Master's Thesis

Technological Innovation Performance Analysis Using Multilayer Networks: Evidence from the Printer Industry

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2020

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A thesis/dissertation
submitted to the Graduate School of UNIST
in partial fulfillment of the
requirements for the degree of
Master of Science

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12. 13. 2019
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Abstract

The importance of collaboration and technology boundary spanning has been emphasized in other inquiries into technological innovation. Therefore, this research project first tried to investigate the effect of collaboration on technology boundary spanning. Then, we investigated the effect of collaboration and technology boundary spanning on technological innovation within a firm by using a multilayer network to analyze patent data. The aim of this paper is to provide new insight into the process of analyzing patent data using multilayer networks. This empirical study is based on a sample of 408 firms within the printer industry from 1996 to 2005.

Starting with a theoretical discussion of R&D collaboration, technology boundary spanning and innovation performance, the importance of a firm's collaboration and technology boundary spanning in its technology innovation performance was empirically analyzed using patent data. We followed changes in collaboration networks, technology class networks and the connection between them and tried to find the meaning of those changes in firms' technology innovation performances. We used degree centrality within the collaboration network and the ratio of collaborated patents to the total number of patents in order to measure a firm's collaboration and formulated technology boundary spanning represented by exploitation and exploration by using edges of the multilayer network. As dependent variables, we used the number of patents and the average number of citations received over three, five, and 10 years to measure the firm's quantitative and qualitative innovation performance respectively.

The results of the analysis can be summarized as follows: a firm's collaboration has positive effects on both exploitation and exploration. Firms with more collaborations show higher quantitative innovation performances while firms with more collaborations exhibit lower qualitative innovation performance. Exploitation has a positive impact on a firm's quantitative innovation performance while exploration has negative effects on a firm's quantitative innovation performance. The relationship between a firm's exploration activities and a firm's qualitative innovation performance manifests as an inverted U-shape. On the other hand, a firm's exploitation activities have a U-shape relationship with the firm's qualitative innovation performance.

The implication of this study is that multilayer networks can be used to analyze patent data. This study used multilayer networks to formulate the exploitation and exploration only. However, in further research it can be utilized to find the hub firms that fuse technologies.

Contents

1. Introduction

R&D cooperation is a method of accessing external resources and knowledge (Fey & Birkinshaw, 2005). Therefore, research on R&D cooperation has been studied in various ways. In particular, the relationship between R&D collaboration and technology innovation has been studied steadily as the complexity, cost and risk associated with innovation grows. Because firm technology innovativeness has significant effects on firm performance (Calantone & Cavusgil & Zhao, 2002), it is important to manage collaboration partners for firms' technology innovations. Essentially, R&D collaboration has a positive effect on the technological innovation performance of a company (Becker & Dietz, 2004), but its effects vary depending on the collaboration partners. Previous researches distinguished between competitive and non-competitive partners (Huang & Yu, 2010). Collaboration with non-competitive partners, such as universities and research institutes, has significant effects on technology innovation performance, while collaboration with competitive partners, such as a firm in the same industry, does not. However, the discussion about the relationship essentially focuses on whether firms collaborate or not. In this study, we adopted the network theory to consider collaboration between firms. We investigated the effect of the quantity of a firm's collaboration experiences on its technological innovation performance.

Previous studies have seized the collaboration from the detailed archive of media and taken the innovation performance from the number of patents, which represents outputs of R&D. This study captures collaboration from patent data and takes the average forward citation as a measure of innovation performance. The patent issuance through technology development could be understood as an innovation performance. However, the quality of developed technology is also as important as the number of developments. Additionally, this study considers the relationship between the firm and the class of patents through multilayer networks.

