to the steady decline in the number of patents filed by Korean ICT firms with the Korean Intellectual Property Office after peaking in 2005. In addition, the decrease in the number of patents in the 2010s is related to the decrease in the number of patents of Samsung

The overall collaborative innovation performed by ICT firms and the trajectory of the collaborative innovation in the ICT industry are very similar. By the early 1990s, most collaborative innovation of ICT firms was performed only in the ICT industry. Since the mid-1990s, a gap between the two has begun to emerge, indicating that the collaborative innovation target of ICT firms has expanded to firms outside the ICT industry. It is also evident that the collaborative innovation involving the GRI in the overall collaborative innovation was high until the 1990s and most of the collaborative innovations undertaken by ICT firms were part of a government-led initiative. In the 2000s, the gap between collaborative innovation and collaborative innovation including GRI increased. In particular, since the mid-2000s, the proportion of collaborative innovation and inter-firm collaborative innovation, including universities, has increased, and, since 2010, the proportion of inter-firm collaborative innovation has been the highest among all the collaboration types. This indicates that the government-led collaborative innovation initiated from the end of the 1980s was a major part of the collaborative innovation by the end of the 1990s, while the collaborative innovation ecosystem was created in the 2000s and the government-led collaborative innovation was gradually replaced by collaborative innovation between firms.

Second, this study examines the summary statistics of all the variables by type. The summary statistics of this study are shown in Table 4.3 below.

Table 4.3 Descriptive Statistics of the Variables (1980-2015)

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
Dependent Variable					

Electronics. The Korean ICT industry follows a pattern in which a small number of firms with high market concentration dominate innovation. Since Samsung Electronics accounts for a large portion of the total patents, the patent performance of the industry shows a similar slope to that of Samsung Electronics.

Technological Convergence	9,882	0.8279	9.9783	0	431
Independent Variable					
Collaborative Innovation	9,882	1.0041	15.2074	0	579
CI (ICT Industry)	9,882	0.7957	13.8721	0	535
CI (Univ. Included)	9,882	0.2088	4.9326	0	287
CI (GRI Included)	9,882	0.5074	11.3525	0	481
CI (Inter-firm)	9,882	0.2727	2.7625	0	125
CI (Inter-ICT firm)	9,882	0.0578	0.7375	0	32
Control Variable					
Ln(Firm Size)	8,661	4.9529	1.3908	0	11.5324
Ln(R&D Exp.)(mil.)	7,090	7.2874	1.8118	-1.9290	16.5450
Ln(Productivity)(mil.)	8,661	5.4180	1.0995	-0.3352	10.7682
Group	9,882	0.7816	0.4131	0	1
Firm Age	9,882	12.1258	10.0161	0	66
Large Firms	9,882	0.3760	0.4844	0	1
IPO	9,882	0.4744	0.4994	0	1
Year	9,882	2004.237	8.0585	1980	2015

There are 9,882 observations for 525 firms over 35 years, including those firms created or listed between 1980 and 2015. The mean and standard deviation of technological convergence, which is a dependent variable, and collaborative innovation, which is an independent variable, indicate that the innovation of the Korean ICT industry is severely polarized. The standard deviation of technological convergence is 10 times greater than the average, indicating that some market-dominant firms are producing most of the technological convergence in the industry. The standard deviation of the independent variables is also more than 10 times greater than the average, indicating that the collaborative innovation is concentrated in a small number of firms.

The mean of collaborative innovation is close to 1, and most firms seem to experience collaborative innovation, but the standard deviation is more than 15, indicating that collaborative innovation is concentrated in a small number of firms. The mean of collaborative innovation by type is in the order of CI (ICT Industry), CI (GRI Included), CI (Inter-firm), CI (Univ. Included), and CI (Inter-ICT firm). As shown in Figure 4.2, the collaborative innovation including the GRI was the most prevalent until the 1990s according to past government policies, and inter-firm collaborative innovation has been the most frequent since the 2000s.

Unlike dependent variables or independent variables, control variables except for IPOs are found to have a mean value greater than a standard deviation. Some missing values are found in firm size, R&D expenditure, and capital intensity. The causes of these missing values can be divided into four major categories. First, only a listed firm has to disclose firm information. The data published in DART include only data after the IPO. In this case, even if it was established in the 1980s, if it was listed in the 2000s, only data from the 2000s are available. Second, corporations listed on the KOSPI or KOSDAQ and unlisted corporations with total assets of more than 12 billion, more than 300 employees, and assets totaling more than 7 billion are obligated to disclose their management in the DART system. In other words, since not all corporations are subject to disclosure, information from small corporations without external auditing cannot be obtained from the DART system. Third, some firms do not disclose their research and development costs in some years even though they are subject to disclosure. Fourth, no data were published in DART before 1998, and only some KIS-Value data exist. Although this study collected all the available data from KIS-Value and business reports published in DART, there are some missing values for these reasons. However, because the missing values are found only in some of the control variables and the proportion of

the total observations is small, they are not considered to have a significant effect on the analysis results.

From the dummy variables, it is apparent that 78% of the firms surveyed are group affiliates, 37% are classified as large firms, and 47% are listed firms. The average age of the firms is 12 years. However, given that these figures are the average of a 35-year time series, the proportion of large firms and listed firms is expected to increase over time.

Third, this study conducts an over-dispersion test to ascertain whether technological convergence, a dependent variable, is over-dispersed. Over-dispersion can be diagnosed by the variance to mean ratio (VMR). When VMR = 0, it is classified as not dispersed. When 0 < VMR < 1, it is classified as under-dispersed and considered as a binomial distribution. When VMR = 1, it is considered to have a Poisson distribution. When VMR > 1, it is considered to have over-dispersion and negative binomial distribution. The VMR test results are shown in Table 4.4.

Table 4.4 Result of the Over-Dispersion Test

Dependent Variable	Mean	Variance	VMR (Variance-to-Mean Ratio)
Technological Convergence	0.8279	99.5665	120.2639

The results show that the VMR is quite high at about 120. Therefore, technological convergence, which is a dependent variable, can be regarded as having a negative binomial distribution with over-dispersion. Considering the high level of over-dispersion, this study concludes that it is appropriate to perform regression analysis with the panel negative binomial model presented in this research design.

4.4 Results

This study examines the correlation between the dependent variables and the independent variables through Pearson correlation analysis before performing regression analysis and investigates whether there are variables that should not be included in the regression model. If the correlation coefficient is 0.7 or more, it is considered to have multicollinearity. In this study, the regression equation is estimated by dividing the model into 6 independent variables. The results of the Pearson correlation analysis including the dependent variable and the control variable are presented in Table 4.5, and the results of the Pearson correlation between the independent variables and the control variables are presented in Table 4.6.

The results presented in Table 4.5 show that most of the control variables have weak or moderate correlations with each other. The Pearson correlation coefficient between the year and Ln (Productivity) variables is the highest at 0.6384, but it is less than 0.7, so it can be considered that there is no risk of multicollinearity due to the correlation between the control variables in this study model. In addition, the results presented in Table 4.6 indicate that there is a weak correlation or no correlation between each independent variable and the control variable. The Pearson correlation coefficient between the Collaborative Innovation and the Ln (FirmSize) variables is the highest at 0.2370, but it is less than 0.7, so it is evident that there is no risk of multicollinearity due to the correlation between the independent and the control variables in this model. In conclusion, there is no multicollinearity problem in the regression model presented in this study.

Table 4.5 Pearson's Correlation Coefficients (Dependent Variable and Control Variables)

	Tech. Conv. (Dependent)	Ln (FirmSize)	Ln (R&D Exp.)	Ln (Productivity)	Group	Firm Age	Large Firms	IPO	Year
Tech. Conv. (Dependent)	1								
Ln(FirmSize) (P-value)	0.2286*** (0.0000)	1							
Ln(R&D Exp.) (P-value)	0.2458*** (0.0000)	0.5524*** (0.0000)	1						
Ln(Productivity) (P-value)	0.0616*** (0.0000)	0.0370*** (0.0006)	0.4509*** (0.0000)	1					
Group (P-value)	0.0299** (0.0029)	0.1524*** (0.0000)	0.0158*** (0.0000)	0.0833*** (0.0000)	1				
Firm Age (P-value)	0.1161*** (0.0000)	0.4897*** (0.0000)	0.3318*** (0.0000)	0.3555*** (0.0000)	0.0676*** (0.0000)	1			
Large Firms (P-value)	0.0726*** (0.0000)	0.4772*** (0.0000)	0.2038*** (0.0000)	0.0389*** (0.0003)	0.3198*** (0.0000)	0.2254*** (0.0000)	1		
IPO (P-value)	-0.0588*** (0.0000)	-0.3634*** (0.0000)	-0.3893*** (0.0000)	-0.5365*** (0.0000)	-0.1331*** (0.0000)	-0.5277*** (0.0000)	-0.1192*** (0.0000)	1	
Year (P-value)	0.0353*** (0.0004)	-0.0432*** (0.0001)	0.3656*** (0.0000)	0.6384*** (0.0000)	-0.0427*** (0.0000)	0.2684*** (0.0000)	-0.1734*** (0.0000)	-0.4745* (0.0000)	1

Note: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

Table 4.6 Pearson's Correlation Coefficients (Independent Variables)