Technology boundary spanning, which is represented by exploitation and exploration, has contributed to several issues in studies on organizational learning and technological innovation. March (1991) said: 'Exploration includes things captured by terms such as search, variation, risk-taking, experimentation, play, flexibility, discovery and innovation. Exploitation includes such things as refinement, choice, production, efficiency, selection, implementation and execution.' In short, exploration is   and exploitation is a stable and efficacy-oriented activity. Previous studies have focused on the balance between exploitation and exploration, and others have focused on the timing of exploitation and exploration. However, previous interpretations of both balance and timing effects on firms' technological innovation performances have differed. This study provides new insight onto approach exploitation and exploration using multilayer network analysis.

Network analysis has been used in many fields, including patent analysis. Technology fusion and its effects on innovation performance were explained through the class coupling network (Yayavaram

& Chen, 2015). Core technologies in the field were detected through the patent citation network (Li, 2007). However, most of the previous studies have focused on a single layer. Although these studies considered more than two networks, they analyzed the networks separately. In this study, we use the multilayer networks composed of the firm layer and technology class layer. By using the multilayer network, we tried to provide new insight to analyze patent data.

The rest of this paper is organized as follows. We start by proposing the hypothesis with a theoretical framework. Then, we exhibit descriptions of our data and sample. We test our hypothesis with samples of the printer industry from 1996 to 2005. Finally, we present the results of our analysis and its implications and limitations, while providing a meaningful conclusion. Finally, we suggest further research directions.

2. Literature review

2.1 Motivations for collaboration

Technology innovation was thought to be a product of individual entities until 1990s. However, as the level of technological complexity increases, and the life cycle of technology has recently become shorter, it's difficult to achieve technological innovation individually. Due to radical innovation, it is normal that investments in technology come with risks. The reasons for those risks are different for incumbents firms and new entrant firms. Incumbents have difficulty to adopt radical innovation because of inflexibility and new entrant has high risk because of investment in unproven technologies (Hill & Rothaermel, 2003). Moreover, the cost of technological inventions is increasing in many technology fields (Teece, 2002). Thus, technological collaborations provide opportunities to generate new ideas and new technologies by reducing the risks and costs associated with technological activities. Collaboration decreases the risk of technological failure by allowing firms to use shared research personnel and key equipment from partners to develop new technologies (Dyer & Singh, 1998). Collaboration decreases the R&D costs by spreading them among partners, since collaboration partners also agree to share the financial risk associated with technological activities (Hagedoorn, 1993).

Considering collaboration's effect of reducing the technological and financial risk of technological activities, collaborations may improve the firm's capabilities to develop new technology, which leads to innovation within a firm. Many prior studies confirm the effect of different types of collaboration on innovation. Huang and Yu (2010) distinguished non-competitive collaboration with universities from competitive collaboration with firms. They found non-competitive collaborations have direct positive effects on a firm's innovation performance and both sources of collaboration have positively moderating effects on internal R&D efforts on the innovation performance within firms. Additionally, other scholars (Belderbos et al., 2014) have categorized the period of collaboration.

They found that all varieties of persistent collaborations have positive effects on a firm's innovativeness, while only the recently formed collaborations with universities or research institutes significantly improve a firm's innovativeness. Other temporal collaborations do not have significant effects on a firm's innovativeness. Both previous studies focus on whether firms collaborate rather than on how many times the firm collaborates.

Although collaboration has many positive effects, such as reducing risks and costs, it may introduce several potential risks. Collaboration partners may engage in opportunistic behaviors such as cheating and distorting information (Das & Teng, 1998). Moreover, firms that collaborate to a high degree can suffer negative effects because of repetition of invention (Cowan & Jonard, 2003).

2.2 Technology boundary spanning and a firm's innovation performance

In organizational learning studies, technological activities are divided into exploration and exploitation. Exploitation strengthens existing capabilities through activities such as refinement. Exploration creates new capabilities through activities such as search and experimentation (March, 1991). Others have described exploration in terms of technological innovation activities intended to create new product markets, while conceptualizing exploitation as consisting of activities that improve the existing product market (He & Wong, 2004; Jansen et al., 2006). Exploration entails searching for technology to meet future market demand while exploitation involves searching for technology to meet the current market demand (Jayanthi & Sinha, 1998).

Previous research investigated the importance of striking a balance between exploitation and exploration (Raisch et al., 2009; Cao et al., 2009). They have recognized the independent effects of both exploitation and exploration, and there are synergistic benefits when the firm achieves high levels in both dimensions. Others investigate the timing for exploitation and exploration (Katila & Chen, 2008). They categorize the situations of rival firms and confirm the different effects of exploitation and exploration on the firm's products and its innovativeness when relying on rival firms' situations.

Previous studies also investigate the effect of each activity on a firm's performance. Rosenkopf and Nerka (2001) divided technology boundaries into two dimensions: the technological boundary and the organizational boundary (Rosenkopf & Nerka, 2001). They differentiate 4 type of technology boundary spanning using those 2 dimensions and they also differentiate the subsequent of technology evolutions by using them. The authors found different effects of each type of boundary spanning on each type of technological evolutions for innovation. Atuahene-Gima (2005) found that exploration activities have positive effects on radical innovation, and exploitation activities have positive effects on incremental innovation based on a test of 500 firms in China. Other scholars (Belderbos et al., 2010) have investigated the effects of exploitation and exploration on a firm's financial performance.

They confirm the inverted U-shape relationship between the share of explorative technology activities and financial performance.

3. Hypothesis

3.1 The firm's collaboration and technology boundary spanning

In many previous studies, collaboration has been considered a method of exploration and exploitation. Exploitative collaborations can increase revenue by pooling complementary resources that partners are not interested in (Koza & Lewin, 1998). However, explorative collaborations can be used as strategic and organizational tools to probe and co-develop new markets, products or technological opportunities (Koza & Lewin, 2000). Because they have the objectives of exploiting and exploring contexts in which firms collaborate with other firms, previous studies have investigated the effect of collaboration in terms of exploitation and exploration.

Many previous studies investigate the effect of exploitative collaboration and explorative collaboration separately. Yang and Lin (2007) categorized collaboration partners into exploitation alliance and exploration alliance and found that exploration alliance is more likely to result in the acquisition of a partner. Another study investigated the effect of exploitation alliance and exploration alliance on a firm's values, particularly when small firms collaborate with large firms (Yang et al., 2013). Generally, exploitation alliances will generate higher values than exploration alliances because of the high risk in the appropriation of exploration alliances. However, if small firms properly manage alliance governance, firms can increase their valuation through exploration alliance. Although many studies consider technology boundary spanning and collaboration at the same time, few studies investigate the effect of collaboration on exploitation and exploration. Therefore, in this study, we hypothesize hypothesis 1a and hypothesis 1b to confirm the effect of collaboration on exploitation and exploration.

Hypothesis 1a: A firm's collaborations have positive effects on its exploitation activities.

Hypothesis 1b: A firm's collaborations have positive effects on its exploration activities.

3.2 The firm's collaboration experience and innovation performance

Firms require continuous technological innovation to survive. It is difficult to develop innovative technologies because of their cost, complexity and risk. Recently, the risk to secure technology through in-house R & D has grown because of the rapid development speed of advanced technology. Collaboration is a method of reducing risk and approaching external resources. In the case of firms with insufficient internal R & D resources, the importance of collaboration increases (Lin, 2003).

Prior studies have focused on whether a firm exhibits a specific type of collaboration. For instance, Huang and Yu (2010) studied the effect of competitive and non-competitive collaboration partners on innovation performance. Belderbos et al. (2014) focused on the effect of continuous collaboration and temporal collaboration on innovation performance. Both studies used binary variables to understand collaboration variables, but this study uses the variables that reflect the number of collaborations.