	Tech. Conv. (Dependent)	Ln (FirmSize)	Ln (R&D Exp.)	Ln (Productivity)	Group	Firm Age	Large Firms	IPO	Year
Collab. Inno.	0.5640***	0.2545***	0.2009***	0.0378***	0.0310**	0.0765***	0.0754***	-0.0147	-0.0148
(P-value)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0020)	(0.0000)	(0.0000)	(0.1449)	(0.1425)
Collab. Inno. (ICT Industry)	0.5267***	0.2397***	0.1810**	0.0320**	0.0285***	0.0646***	0.0694***	-0.0094	-0.0200*
(P-value)	(0.0000)	(0.0000)	(0.0029)	(0.0047)	(0.0000)	(0.0000)	(0.0000)	(0.3510)	(0.0465)
Collab. Inno. (Univ. Included)	0.8869***	0.1713***	0.1855***	0.0431*	0.0202***	0.0923***	0.0491***	-0.0371***	0.0190
(P-value)	(0.0000)	(0.0000)	(0.0001)	(0.0448)	(0.0000)	(0.0000)	(0.0000)	(0.0002)	(0.0590)
Collab. Inno. (GRI Included)	0.1773***	0.1956***	0.1171	0.0146*	0.0229**	0.0274***	0.0563***	0.0098	-0.0341***
(P-value)	(0.0000)	(0.0000)	(0.1744)	(0.0226)	0.0065	(0.0000)	(0.0000)	(0.3314)	(0.0007)
Collab. Inno. (Inter-firm)	0.6561***	0.2645***	0.2627***	0.0650***	0.0375***	0.1302***	0.0890***	-0.0494***	0.0242*
(P-value)	(0.0000)	(0.0000)	(0.0000)	(0.0002)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0160)
Collab. Inno. (Inter-ICT firm)	0.6762***	0.2293***	0.2204***	0.0595**	0.0331***	0.1185***	0.0760***	-0.0516***	0.0154
(P-value)	(0.0000)	(0.0000)	(0.0000)	(0.0010)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.1248)

Note: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

Next, a panel negative binomial regression is performed to investigate the effect of collaborative innovation on technological convergence. Six regression models for each independent variable are estimated to compare the effect of various types of collaborative innovation on technological convergence. This study estimates the regression model as a fixed-effect model and a random-effect model and then performs the Hausman test to determine which estimates are more appropriate.

The LR test results show that the estimated Chi-squared values are statistically significant in all the models. This result shows that technological convergence follows the negative binomial distribution, which indicates that the negative binomial model is the appropriate estimation model for this study.

First, the estimation results of the fixed-effect model are presented in Table 4.7.

Table 4.7 Negative Binomial Regression with Fixed Effects

Variable	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)[1]
Independent Variables						
Collab. Inno.	0.0039*** (0.0005)					
Collab. Inno. (ICT Industry)		0.0040*** (0.0005)				
Collab. Inno. (Univ. Included)			0.0072*** (0.0011)			
Collab. Inno. (GRI Included)				0.0049*** (0.0010)		
Collab. Inno. (Inter-firm)					0.0226*** (0.0025)	
Collab. Inno. (Inter-ICT firm)						0.0603*** (0.0100)
Control Variables						
Ln(FirmSize)	0.0848 (0.0586)	0.0878 (0.0587)	0.1263* (0.0589)	0.0756 (0.0599)	0.1150* (0.0581)	0.0988 (0.0571)
Ln(R&D Exp.)	0.1135** (0.0433)	0.1146** (0.0434)	0.0980* (0.0439)	0.1176** (0.0438)	0.0966* (0.0431)	0.1058* (0.0431)
Ln(Productivity)	-0.0214 (0.0838)	-0.0166 (0.0838)	0.0060 (0.0835)	-0.0268 (0.0840)	-0.0327 (0.0835)	-0.0300 (0.0823)
Group	-0.5393*	-0.5393*	-0.5436*	-0.5380*	-0.5490*	-0.5653*

	(0.2531)	(0.2529)	(0.2528)	(0.2529)	(0.2536)	(0.2322)
Firm Age	-0.0132 (0.0072)	-0.0132* (0.0072)	-0.0150* (0.0072)	-0.0126 (0.0072)	-0.0170* (0.0072)	-0.0155* (0.0071)
Large Firms	-0.0507 (0.1918)	-0.05741 (0.1916)	-0.0804 (0.1910)	-0.0480 (0.1914)	-0.0677 (0.1916)	(Omitted)
IPO	-0.4243*** (0.1277)	-0.4170** (0.1277)	-0.3908** (0.1275)	-0.4364*** (0.1291)	-0.5127*** (0.1291)	-0.4223*** (0.1269)
Year	0.1294*** (0.0106)	0.1288*** (0.0106)	0.1266*** (0.0105)	0.1298*** (0.0105)	0.1302*** (0.0105)	0.1299*** (0.0101)
Constant	-261.2291*** (21.0624)	-260.0252*** (21.0149)	-255.7600*** (20.9549)	-262.0004*** (20.9034)	-262.7715*** (20.9869)	-262.1929*** (20.1728)
Observations	3,849	3,849	3849	3849	3849	3849
Log Likelihood	-2635.7803	-2638.1513	-2641.7682	-2643.8136	-2632.6903	-2641.7891
LR Chi-squared	834.02***	829.28***	822.04***	817.95***	840.20***	822.00***
Prob > Chi-squared	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Note: * p<0.05; ** p<0.01; *** p<0.001; Standard errors in parentheses.

1) In the case of Model (6), the log-likelihood estimation failed until the maximum iteration in the model estimation. Instead, the model is estimated excluding the *Large Firms* variable.

The estimates of the FENB model show that the independent variables have statistically significant positive effects in all six models. The magnitude of the effect is the greatest for the Inter-ICT Firm variable, followed by Inter-firm, Univ. Included, GRI Included, ICT Industry, and Collaborative Innovation.

The results of the analysis show that collaborative innovation has a positive effect on technological convergence. It also shows that inter-ICT firm collaborative innovation has a larger effect on technological convergence than other types of collaborative innovation.

Next, the estimation results of the random-effect model are presented in Table 4.8.

Table 4.8 Negative Binomial Regression with Random Effects

Variable	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
Independent Variables						
Collab. Inno.	0.0039*** (0.0004)					
Collab. Inno. (ICT Industry)		0.0039*** (0.0005)				
Collab. Inno. (Univ. Included)			0.0071*** (0.0010)			
Collab. Inno. (GRI Included)				0.0050*** (0.0010)		
Collab. Inno. (Inter-firm)					0.0227*** (0.0024)	
Collab. Inno. (Inter-ICT firm)						0.0596*** (0.0091)
Control Variables						
Ln(FirmSize)	0.0518 (0.0563)	0.0545 (0.0564)	0.0869 (0.0568)	0.0414 (0.0574)	0.0774 (0.0561)	0.0658 (0.0561)
Ln(R&D Exp.)	0.1668*** (0.0420)	0.1679*** (0.0421)	0.1549*** (0.0427)	0.1708*** (0.0425)	0.1510*** (0.0420)	0.1596*** (0.0419)
Ln(Productivity)	-0.0090 (0.0772)	-0.0047 (0.0772)	0.0149 (0.0771)	-0.0162 (0.0775)	-0.0207 (0.0771)	-0.0154 (0.0764)
Group	-0.3646* (0.1755)	-0.3651* (0.1755)	-0.3684* (0.1753)	-0.3644* (0.1758)	-0.3775* (0.1756)	-0.3644* (0.1754)
Firm Age	-0.0122* (0.0061)	-0.0122* (0.0061)	-0.0137* (0.0061)	-0.0116 (0.0061)	-0.0155* (0.0061)	-0.0138* (0.0061)
Large Firms	0.1361 (0.1515)	0.1305 (0.1514)	0.1093 (0.1511)	0.1416 (0.1514)	0.1225 (0.1512)	0.1340 (0.1513)
IPO	-0.4442*** (0.1211)	-0.4370*** (0.1211)	-0.4126*** (0.1210)	-0.4579*** (0.1225)	-0.5387*** (0.1223)	-0.4444*** (0.1205)
Year	0.1202*** (0.0095)	0.1197*** (0.0094)	0.1170*** (0.0094)	0.1212*** (0.0094)	0.1205*** (0.0094)	0.1194*** (0.0095)
Constant	-243.4704*** (18.8429)	-242.4423*** (18.8011)	-237.1636*** (18.7664)	-245.2931*** (18.7252)	-243.8032*** (18.7965)	-241.8219*** (18.8147)
Observations	6,891	6,891	6,891	6,891	6,891	6,891
Log Likelihood	-3733.8929	-3736.3406	-3739.8307	-3742.957	-3730.6348	-3740.242
Ln(r)	0.2197 (0.1077)	0.2180 (0.0916)	0.2181 (.0916)	0.2112 (0.0915)	0.2212 (0.0918)	0.2166 (0.0916)
Ln(s)	-0.8683 (0.1083)	-0.8679 (0.1077)	-0.8648 (0.1079)	-0.8749 (0.1075)	-0.8662 (0.1078)	-0.8695 (0.1077)
LR Chi-bar-squared	1415.06***	1420.75***	1397.92***	1452.71***	1365.38***	1395.65***
Prob > Chi-bar-squared	0.000	0.000	0.000	0.000	0.000	0.000

Note: * p<0.05; ** p<0.01; *** p<0.001; Standard errors in parentheses.