According to Allen's (1983) argument, firms can collectively invent new technology by sharing their knowledge with their competitors. From that knowledge sharing, a firm can generate fast knowledge accumulation and high invention rates. In other words, collaboration enables firms to achieve a higher quantity of patents that could represent the firm's quantitative innovation performance.

Hypothesis 2a: A firm's collaborations have positive effects on its quantitative innovation performance.

However, Cowan and Jonard (2003) have indicated that highly collaborated firms can suffer negative effects because of repetition. In highly collaborated networks, exchanged knowledge between neighborhoods is similar and can lead to redundancy in inventions. As a result, we can expect that a firm's collaborations could affect the average number of citations received because the competitors already hold similar technologies on their own.

Hypothesis 2b: A firm's collaborations have negative effects on its qualitative innovation performance.

3.3 Technology boundary spanning and a firm's innovation performance

Firms can expand their technological boundaries by developing technology that strengthens their competence by acquiring and recombining knowledge (Rosenkopf & Nerka, 2001). There are two kinds of boundaries. One is organizational and the other is technological. In this study, we focus on the organizational boundary only. Technology boundary spanning is categorized into two features. One is exploration built on similar technologies within a firm. The other is exploitation that is built on technology outside of the firm. The aim of exploration is to find something new outside of the organizational boundary, while the aim of exploitation is to enhance core competency. In the short term, exploitation exhibits the positive performance, but it may come to be at the expense of long-term profit because of the decrease in variety that accompanies adaptation to environmental change. To improve the capacity to adapt to environmental change, balancing exploration is important. It encourages the firm to acquire new knowledge and provides the possibility of long-term prosperity.

In a previous study by Li (2008), there are two points of view. One is the perspective that regards exploitation and exploration as outcomes of innovation, and the other is the perspective that regards them as part of the process of innovation. In this study, we considered both perspectives. A patent could be the outcome of innovation itself. However, it could also be the process with a potential for future use. We used quantitative innovation performance as the outcome of innovation and used qualitative innovation performance as the process of innovation.

Based on the above explanation, we can expect that exploitation will have a positive impact on quantitative innovation performance, which is the present outcome, while exploration will have a negative effect. In addition, we hypothesize that exploitation has a negative effect on qualitative innovation performance because of the firm's ability to adapt to environmental change. It is important to balance exploration due to the risk of future failure.

Hypothesis 3a: The firm's exploitation activities have positive effects on its quantitative innovation performance.

Hypothesis 3b: The firm's exploitation activities have negative effects on its qualitative innovation performance.

Hypothesis 4a: The firm's exploration activities have negative effects on its quantitative innovation performance.

Hypothesis 4b: The firm's exploration activities have negative effects on its qualitative innovation performance.

Hypothesis 4c: The relationship between the firm's exploration activities and its qualitative innovation performance is curvilinear (inverse U-shaped).

4. METHODS

4.1 Data

The data that are used to test our hypothesis come from a patent database called the United States Patent and Trademark Office (USPTO). From 1996 to 2005, the patent data, which includes 'printer' as a keyword, were collected to explore the printer industry. Because the USPTO full text and image database provides only the most recent assignees of patents, data related to changes in assignees can't be collected from the USPTO. To solve this problem, a Google patent was used to collect data about changes in assignees. Data including patent number, patent assigned date, patent assignee, patent International Patent Classification (IPC) and the referenced patents' numbers were collected. Originally, 82,692 patents that included 'printer' as a keyword were listed in the database during the period. However, only the data from firms that had collaboration or patent transaction experience with the 10 firms that are patented the most were selected because of the data size problem. Finally, data from the 29,488 patents from 440 firms were used in this study.

Patent data has been used to analyze innovation within firms. Previous studies include analyses of the effects of economic factors or R&D input such as expenditure on the patents. Patents were used as measures of the output of knowledge production through R&D. Although not all the knowledge production of firms is patented, and the rate of patenting varies by industry, patents are still important indicators for measuring the performance of firms. Approximately 70% of inventions are patented electronic devices, a figure that includes the printer industry. In this paper, we use two indicators: the number of patents and the number of citations received. Because the value distribution of patents is highly skewed, we can't determine the degree of firms' innovation with only the number of patents. Some patents provide substantial value to the firm while others provide little value. This paper tried to test the effect of some factors on not only the quantitative innovation performance measured as the number of patents but also the qualitative innovation performance measured as the average of patent citations that the firm received. This study used the data from USPTO because it is easy to understand its relationship with prior works. The U.S. patent system makes applicants cite all relevant patents and non-patent literature, otherwise the system associated with Japan and Europe recommends providing a minimum number of the most relevant prior art references (Nagaoka et al., 2010). Moreover, it is easy to determine the substantive collaboration between firms because the data based on USPTO includes the information from co-assignees.

The printer industry had developed steadily until the 1980s. In 1984, as the low-cost laser printer was introduced by Hewlett Packard, the competition to make better printers at cheaper prices became intensive. In 1988, the inkjet printer that produces lower printing quality depending on the paper was introduced. Due to the low cost of the inkjet systems, the technology developed rapidly in the 1990s. Finally, high-quality printers could be supplied at low prices until the 2000s. In the process of development, there were a lot of collaborations between firms. To confirm the effect on innovation, there should be visible technological development. Therefore, the printer industry is apt for the test that we tried to run in this study. Because 10 firms steadily demonstrated active activity for 10 years, we selected the sample of firms that had interactions with these 10 most active firms.

The sample of this data includes 52 firms in 1996 and 408 firms in 2005. Because of missing values, the resulting sample includes panel data with 2186 firm-year observations. Table 1 summarizes the number of firms and classes and the accumulated number of patents for each year. It also shows the density of firm collaboration networks for each year. The density of firm collaboration starts from 0.0143 in 1996. With a steady decline, it finishes at 0.0036 in 2005. Because this study entails confirming the effect of exploitation and exploration, which requires data for the year before the target year, we excluded data from 1996. Finally, the sample is constructed with panel data with 2134 firm-years, including the data associated with exploitation and exploration.

Year	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005
Firm	52	82	120	167	194	226	266	314	357	408
Patent	1941	3889	6864	9752	12775	16169	19590	22933	26461	29488
Class	160	210	250	287	315	352	377	404	427	440
Density	0.014329	0.012948	0.010644	0.007287	0.006837	0.005703	0.00505	0.004518	0.004217	0.003613