The results of the RENB model also show that the independent variables have

a statistically significant effect in all six models. As in the FENB model, the magnitude of the effect is the greatest for the Inter-ICT Firm variable, followed by Inter-firm, Univ. Included, GRI Included, ICT Industry, and Collaborative Innovation.

The results for the RENB model also show that collaborative innovation has a positive effect on technological convergence. They also show that inter-ICT firm collaborative innovation has a larger effect on technological convergence than other types of collaborative innovation.

Next, the Hausman test results for the fixed-effect model and the random-effect model are shown in Table 4.9.

Table 4.9 Hausman Test (FE vs. RE)

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
Chi-Squared	66.39***	65.00***	74.74***	107.35***	73.83***	43.89***
Prob > Chi-Squared	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Regression Model	FE	FE	FE	FE	FE	FE

Note: * p<0.05; ** p<0.01; *** p<0.001

The results of the Hausman test show that the estimated Chi-squared values are statistically significant in all the models. Therefore, this study adopts the estimation results of the FENB model.

Next, this study uses an instrumental variable approach to resolve the potential bias due to the reverse causality between the independent and the dependent variables. To control the potential endogeneity resulting from concurrency, the IV

Poisson GMM model is set up and estimated together with the robust standard error. The weak IV test is also performed on the linear 2SLS model to ensure the robustness of the model. Stock and Yogo (2005) reported that, when the F-statistic of the first-stage regression is less than 10, the corresponding instrumental variables are weak and the estimates are seriously biased. In all of the six models used in this study, the null hypothesis that the instrumental variables are weak is rejected, because the F-statistic is greater than 10. Thus, the instrumental variables used in this study are not weak IVs, and there is no possibility of bias related to them. The estimation results of the IV Poisson GMM model are presented in Table 4.10.

Table 4.10 IV Poisson GMM with VCE(Robust)

Variable	Model (1)	Model (2)	Model (3)	Model (4)	Model (5) [1]	Model (6)
Independent Variables						
Collab. Inno.	0.0015 (0.0008)					
Collab. Inno. (ICT Industry)		0.0015 (0.0010)				
Collab. Inno. (Univ. Included)			0.0035* (0.0014)			
Collab. Inno. (GRI Included)				-0.0012 (0.0026)		
Collab. Inno. (Inter-firm)					0.0214*** (0.0053)	
Collab. Inno. (Inter-ICT firm)						0.0697** (0.0258)
Control Variables						
Ln(FirmSize)	0.4564*** (0.1167)	0.4587*** (0.11676)	0.4780*** (0.1093)	0.4928*** (0.1260)	(Omitted)	0.4713*** (0.1112)
Ln(R&D Exp.)	0.4193*** (0.0552)	0.4242*** (0.0562)	0.4010*** (0.0553)	0.4349*** (0.0654)	0.5905*** (0.0401)	0.3390*** (0.0630)
Ln(Productivity)	-0.2569 (0.1739)	-0.2578 (0.1738)	-0.2362 (0.1711)	-0.2467 (0.1814)	-0.4093** (0.1526)	-0.1806 (0.1690)
Group	0.0428 (0.1422)	0.0406 (0.1421)	0.0432 (0.1413)	0.0266 (0.1420)	0.1448 (0.1340)	0.0502 (0.1406)
Firm Age	-0.0299* (0.0125)	-0.0298* (0.0125)	-0.0317* (0.0124)	-0.0313* (0.0130)	(Omitted)	-0.0343* (0.0137)
Large Firms	0.5498*** (0.1429)	0.5373*** (0.1431)	0.5552*** (0.1387)	0.4631** (0.1482)	0.9089*** (0.1211)	0.6661*** (0.1502)

IPO	-1.0111*** (0.2405)	-1.0048*** (0.2420)	-0.9055*** (0.2336)	-0.8666*** (0.2258)	-0.9001*** (0.1931)	-0.8569*** (0.2417)
Year	0.0728*** (0.0128)	0.0721*** (0.0128)	0.0711*** (0.0125)	0.0666*** (0.0131)	0.0513** (0.0176)	0.0801*** (0.0139)
Constant	-151.0886*** (25.2727)	-149.7566*** (25.2488)	-147.6601*** (24.6526)	-138.9578*** (25.7383)	-106.5242** (34.6730)	-165.6213*** (27.5088)
Observations	6,851	6,851	6,851	6,851	6,851	6,851
Weak IV Test	152.18	134.05	372.36	77.69	264.40	233.65

Note: * p<0.05; ** p<0.01; *** p<0.001; Standard errors in parentheses.

1) Model (5) cannot be estimated because the Hessian is not positive semidefinite. Therefore, it is estimated excluding the *Ln(FirmSize)* and *FirmAge* variables.

The IV Poisson GMM model estimation result is different from the estimation result of the panel negative binomial model. Specifically, the independent variables have statistically significant positive effects in only three of the six models. Inter-ICT firm, Inter-firm, Univ. Included affect technological convergence, but the remaining types of collaborative innovation do not affect technological convergence.

This study tests whether the instrumental variable approach is necessary. Since the instrumental variable approach assumes a Poisson distribution, the LR test or VMR test results show that the dependent variable in this study is the negative binomial distribution. Thus, if there is an endogeneity problem in the independent variable, it is best to use the instrumental variable approach even if the Poisson distribution is assumed. Otherwise, it is appropriate to analyze the panel negative binomial model (Yamamura, 2013). The estimation results of the Poisson model are presented in Table 4.11.

Table 4.11 Poisson Regression

Variable	Model (1)	Model (2)	Model (3)	Model (4)	Model (5) [1]	Model (6)
Independent Variables						
Collab. Inno.	0.0017*** (0.0001)					
Collab. Inno. (ICT Industry)		0.0017*** (0.0001)				
Collab. Inno. (Univ. Included)			0.0040*** (0.0002)			
Collab. Inno. (GRI Included)				-0.0002 (0.0003)		
Collab. Inno. (Inter-firm)					0.0188*** (0.0006)	
Collab. Inno. (Inter-ICT firm)						0.0420*** (0.0015)
Control Variables						
Ln(FirmSize)	0.4500*** (0.0160)	0.4520*** (0.0160)	0.4737*** (0.0160)	0.4793*** (0.0162)	(Omitted)	0.4706*** (0.0160)
Ln(R&D Exp.)	0.4190*** (0.0122)	0.4240*** (0.0122)	0.3977 *** (0.0123)	0.4393*** (0.0122)	0.6087*** (0.0062)	0.3889*** (0.0122)
Ln(Productivity)	-0.2594*** (0.0228)	-0.2604*** (0.0227)	-0.2358*** (0.0228)	-0.2557*** (0.0225)	-0.4207*** (0.0228)	-0.2215*** (0.0227)
Group	0.0397 (0.0586)	0.0375 (0.0586)	0.0402 (0.0586)	0.0241 (0.0587)	0.1379* (0.0582)	0.0364 (0.0586)
Firm Age	-0.0292*** (0.0013)	-0.0291*** (0.0013)	-0.0311*** (0.0014)	-0.0301*** (0.0013)	(Omitted)	-0.0317*** (0.0014)
Large Firms	0.5570*** (0.0433)	0.5446*** (0.0433)	0.5648*** (0.0433)	0.4728*** (0.0435)	0.8859*** (0.0408)	0.5769*** (0.0432)
IPO	-1.0161*** (0.0571)	-1.0116*** (0.0571)	-0.8966*** (0.0563)	-0.9005*** (0.0577)	-0.8840*** (0.0567)	-0.8859*** (0.0563)
Year	0.0731*** (0.0026)	0.0725*** (0.0026)	0.0712*** (0.0026)	0.0675 *** (0.0026)	0.0495*** (0.0026)	0.0734*** (0.0027)
Constant	-151.6265*** (5.2714)	-150.3693*** (5.2456)	-147.8649*** (5.2471)	-140.7343*** (5.1004)	-103.0592*** (5.1228)	-152.2376*** (5.3034)
Observations	6,891	6,891	6,891	6,891	6,891	6,891

Note: * p<0.05; ** p<0.01; *** p<0.001; Standard errors in parentheses.

1) 1) Model (5)is estimated to exclude the Ln (FirmSize) and firm age variables from the existing model so that it is the same as the IV Poisson GMM model to perform the Hausman test.

The Hausman test between the IV Poisson GMM model and the Poisson model

is performed to identify the presence of endogeneity due to simultaneity in the independent variables. The test results are presented in Table 4.12.

Table 4.12 Hausman Test (IV Poisson GMM vs. Poisson)

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
Chi-Squared	0.75	0.84	2.52	0.65	1.97	22.68**
Prob > Chi-Squared	0.9998	0.9997	0.9802	0.9999	0.9613	0.0069
Regression Model	Poisson	Poisson	Poisson	Poisson	Poisson	IV Poisson GMM

Note: * p<0.05; ** p<0.01; *** p<0.001

The Hausman test results show that the estimated Chi-squared value is statistically significant only in Model (6). The test results show that the IV Poisson GMM model is more suitable than the Poisson model only in Model (6). This implies that endogeneity exists in the Inter-ICT Firm variable, which is an independent variable of Model (6).

The existence of endogeneity in the collaborative innovation variables means that there is simultaneity whereby technological convergence also affects collaborative innovation. This implies that firms use collaborative innovation strategically as a means to produce technological convergence. This tendency is observed only in the Inter-ICT Firm variable. Therefore, this endogeneity test result can be interpreted as showing that ICT firms utilize inter-ICT firm collaborative innovation among various collaborative innovation types as a strategic tool for technological convergence.

In conclusion, this study adopts the estimation result of the IV Poisson GMM

model for Model (6), because it has endogeneity in the independent variables. The remaining models adopt the estimation results of the FENB model according to the LR test results and the Hausman test results between the FENB and the RENB. The incident rate ratio (IRR) for the effect of each type of collaborative innovation on technological convergence is presented in Table 4.13.

Table 4.13 IRR of Technological Convergence by Various Types of Collaborative Innovation

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
Regression Model	FENB	FENB	FENB	FENB	FENB	IV Poisson GMM
Independent Variables						
Collab. Inno.	1.0039***					
Collab. Inno. (ICT Industry)		1.0040***				
Collab. Inno. (Univ. Included)			1.0072***			
Collab. Inno. (GRI Included)				1.0049***		
Collab. Inno. (Inter-firm)					1.0228***	
Collab. Inno. (Inter-ICT firm)						1.0721**

Note: * p<0.05; ** p<0.01; *** p<0.001

The results of the analysis presented in Table 4.12 show the magnitude of the effect of collaborative innovation on technological convergence by type. Thus, the results show that collaborative innovation has a causal relationship that positively affects technological convergence. The size of the estimated IRR is the largest for the Inter-ICT Firm variable, followed by Inter-firm, Univ. Included, GRI Included, ICT Industry, and Collaborative Innovation. In other words, inter-ICT firm collaboration have the largest effect on technological convergence among all the

collaborative innovation types. The effect of collaborative innovation involving the GRI appears to be smaller than that of university or inter-firm collaboration.

The IRR indicates how many times the mean of the dependent variable changes when the explanatory variable is increased by one unit. For example, when collaborative innovation increases by one, technological convergence increases by IRR times. Figure 4.3 shows the expected incident rate of technological convergence as the amount of collaborative innovation increases.

Figure 4.3 Incident Rate of Technological Convergence by the Frequency of Collaborative Innovation

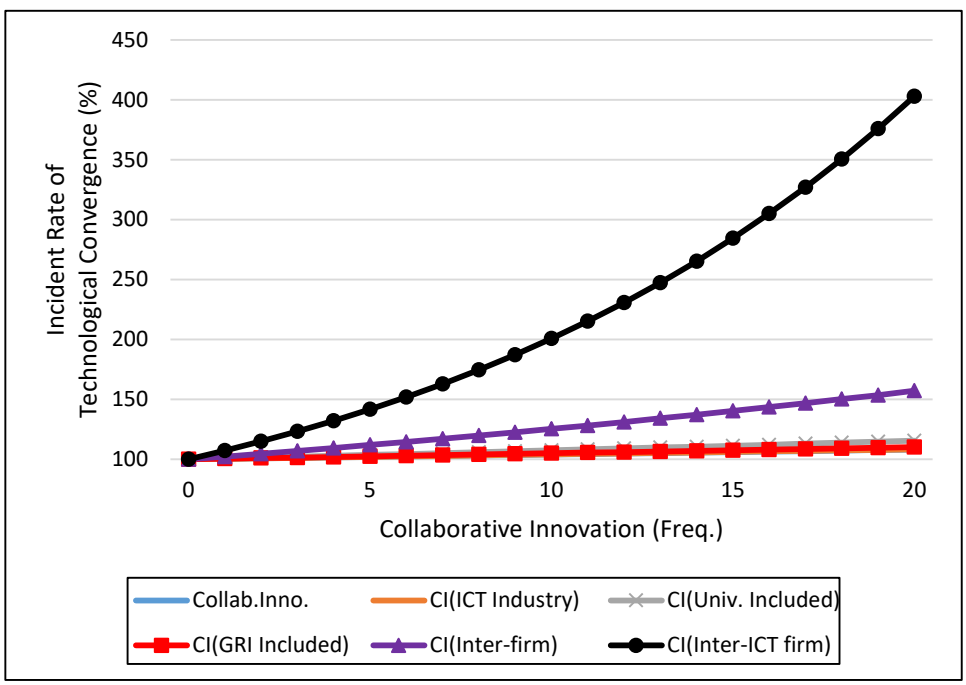


Figure 4.3 shows that inter-ICT firm collaborative innovation is much more effective than other types of collaborative innovation. As the amount of inter-ICT

firm collaborative innovation increases by 10, technological convergence doubles, and when it increases by 20, technological convergence increases by more than 4 times. Inter-firm collaborative innovation including non-ICT firms is the second most effective type, but the magnitude is very small. The remaining types of collaborative innovation have significant effects, although the magnitude is also very small.

The results can be interpreted as showing that the types of innovation entity are subject to different levels of control from the government; that is, the types of innovation partner experience different levels of control from the government. First, the GRI has been used as a government policy instrument for a long time and has played the role of supporting innovative resources mainly for firms that are not able to cover the innovation costs or lack the technology or workforce needed for innovation. Therefore, the motivation for collaborative innovation, which includes the GRI, can be seen as the motivation for firms to reduce their costs rather than the motivation to cope with the diversified technology demand in the market. Second, universities also play a role in supporting innovative resources for firms with insufficient innovation capacity, but they perform these activities mainly through incentives, unlike GRIs. Instead, universities have relatively high autonomy in selecting innovation subjects compared with GRIs. Although universities are not as sensitive to changes in the technology demand as firms, firms have a relatively high level of collaborative innovation aimed at producing convergent technology through a combination of heterogeneous technologies. Third, unlike universities, which are driven by GRIs and government incentives and firm grants driven by government budgets and strong controls, firms fund most research from their budgets, especially

large firms with high financial capacities. In addition, the firm is very sensitive to changes in the technology demand in the market for survival, so, despite the transaction costs, the motivation to produce convergent technology through collaborative innovation is relatively strong. In particular, because the innovation process takes time, the firm prefers to preempt the technology relatively quickly through collaborative innovation with other firms that have different technologies, rather than developing all the technologies as internal innovations. In conclusion, the results are based on the level of control by the government, the autonomy of selecting innovation subjects according to the source of innovation costs, and the level of sensitivity to changes in the technology demand in the market.

The results of this study show that the policy argument that promotes technological convergence through the activation of collaborative innovation implemented in various countries is reasonable. However, as in the case of Korea's Convergence Technology Development Project for SMEs, it is inefficient not to make a difference in the budget and the amount of support at the stage of application depending on the partner type. Given that the purpose of this incentive system is to create a collaborative innovation ecosystem in the long term, it is necessary to target the focus of the policy to the most effective collaboration type. Therefore, this study suggests that the government should provide relatively higher incentives for firms' participation in inter-ICT firm collaborative innovation than other types of collaborative innovation. In conclusion, technological convergence in the ICT industry can be promoted further when governments use differential incentives to encourage firms to participate more in inter-ICT firm collaborative innovation.

4.5 Conclusions

This study shows that governments, including the Korean Government, have been implementing policies to promote technological convergence through the activation of firms' collaborative innovation from the very beginning of the technological convergence policy. It then examines empirical studies on the relationship between collaborative innovation and technological convergence, pointing out that the discussion of previous studies remains at the level of correlation and does not adequately control the possibility of bias from endogeneity in the research design. Therefore, this study analyzes whether the collaborative innovation of ICT firms has a positive effect on technological convergence and evaluates whether the rationality of the government's policy approach following resource-based theory is reasonable. This study also explains which type of collaborative innovation best facilitates technological convergence and provides a basis for designing a more effective incentive system. It builds a firm-level panel data set by merging 36 years of patent data and firm data and performs a regression analysis. To overcome the limitations of the previous studies, various variables affecting innovation are appropriately controlled, and the possibility of endogeneity due to simultaneity in the independent variables is tested. Finally, this study presents the incident rate of technological convergence by the frequency of collaborative innovation by converting the effect of each type of collaborative innovation on technological convergence into the IRR and a graph.

The results can be summarized as follows. First, collaborative innovation has a positive effect on technological convergence. Therefore, the government's policy approach to promoting technological convergence in the industry by activating the

collaborative innovation of firms is reasonable.

Second, in the case of inter-ICT firm collaborative innovation, there is simultaneity in which technological convergence affects collaborative innovation. Previous studies, including empirical studies and theoretical discussions, have assumed that collaborative innovation affects technological convergence but not vice versa. However, this study reveals reverse causality in inter-ICT firm collaborative innovation. This implies that ICT firms' choice of ICT firms as collaborative innovation partners may be a strategic action for technological convergence.

Third, this study shows that the inter-ICT firm collaborative innovation have the largest effect on technological convergence. This study estimates the effect of each type of collaborative innovation on technological convergence by eliminating endogeneity due to simultaneity. The results show that inter-ICT firm collaboration is the most effective, followed by inter-firm, university included, GRI included, ICT industry, and collaborative innovation. The collaboration types except for the inter-ICT firm type and the inter-firm type show that the magnitude of the effect is very small. The results of this analysis show the necessity to reorganize the incentive system, which does not differentiate according to the existing partner type. In Korea, the Convergence Technology Development Project for SMEs provides incentives for firms to engage in collaborative innovation to promote technological convergence. However, this study suggests that such an incentive system is inefficient. The results also show that the government can promote technological convergence in the industry more effectively by designing a more effective incentive system that gives a relatively larger incentive to participate in inter-ICT firm and inter-firm collaborative innovation.