Table 1 Description of Sample

4.2 **Network**

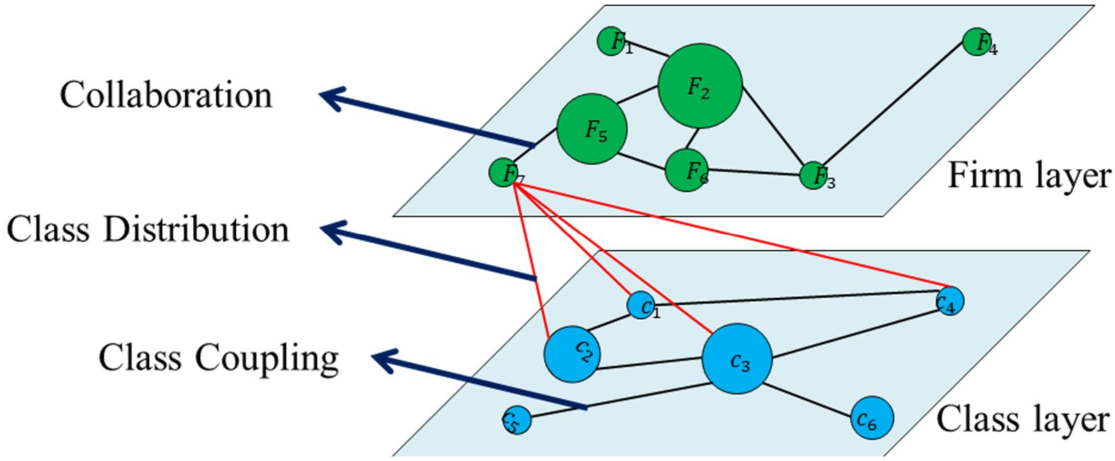

Figure 1 Structure of Multilayer Network

Network analysis has been used in many fields. It is a technique to investigate the social structure through the networks. The network is composed of nodes and edges. Nodes are individual actors in the network and edges represent a relationship between those nodes. Network analysis focuses on the characteristics of relationship between nodes rather than the characteristics of individual nodes. Size of nodes is one of the individual nodes' characteristics that can present the power of nodes. However, in network analysis, centrality of nodes that is measured through the edges in the networks is more important than the size of nodes. There are several kinds of centrality and each centrality has different meanings.

In case of multilayer network, each layer is composed of the network of nodes connected by same relationship and complex system structure is formed by connection between nodes in different layers. In this study, we used a multilayer network to express the relationship between firms, the relationship between technology classes and the interaction between them. We created networks for each year from 1996 to 2005 and observed the changes in the networks.

In the case of the firm layer, we used the collaboration to express the relationship between firms. We defined collaboration as the co-assignment of a patent. By using assignee data from USPTO and Google patent, we created a collaboration network of firms. The nodes included all the firms that were involved in the printer industry for each year. The size of a node was determined by the number of patents that were owned by the firm. The edge between firm F1 and firm F2 represented the collaboration between firm F1 and firm F2, and the edge weight represented the number of collaborations between them. For instance, if the edge weight between firm F1 and F2 was 10, it meant that there were 10 collaborating patents between two firms.

In the case of the technology class layer, we used class coupling to present the relationship between classes. Class coupling is defined as the combination of elements in two domains within the new inventions (Yayavaram & Chen 2015). The size of a node is the number of patents involved in the technology class. When a patent is included in class C1 and class C2 at the same time, it creates an edge between class C1 and C2. The edge weight refers to the number of patents that include class C1 and class C2 together. For example, if the edge weight between class C1 and class C2 is 15, there are 15 patents that include class C1 and class C2 together. A high level of class coupling between class C1 and class C2 implies a high possibility of combining C1 and C2 when the firm in the printer industry searches for a new invention.

The interactions between two layers present the distribution of technology classes in which the firm invests. If firm F1 owned a patent that involved class C1, the edge between firm F1 and class C1 is made. In the case of a patent that has more than two technology classes, the edge weight made by that patent is one divided by the number of technology classes for each technology class.

4.3 Variables

4.3.1 Dependent Variables

Our dependent variable is the firm's technological innovation performance. To measure the innovation performance, previous studies tended to use the patent tendency, the number of new products or the patent citation. In this study, we classified the dependent variables into two categories. One dependent variable was the patent tendency measured as the number of patents that a firm owned in year t. We considered the firm owning a patent when the patent's assignee was the firm. Based on the data provided by USPTO and Google patent, we counted the number of patents with assignees that corresponded with each firm. This indicated the firm's quantitative technological innovation performance. The number of patents is generally accepted as a key measure of a firm's technological development (Bjorn, 1987). In this study, the collaboration between firms and a firm's technological development tendencies were expected to affect a firm's technology development such that they would affect the number of patents that a firm owned in year t.

The other dependent variable was the patent citation, which is measured as the average of the number of citations received over the specific periods since the grant of patents owned by the firm. We used this function to search for patents that referenced the specific patents provided by USPTO. To explore the effect of the independent variable for the different time periods, we tested four different time periods (three, five and 10 years after the grant). However, we mainly used the citation received within the first five years because more than 50% of the citations received in the entire lifetime of a patent occurred within five years based on USPTO patents. This indicated the qualitative innovation performance. The number of citations received was generally accepted as a significant measure for presenting a patent's value. In this study, we calculated the average of the patents that a firm owned; thereby we could predict the average technological value of a firm's invention.