The results of this study can contribute to the theoretical development of innovation research. First, this study extends the level of discussion on the relationship between collaborative innovation and technological convergence to the causal relationship at the level of correlation. This indicates that the argument of resource-based theory that firms perform collaborative innovation to complement their technologies with those of other firms is also applicable to a real industry.

Second, this study reveals that there is endogeneity due to simultaneity between inter-ICT firm collaborative innovation and technological convergence through the endogeneity test. This indicates that ICT firms use collaborative innovation with ICT firms strategically for technological convergence. By confirming the existence of reverse causality, which has not been discussed before, this study can be a starting point for a discussion regarding the effect of technological convergence on collaborative innovation.

Third, this study shows that the inter-ICT firm and inter-firm collaborative innovation have the largest effect on technological convergence among the various types of collaborative innovation, and the rest have a statistically significant effect but the magnitude is very small. These results suggest a need to consider that the cooperative mechanisms can be different for different types of partners in existing innovation theories including resource-based theory.

The results of this study can also contribute to the government policy to promote technological convergence. They show that participation in firms' collaborative innovation promotes technological convergence and thus that the argument for a policy following the resource-based approach is reasonable. However, different types of collaborative innovation have different effects on technological

convergence, suggesting that the existing incentive system, which does not make a difference in the budget or the amount of support in the application stage, is inefficient. Therefore, this study suggests the need to allocate incentives differentially to partner types when designing support projects to promote technological convergence. For example, governments may be able to pay more innovation subsidies or reduce the cost of innovation activities when firms choose firms as collaborative innovation partners. These differential incentive systems can reduce unnecessary financial turmoil and improve policy efficiency.

This study finds that inter-ICT firm collaborative innovation has the greatest effect on technological convergence, suggesting that the government should concentrate on activation of the inter-ICT firm collaborative innovation ecosystem in order to build a technologically convergent production system. The government can allocate a higher proportion of the budget to inter-ICT firm collaborative innovation in the existing program, or implement a new program supporting inter-ICT firm collaborative innovation separately from the existing program. Through such program coordination or differential allocation of budgets, governments can focus their investments on the type of collaborative innovation that has the greatest effect on technological convergence. Of course, from the viewpoint of the technological innovation framework, it is also important to create an innovation ecosystem in which various participants interact complementarily, and other types of collaborative innovation also need to be activated (Freeman, 1987). However, in order to achieve the policy goal of promoting technological convergence under a budget constraint, it is necessary to concentrate policy competence on the type of collaborative innovation with the greatest effect on technological convergence rather

than including collaborative innovation types that are not effective in terms of technological convergence. In conclusion, it is most effective for a government to focus its policy capacity on collaborative innovation between ICT firms to promote technological convergence in the ICT sector. Therefore, this study suggests the need to redesign the existing incentive systems.

This study also has some limitations. It focuses on determining which type of collaborative innovation produces the largest amount of convergent technology, and there is no discussion on the quality of convergent technology. Therefore, this study suggests a discussion and policy recommendations on the assumption that the quality of all convergent technology is the same. However, not all convergent technologies have different qualities, and, although they have not been considered to be as important as the amount of innovation in innovation research, the difference in externality between important technology and less important technology is large. Therefore, a government may be interested in high-quality convergent technology, which has a relatively high level of externality. If the quality of convergent technology produced by collaborative innovation differs, the government can implement the policy that gives the highest incentive to the collaborative innovation type that produces the highest-quality convergent technology. For example, if other types of collaborative innovation, excluding inter-ICT firm collaborative innovation, yield the highest-quality convergent technology, the government can design an incentive system with an appropriate weight between the quantity and the quality of the convergent technology. Therefore, subsequent studies need to focus on analyzing which types of collaborative innovation produce the highest-quality convergent technology.

Bibliography

Aldrich, H. E., & Pfeffer, J. (1976). Environments of Organizations. *Annual Review of Sociology*, 2(1): 79-10.

Balsmeier, B., Buchwald, A., & Stiebale, J. (2014). Outside Directors on the Board and Innovative Firm Performance. *Research Policy*, 43(10): 1800-1815.

Barney, J. B. (1991). Firm Resources and Sustained Competitive Advantage. *Journal of Management*, 17(1): 99-120.

Bernstein, S. (2015). Does Going Public Affect Innovation?. *The Journal of Finance*, 70: 1365–1403.

Bessen, J., & Hunt, R. M. (2007). An Empirical Look at Software Patents. *Journal of Economics & Management Strategy*, 16(1): 157-189.

Borés, C., Saurina, C., & Torres, R. (2003). Technological Convergence: A Strategic Perspective. *Technovation*, 23(1): 1-13.

Briggs, K., & Wade, M. (2014). More is Better: Evidence that Joint Patenting leads to Quality Innovation. *Applied Economics*, 46(35): 4370-4379.

Cantner, U., & Graf, H. (2006). The Network of Innovators in Jena: An Application of Social Network Analysis, *Research Policy*, 35 (4), 463–480.

Cho, Y., Yang, I., Suh, Y., & Jeon, J. (2015). Analysis of Current Situation and Relationship among National R&D Projects for Technology Convergence. *Journal of the Korean Institute of Industrial Engineers*, 42(3): 305-323.

Coase, R. H. (1937). The Nature of the Firm. *Economica*, 4(16): 386–405.

Crepon, B., Duguet, E., & Mairesser, J. (1998). Research, Innovation, and

Productivity: An Econometric Analysis at the Firm Level. *Economics of Innovation and New Technology*, 7(2): 115-158.

Curran, S., & Leker, J. (2011). Patent Indicators for Monitoring Convergence – Examples from NFF and ICT, in: *Technological Forecasting and Social Change*, 78 (2): 256-273.

Czarnitzki, D., Kraft, K., & Thorwarth, S. (2009). The Knowledge Production of 'R' and 'D'. *Economics Letters*, 105(1): 141-143.

Duysters, G., & Hagedoorn, J. (1998). Technological Convergence in the IT Industry: The Role of Strategic Technology Alliances and Technological Competencies, *International Journal of the Economics of Business*, 5(3): 355-368.

Faria, P., Lima, F., & Santos, R. (2010). Cooperation in Innovation Activities: The Importance of Partners. *Research Policy*, 39(8): 1082-1092.

Freeman, C. (1987). *Technology Policy and Economic Performance : Lessons from Japan.* London: Frances Pinter.

Griliches, Z. (1990). Patent Statistics and Economic Indicators: A Survey, *Journal of Economic Literature*, 28(4):1661-1707

Guan, J., & Liu, N. (2016). Exploitative and Exploratory Innovations in Knowledge Network and Collaboration Network: A Patent Analysis in the Technological Field of Nano-Energy, *Research Policy*, 2016: 45(1): 97-112.

Hall, B. H., & Ziedonis, R. H. (2001). The Patent Paradox Revisited: An Empirical Study of Patenting in the U.S. Semiconductor Industry, 1979-1995. *RAND Journal of Economics*, 32(1): 101-128.

Hausman, J. A., Hall, B., & Griliches, Z. (1984). Econometric Models for Count

Data with an Application to the Patents-R&D Relationship. *Econometrica*, 52(4): 909-938.

Hilbe, J. M. (2011). *Negative binomial regression (2ed)*. Cambridge: Cambridge University Press.

Hong, W., & Su, Y-S. (2013). The Effect of Institutional Proximity in Non-Local University-Industry Collaborations: An Analysis Based on Chinese Patent Data. *Research Policy*, 42(2): 454-464.

Hottenrott, H., & Bento, C. L. (2012). *Quantity or Quality? Collaboration Strategies in Research and Development and Incentives to Patent. Collaboration Strategies in Research and Development and Incentives to Patent.* Working Paper No. 2012-29. Luxembourg. CEPS INSTEAD.

Inoue, H., & Liu, Y-Y. (2015). Revealing the Intricate Effect of Collaboration on Innovation. *PLoS ONE*, 10(3): e0121973.

ITU. (2016). *Measuring the Information Society Report 2016*, Geneva: ITU Report.

Jeong, S., Lee, S., Kim, J., Oh, S., & Kwak, K. (2012). Organizational Strategy for Technology Convergence. *International Journal of Social, Behavioral, Educational, Economic, Business and Industrial Engineering*, 6(8): 1989-1995.

Jeong, S. (2014). Strategic Collaboration of R&D Entities for Technology Convergence: Exploring Organizational Differences within the Triple Helix. *Journal of Management & Organization*, 20(2): 227-249.

Kim, J. Y., & Youn, Y. J. (2009). Firm Size and Patent Productivity. *Korea Review of Applied Economics*, 11(1): 177-194.

KISTEP. (2007). *Converging Technologies Trends in the United States and Japan*.

Seoul: KISTEP Report.

Kodama, F. (1991). *Analyzing Japanese High Technologies: The Techno-Paradigm Shift*. New York: Pinter.

Lee, H & Zo, H. (2013). *Technological Convergence in ICT and Determinants of Convergence from the Perspective of R&D Alliance*. 2013 International Conference on ICT Convergence (ICTC), Jeju: 819-823.

Lee, H. S. (2011). *Research on Open Innovation Policy in Connection with Development of Gyeonggi-do Innovation Cluster*, Gyeonggi: GSTEP Report.

Lee, H., Kim, P. R., & Zo, H. (2017). Effect of Cooperative R&D Projects on ICT-Based Technology Convergence. ETRI Journal, 39(4): 467-479.

Lee, K., Sung, T. (2009). *University-Industry Collaboration for Activating the Innovation of Fusion Technology*. Seoul: STEPI Report.

Lee, Y-G., Lee, J-H., Song, Y-I., & Kim, H-J. (2017). Technological Convergence and Open Innovation in the Mobile Telecommunication Industry. *Asian Journal of Technology Innovation*, 16(1): 45-62.

Maggioni, M., Nosvelli, M., & Uberti, E. (2007). Space versus Networks in the Geography of Innovation: A European Analysis. *Papers in Regional Scienc*e, 86(3): 471–493.

Mullahy, J. (1997). Instrumental-Variable Estimation of Count Data Models: Applications to Models of Cigarette Smoking Behavior. *The Review of Economics and Statistics*, 79(4): 586-593.

Nelson, R. R., & Winter, S. G. (1982). *An Evolutionary Theory of Economic Change.* Cambridge, Mass.: Belknap Press of Harvard University Press.

Nordmann, A. (2004). *Converging Technologies - Shaping the Future of European*

Societies. Brussels: European Commission.

NSF & DOC. (2002). *Converging Technologies for Improving Human Performance: Nanotechnology, Biotechnology, Information Technology and Cognitive Science*. Edited by M.C. Roco and W.S. Bainbridge, National Science Foundation. Publ. by: Kluwer Acad. Publ., currently Springer, Dordrecht.

Pakes, A., & Griliches, Z. (1984). *Patents and R&D at the Firm Level: A First Look*. In Griliches, Z., editor, R&D, Patents, and Productivity, Chicago: University of Chicago Press.

Pennings, J., & Puranam, P. (2001). *Market Convergence & Firm Strategy: New Directions for Theory and Research*, ECIS Conference, The Future of Innovation Studies, Eindhoven, Netherlands.

Penrose, E. (1959). *The Theory of the Growth of the Firm*, New York: Oxford University Press.

Prahalad, C. K., & Hamel, G. (1990). The Core Competence of the Corporation. *Harvard Business Review*, 68(3): 79-91.

Rikkiev, A., & Makinen, S. J. (2013). Technology Convergence and Intercompany R&D Collaboration: Across Business Ecosystems Boundaries. *International Journal of Innovation and Technology Management*, 10(4): 1350009-1 - 1350009-28.

Rosenberg, N. (1963). Technological Change in the Machine Tool Industry, 1840–1910. *The Journal of Economic History*, 23(4): 414-443.

Schumpeter, J. A. (1942). *Socialism, Capitalism and Democracy*. New York: Harper and Brothers.

SMBA. (2016). *Announcement of Plan for the Implementation of the Convergence*

Strategy Project for SME's Converging Technology Development. Daejeon, SMBA Report.

Stock, J., & M. Yogo. 2005. *Testing for weak instruments in linear IV regression*. In D.W.K. Andrews and J. H. Stock (eds.), Identification and Inference for Econometric Models (pp. 80-108). New York: Cambridge University Press.

Suh, D., Hwang, W., Kim, S., Kim, S., & Oh, I. (2015). *Analysis of the Economic Effect of ICT Diffusion – Developing a Quantitative Platform for Ex Ante Policy Analysis*. Seoul: KIET Report.

Teece, D. (1986). Profiting from Technological Innovation: Implications for Integration, Collaboration, Licensing, and Public Policy. *Research Policy*, 15(6): 285–305.

Tether, B. (2002). Who Co-operates for Innovation, and Why. An Empirical Analysis. *Research Policy,* 31(6): 947-967.

Van Tulder, R., & Junne, G. (1988). *European Multinationals in Core Technologies*. Chichester: John Wiley.

Williamson, O. E. (1981). The Economics of Organization: The Transaction Cost Approach. *American Journal of Sociology*, 87(3): 548-577.

WIPO. (2016). *World Intellectual Property Indicators*. WIPO Report.

Yamamura, E. (2013). Public Sector Corruption and the Probability of Technological Disasters. *Economics of Governance*, 14(3): 233–255.

Chapter 5. Conclusions

This study aims to expand the understanding of inter-firm collaborative innovation and to come closer to its essence through a multifaceted analysis of collaborative innovation in the Korean ICT industry. Collaborative innovation is a voluntary action resulting from firms' survival strategies, but the government has encouraged firms to participate in collaborative innovation to maximize the external effects of collaborative innovation on industry and the economy as a whole. However, despite these efforts, collaborative innovation has been limited in the industry. Because collaborative innovation is one of the survival strategies of firms, firms can choose between collaborative innovation and internal innovation as needed. However, firms are reluctant to engage in collaborative innovation, recognizing the transaction costs involved in collaborative innovation as a burden. Therefore, in order to induce firms to participate in collaborative innovation, the government needs to present the corresponding incentives to firms. Governments have tried various policy approaches to increase the utility of participating in collaborative innovation. However, critical studies of these policy approaches are insufficient. Therefore, this study aims to contribute to more effective policy design by examining the arguments of collaborative innovation policies through the analysis of collaborative innovation from various perspectives.

In spite of the efforts of the government, the reason that collaborative innovation is not sufficiently activated may be due to the inefficiency of the policy instrument or the fundamental problem that the policy has not covered. This study used three essays to better approach the answers to these questions. Specifically, this study

approached collaborative innovation from three perspectives: agents, structure, and interaction between agents and structure.

The first essay discussed the effects and interactions of incentives and regulations to promote collaborative innovation, and explores the effect of industry characteristics on collaborative innovation by analyzing the relationship between intra-industry heterogeneity and collaborative innovation. The results showed that the lower the intra-industry heterogeneity, the more firm's cooperative behavior increases and the collaborative innovation becomes active. Lower intra-industry heterogeneity had a positive effect on collaborative innovation because the hierarchical relationship among firms is weakened and the skewness of innovation is relaxed. Furthermore, the analysis of the effect of government policy on collaborative innovation showed that incentives such as subsidies and regulations on opportunistic behavior have a positive impact on collaborative innovation. Although incentives were shown to have both greater main effects and interaction effects than regulation, regulations were also important because they have a substantial interaction effect that amplifies the effectiveness of incentives.

The second essay explored the structural characteristics of the collaborative innovation network evolution in the Korean ICT industry, identified the openness of the network by analyzing the determinants of inter-firm homophily, and examined the factors that promote firms' participation in collaborative innovation. Descriptive network analysis results showed that the collaborative innovation network of the Korean ICT industry has evolved around some large firms that are leading innovation, depicting a topology of sparse scale-free networks. In addition, network regression analysis results showed that innovation factors such as technological overlap have a

greater effect on inter-firm homophily than relational factors. This indicates that firms choosing collaborative innovation partners prefer firms with sufficient technology portfolios. However, the results of the analysis showed that collaborative innovation among the same affiliates is also frequently performed. Therefore, this study can conclude that although firms select collaborative innovation partners according to their technological preferences, they make decisions under the constraints of transaction costs.

The third essay explored the effect of collaborative innovation on technological convergence and analyzed what types of collaborative innovation is most effective in promoting technological convergence. The results showed that collaborative innovation has a causal relationship that positively affects technological convergence. Also, inter-ICT firm collaborative innovation had the greatest effect on facilitating technological convergence, while other types of collaborative innovation had little effect on promoting technological convergence. This analysis suggests that firms that respond most sensitively to technological changes in the market are most aggressive in responding to the demand for convergent technology. Furthermore, the results of the endogeneity test showed that there is a simultaneity between inter-ICT firm collaborative innovation and technological convergence, suggesting that ICT firms can strategically select ICT firms as collaborative innovation partners for convergent technology output.

The results of this study can contribute to the development of theoretical discussion on collaborative innovation. On the controversy between resource-based theory and transaction cost theory in relation to collaborative innovation, the results of this study showed that resource-based theory has more explanatory power.

Specifically, the effect of incentives on regulatory compliance was better than that of regulations in the first essay, indicating that firms are more sensitive to the benefits than to the costs associated with collaborative innovation. Also, the result of the second essay, that the innovation factor was more effective than the relationship factor, suggests that the firm considers the technological resources, such as the technology portfolio, of the counterpart firm as the top priority and considers the transaction cost as the constraint when selecting a collaborative innovation partner. Finally, the result of the third essay, that collaborative innovation has a positive impact on technological convergence, indicates that a mutually complementary combination of disparate technologies among firms is assumed in resource-based theory. Therefore, the results of this study suggest some rationale supporting the resource-based theory. The study also provides the theoretical underpinnings of the effects and interactions of incentives and regulations in the policy mix, which are considered important in relation to collaborative innovation policy. Furthermore, the results of this study suggest that the effects of collaborative innovation on technological convergence are different, implying that innovation theories such as resource-based theory should consider collaborative innovation type more thoroughly.

Finally, this study suggests focusing on the structural characteristics of the industry as an alternative to the empirical limitations of the Schumpeterian hypothesis, which has been regarded as foundational in the field of innovation. In particular, the results of this study on the relationship between intra-industry heterogeneity and collaborative innovation have further elaborated on the relationship between firm size distribution and innovation, which has been discussed

only conceptually in the past. The study can contribute to knowledge growth. In particular, the results of this study on the relationship between intra-industry heterogeneity and collaborative innovation can contribute to the knowledge growth of innovation theory through the formulation of discussions on the relationship between firm size distribution and innovation and the introduction of new hypotheses for subsequent researchers. In conclusion, the results show that the resource-based theory is more dominant for explaining collaborative innovation in the debate between resource-based theory and transaction cost theory and they emphasize the need to focus on the structural factors of industry beyond the debate.

In addition, the results of this study can contribute to redesigning government policies related to collaborative innovation more effectively. The results of the first essay suggest that it would be more effective to pay more grants to technologies with higher value and higher business value than to pay the same amount of grants to all firms regardless of the value of the technology. These results also suggest that, when designing a damages system for opportunistic behavior, the estimation of compensation based on expected returns rather than the calculation of compensation based on actual damage may be more effective in reducing firms' opportunistic behavior. The results of the simulation that collaborative innovation is more actively conducted as the level of intra-industry heterogeneity is lowered suggests that the government needs to consider indirect factors besides direct support or regulation of the collaborative innovation policy. For example, governments can intervene to regulate unfair practices of large firms, subsidize SMEs, and improve the workforce structure of large firms in order to lower the level of intra-industry heterogeneity. The results of the second essay suggest that broadening the scope of support to a

collaborative innovation between large firms and SMEs when the government implements a network-based technology development program for SMEs may be more effective in facilitating SMEs entering the collaborative innovation network. Furthermore, the results of the third essay show that the argument that the technological convergence policy promotes technological convergence by activating collaborative innovation is reasonable. However, this study suggests that the government needs to focus more on inter-ICT firm collaborative innovation, which is the most effective for technological convergence, in order to create a collaborative innovation ecosystem capable of self-production of convergent technologies more effectively.

This study has conducted analyses from various perspectives in order to get closer to the essence of collaborative innovation. The results from this study extend the understanding of collaborative innovation by deriving some simple mechanisms inherent in the complex interaction of collaborative innovation. This can lead to an answer to what approach governments should take to promote collaborative innovation. The existing collaborative innovation policies have mainly made direct interventions such as subsidies or regulation of firms. However, the results of this study, in which firms' collaborative innovation is sensitive to industrial structural factors such as intra-industry heterogeneity, suggests that the scope of government intervention needs to be expanded to shift the paradigm of collaborative innovation policy. In conclusion, the results of this study emphasize the need to design a more detailed and differential policy to eliminate the blindness of the policy effects arising from differences in technology value or collaborative innovation type. It also suggests that more discussion and policy approaches are needed for industrial

structure factors.

This study has conducted analyses from various perspectives in order to get closer to the essence of collaborative innovation. The results from this study extend the understanding of collaborative innovation by deriving some simple mechanisms inherent in the complex interaction of collaborative innovation. This can lead to an answer to what approach governments should take to promote collaborative innovation. The existing collaborative innovation policies have mainly made direct interventions such as subsidies or regulation of firms. However, the results of this study, in which firms' collaborative innovation is sensitive to industrial structural factors such as intra-industry heterogeneity, suggests that the scope of government intervention needs to be expanded to shift the paradigm of collaborative innovation policy. The government has been implementing collaborative innovation policies under the premise of direct intervention in the firm, but the government needs to focus not only on direct interventions for firms but also on environmental factors that hinder effective operation of the collaborative innovation ecosystem. Thus, the government needs to consider environmental factors, including industrial structural factors, to create open innovation ecosystems as well as direct interventions for firms. In conclusion, this study suggests that the collaborative innovation policy needs to be redesigned more effectively and the paradigm of the collaborative innovation policy should be changed by recognizing the importance of structural factors in addition to these direct interventions.

This study has limitations in terms of the scope of the discussion and research methodology. Theoretical hypotheses presented in this study need to be verified through subsequent empirical studies. Also, the methodological limitations

mentioned in each essay need to be discussed more in academia. Finally, this study focused on the amount of collaborative innovation and limits the quality of the innovation. Subsequent studies can contribute to the design of policies that have appropriate weighting between innovation quantity and quality through research that considers both the quality and the quantity of innovation.

국 문 초 록

본 논문은 한국 ICT 산업 내 협력적 혁신에 관한 세 개의 연구로 구성되어 있다. 기업은 시장에서 생존하고 경쟁 우위를 점하기 위해 동일 산업 내의 타 기업과 경쟁하지만, 동일한 목적에서 타 기업들과 전략적으로 협력하기도 한다. 협력적 혁신은 기업들의 생존 전략에서 비롯된 자발적인 행동이지만 정부는 협력적 혁신이 산업 및 경제 전반에 미치는 외부효과를 극대화하기 위해서 기업들의 협력적 혁신 참여를 촉진해왔다. 그러나 이러한 정부의 노력에도 불구하고 산업 내에서 협력적 혁신은 제한적으로 수행되어오고 있다. 정부의 노력에도 불구하고 협력적 혁신 생태계가 충분히 활성화되지 않는 이유는 정책 수단의 비효율성에서 기인할 수 있고, 혹은 정책이 접근하지 못해왔던 근본적인 문제에서 기인할 수도 있다. 따라서 본 연구는 이러한 의문들에 대한 답에 보다 효과적으로 다가가기 위하여 세 가지 에세이의 형태로 분석을 수행한다. 구체적으로 첫 번째 에세이는 행위자와 구조 간 상호작용의 관점에서 산업 구조 요인과 정부 정책이 기업들의 협력 행동에 미치는 영향을 탐구한다. 두 번째 에세이는 구조의 관점에서 혁신 요인과 관계 요인이 협력적 혁신 네트워크의 진화에 미치는 영향을 탐구한다. 세 번째 에세이는 행위자의 관점에서 기업의 협력적 혁신 참여가 기술융합에 미치는 영향을 분석한다. 이러한 다각적 분석을 통해 본 연구는 기업 간 협력적 혁신에 대한 이해를 넓히고 그 본질에 보다 가까이 다가가고자 한다.

첫 번째 연구는 산업 내 이질성과 정부 정책이 협력적 혁신에 미치는 영향을 분석한다. 본 연구는 슘페터 가설의 실증적 한계에 대한 해결책으로 기업 규모와 혁신에 관한 기존 논의의 초점을 기업 수준에서 산업 수준으로 확장하여 산업 내 기업규모분포에 초점을 맞출 것을 제안한다.

본 연구의 목적은 크게 두 가지로 나눌 수 있다. 첫째, 본 연구는 산업 내 규모 이질성에 따라 협력적 혁신 패턴이 어떻게 다르게 발현되는지 알아본다. 둘째, 본 연구는 규모 이질성이 높은 산업에서 정부의 인센티브 및 규제 정책이 협력적 혁신 패턴에 어떠한 영향을 미치는지 탐색한다. 이를 위해 본 연구는 SCP 프레임워크에 의거하여 협력적 혁신 구조와 기업의 협력 행동, 그리고 협력적 혁신의 성과의 변화를 분석한다.

본 연구는 한국 ICT 기업들의 데이터 및 기업 간 협력적 혁신 데이터를 수집하였고 이를 토대로 행위자기반모형을 개발하였다. spatial NIPD game에 기반하는 본 행위자기반모형은 GIS 기반 가상 공간에서의 ICT 산업 내 524개의 기업들 간 협력적 혁신을 구현한다. 본 연구는 모형의 현실 설명력을 높이기 위하여 실증 데이터를 활용한 타당성 검증 과정을 거쳤다. 이후 연구 문제에 따른 두 가지 시뮬레이션을 수행하였다.

분석 결과는 산업 내 이질성과 혁신 패턴에 대한 몇 가지 정형화된 사실들을 제시한다. 첫째, 산업 내 이질성의 감소는 산업 내 협력적 혁신의 구조, 행위, 그리고 성과에 긍정적인 영향을 미친다. 둘째, 인센티브는 동일한 수준의 규제보다 더욱 효과적이며, 특정 수준의

규제는 오히려 역효과를 초래할 수 있다. 또한 정책 조합에서 인센티브와 규제 간 정의 상호작용 효과가 존재하며, 이러한 상호작용 효과는 인센티브와 규제의 수준에 따라 달라진다. 인센티브는 주 효과와 상호작용 효과 모두 규제보다 큰 것으로 나타났지만, 규제 역시 마찬가지로 인센티브의 효과를 증폭시키는 상호작용 효과를 지니기 때문에 중요하다고 볼 수 있다.

본 연구는 기존에 독립변수로 거의 고려되지 않던 산업 내 이질성이 혁신 생태계에서 중요한 변수임을 확인하고, 산업 내 이질성과 협력적 혁신 간 관계에 대한 정형화된 사실들을 제시한다. 또한, 본 연구 결과는 인센티브와 규제가 산업 내 협력적 혁신에 미치는 영향을 밝히고 인센티브와 규제 간 정의 상호작용 효과가 존재함을 보인다. 이러한 연구 결과는 정부가 산업 내 개방형 혁신 생태계를 조성하기 위해서 인센티브나 규제를 통한 보상 체계의 조정뿐만 아니라 산업 내 이질성 역시 중요한 요인임을 인지하고, 산업 내 이질성을 완화하기 위한 접근을 할 필요가 있다는 것을 시사한다. 또한, 본 연구 결과는 규제의 역효과를 예방하기 위해서는 정부가 규제를 단독으로 집행하기보다는 정책 조합의 형태로 적정 수준의 인센티브와 함께 집행하여야 한다는 것을 나타낸다.

두 번째 연구는 한국 ICT 산업에서 협력적 혁신 네트워크의 진화를 분석한다. 본 연구의 목적은 크게 두 가지로 요약할 수 있다. 첫째, 본 연구는 한국 ICT 산업에서 기업 간 협력적 혁신 네트워크의 진화의 구조적 특성을 밝혀내고자 한다. 둘째, 본 연구는 혁신 요인과 관계 요인이 기업 간 동종선호에 미치는 영향을 분석한 후 어떠한 요인이 더

큰 영향을 미치는지 밝혀내고자 한다.

본 연구는 패널 데이터셋을 구축한 후 기업 수준의 1차원 인접행렬로 변환하여 네트워크 회귀분석인 QAP 회귀분석을 수행하였다. 또한, 잠재적인 Large Network Problem에 대응하기 위하여 전체 네트워크 및 연결된 네트워크에 대한 분석을 모두 수행하였다. 추가적으로, 네트워크의 진화과정에서 나타나는 특성들을 보다 다양한 각도에서 탐색하기 위하여 기술 네트워크 분석을 수행하였다.

기술 네트워크 분석의 결과는 한국 ICT 기업 간 협력적 혁신 네트워크의 진화에서 나타나는 몇 가지 특성들을 보여준다. 첫째, 한국 ICT 기업 간 협력적 혁신 네트워크는 협력적 혁신에 참여하는 기업들의 비율이 낮으며 네트워크의 밀도 역시 낮다. 둘째, 네트워크의 진화 과정에서 삼성전자와 KT가 허브 역할을 하며 이른바 ‘mass collaborator' 의 역할을 수행해왔다. 셋째, 한국 ICT 기업 간 협력적 혁신 네트워크는 성긴 형태의 척도 없는 네트워크(Sparse scale-free network)의 형태를 띤다. 또한, 네트워크 회귀분석 결과는 기업이 충분한 기술 포트폴리오를 구축하면 기업이 보유한 기술 포트폴리오라는 자원에 기반한 시장 내 파트너 탐색 메커니즘에 따라 협력적 혁신에 참여하게 된다는 것을 암시한다. 이는 협력적 혁신에 대해 자원기반이론이 제시하는 논거와 일치한다. 따라서 본 연구 결과는 협력적 혁신에 관한 자원기반이론과 거래비용이론 간 논쟁에서 자원기반이론의 현실 설명력이 더욱 높다는 것을 보인다. 하지만, 동일 그룹 내 계열사들 간 동종선호 현상이 존재한다는 본 연구 결과는 협력적 혁신 생태계에서 그룹 수준의 의사결정 역시 이루어지고 있음을 유추 가능케 한다. 본 연구 결과는. 중소기업들이 협력적 혁신 네트워크에 참여하기 위해서는 협력적 혁신

네트워크에서 중심적 위치에 있는 대기업들의 기술 포트폴리오와 유사한 분야의 기술을 개발할 필요가 있다는 것을 보인다. 이를 위해서는 사업 지원 범위를 중소기업 간 협력적 혁신뿐만이 아니라 대기업과 중소기업 간 협력적 혁신으로 확장하는 것이 더욱 효과적일 수 있다.

세 번째 연구는 협력적 혁신이 기술융합에 미치는 영향을 분석한다. 한국 정부를 포함한 각국 정부들은 기업의 협력적 혁신의 활성화를 통해 기술 융합을 촉진하는 정책을 집행해왔다. 그러나 협력적 혁신과 기술 융합 간 관계에 대한 기존의 논의는 상관관계 수준에 머물러 있으며, 선행 연구들은 내생성에 따른 편의의 가능성을 충분히 통제하지 못하였다는 한계를 보인다. 이에 본 연구는 ICT 기업의 협력적 혁신이 기술 융합에 미치는 영향을 분석한다. 또한 본 연구는 어떠한 유형의 협력적 혁신이 기술 융합을 가장 크게 촉진하는지를 분석한다.

본 연구는 36년간의 특허 데이터와 기업 데이터를 활용하여 기업 수준 패널 데이터셋을 구축하고, 이를 통해 회귀분석을 수행하였다. 선행연구들의 한계를 극복하기 위해 연구 설계 시 혁신에 영향을 미치는 다양한 변수들을 적절히 통제하고, 독립변수에 동시성에서 기인한 내생성이 존재할 가능성을 검정하였다.

본 연구 결과를 통해 새롭게 밝혀진 사실을 몇 가지 제시할 수 있다. 첫째, 협력적 혁신은 기술 융합에 긍정적 영향을 미치는 인과관계가 존재한다. 둘째, ICT 기업 간 협력적 혁신의 경우 기술 융합이 협력적 혁신에 영향을 미치는 동시성이 존재한다. 셋째, 다양한 유형의 협력적 혁신 중 ICT 기업 간 협력적 혁신이 기술 융합에 미치는 영향이 가장 크고, 기업 간 협력적 혁신을 제외한 나머지 유형들은 기술 융합에

미치는 효과의 크기가 매우 미미한 것으로 나타난다.

본 연구는 협력적 혁신과 기술 융합 간 관계에 대한 논의를 인과관계의 수준으로 확대한다는 점에서 의의가 있다. 이러한 분석 결과는 자원기반적 접근에 근거한 기존 정책의 논거가 합당하다는 것을 보여준다. 그리고 협력적 혁신과 기술융합 간 동시성의 존재는 ICT 기업이 기술 융합을 위해 ICT 기업과의 협력적 혁신을 전략적으로 사용한다는 것을 나타낸다. 마지막으로 본 연구 결과는 협력적 혁신에서 파트너 유형에 따라 혁신 메커니즘이 달라질 수도 있음을 보여준다. 이러한 결과는 사업 지원 단계에서 혁신 파트너 유형에 따라 예산 할당이나 지원 규모에 차등을 두지 않는 인센티브 시스템이 비효율적일 수 있다는 것을 암시한다. 따라서 본 연구는 기술 융합을 촉진하기 위한 정책 설계 시 파트너 유형별로 인센티브를 차등적으로 부여할 필요성을 제시한다.

이상 세 개의 연구들로부터 도출된 결과들은 협력적 혁신이라는 복잡한 상호작용에 내재된 몇 가지 단순한 메커니즘들을 끌어내어 협력적 혁신에 대한 이해를 확장시켜준다. 본 연구 결과들은 협력적 혁신에 관한 자원기반이론과 거래비용이론 간 논쟁에 대해서 자원기반이론을 지지할 다양한 근거들을 제시한다. 또한 협력적 혁신 정책에서 중요하게 간주되는 policy mix에서 인센티브와 규제의 효과 및 상호작용에 대한 이론적 토대를 제공한다. 뿐만 아니라, 본 연구 결과는 자원기반이론과 같은 혁신 관련 이론들이 협력적 혁신 유형을 보다 중요하게 고려할 필요성을 제시한다. 마지막으로, 본 연구 결과는 혁신 분야의 대 전제로 간주되어 온 슘페터 가설의 실증적 한계에 대한

대안으로 산업의 구조적 특성에 초점을 맞출 것을 제안한다. 특히, 산업 내 이질성과 협력적 혁신 간 관계에 대한 본 연구 결과들은 과거 개념적으로만 논의되어오던 기업규모분포와 혁신 간 관계에 대한 논의를 보다 구체화하고 후속 연구자들에게 새로운 가설을 제시하여 혁신 이론의 지식 성장에 기여할 수 있다.

또한 본 연구의 결과들은 궁극적으로 정부가 협력적 혁신을 촉진하기 위해 어떠한 접근을 취해야 하는지에 대한 단서를 제공한다. 기존의 협력적 혁신 정책들은 주로 기업들에 대한 보조금 지급이나 규제와 같은 직접적인 개입들이 주를 이루었다. 그러나 기업들의 협력적 혁신이 산업 내 이질성과 같은 산업 구조 요인에 민감하게 반응한다는 본 연구의 결과는 정부 개입의 범위를 보다 확장하여 협력적 혁신 정책의 패러다임을 전환할 것을 제시한다. 따라서 정부는 기업에 대한 직접적 개입뿐만 아니라 개방형 혁신 생태계를 조성하기 위한 산업 구조적 요인들을 포함한 환경 요인들에 대한 고려를 할 필요가 있다. 결론적으로 본 연구는 협력적 혁신 정책을 보다 효과적으로 설계하고, 이러한 직접적인 개입들 외에도 구조적 요인들의 중요성에 대한 인식을 통해 협력적 혁신 정책의 패러다임을 전환할 것을 제안한다.

주요어: 협력적 혁신, 산업 내 이질성, 혁신 정책, 행위자 기반 모형, 협력적 혁신 네트워크, 기술 융합
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