4.3.2 Independent Variables

To measure a firm's collaboration experience, we used the degree centrality in the collaboration network of firms. A firm's degree centrality is the quantity of a firm's edges divided by its possible edges. The edge between firms doesn't disappear when the firm's assignee is changed. Therefore, a firm's degree centrality measures its collaboration experience, not its collaboration status. Moreover, an edge does not refer to a patent because there could be three or four assignees in a patent.

$$Degree\ centrality_{F_i,t} = \frac{\text{Count}(E_{F_i,F_j,t} \neq 0)}{The\ number\ of\ node\ in\ firm\ network\ -1}$$

Apart from the collaboration experience, we used the collaboration ratio as an independent variable. As we mentioned above, we defined collaboration as the co-assignment of a patent. Therefore, the collaboration lasts only for the co-assigned period. To measure a firm's collaboration status, we used the ratio of the collaborated patents to the total patents. We counted the firm's patents that were the results of collaboration and divided this figure by the firm's total patents owned.

$$Collaboration\ ratio_{F_i,t} = \frac{The\ number\ of\ collaborated\ patent}{The\ number\ of\ total\ patent}$$

Exploration is defined as a learning mechanism to experiment with new alternatives. It is an activity used to challenge new technologies with which the firm has no experience, so returns from exploration can be uncertain, distant and often negative. Otherwise, exploitation is the concept of securing existing positions with existing technologies so its returns can be realized in shorter terms than with exploration. A firm might explore many new technologies and choose some among those technologies to exploit. However, the outcome of exploration is difficult to measure in the short term. Therefore, it is important to balance exploitation and exploration.

To measure a firm's exploitation and exploration, we used the edge between a firm and patent class in a multilayer network that included a firm and patent class. We defined the exploitation and exploration as the firm's patenting rate on the existing patent class and each new patent class. Therefore, we computed an exploration of year t as the sum of the edge weight that was 0 in year t-1 divided by the difference in the sum of the edge weight between year t and year t-1 and computed the exploitation of year t as the difference between the sum of the edge weight that was not 0 in year t-1 between year t and year t-1 divided by the difference in the sum of the edge weight between year t and year t-1.

$$\text{New\_Patent}_{F_i,t} = \sum_j E_{F_i,C_j,t} - \sum_j E_{F_i,C_j,t-1}$$

$$\text{Exploitation}_{F_i,t} = \frac{\sum_j (E_{F_i,C_j,t} - E_{F_i,C_j,t-1})}{\text{New\_Patent}_{F_i,t}} \qquad \left(\text{where } E_{F_i,C_j,t-1} \neq 0\right),$$

$$\text{Exploration}_{F_i,t} = \frac{\sum_j (E_{F_i,C_j,t} - E_{F_i,C_j,t-1})}{\text{New\_Patent}_{F_i,t}} \qquad \left(\text{where } E_{F_i,C_j,t-1} = 0\right)$$

$E_{F_i,C_j,t}$ represents edge weight from firm F_i to class C_j in year t.

4.3.3 Control Variables

To control for the collaboration tendency in the industry, the density of the collaboration network of the firms was used. This is calculated by the number of collaboration edges divided by the number of all possible collaboration edges. To control for the market situation and the firm's concentration, the average market size of the class in which the firm invested (MARKET_POSITIONING) and the number of classes in which the firm invested (CLASS_IN) were used. The market size of a class is calculated by assessing the number of patents in the class.

$$\text{MARKET\_POSITIONING}_{F_i,t} = \sum_j \left(\frac{E_{F_i,C_j,t}}{\sum_j E_{F_i,C_j,t}} \times \sum_i E_{F_i,C_j,t} \right)$$

$$\text{CLASS\_IN}_{F_i,t} = \text{Count}(E_{F_i,C_j,t} \neq 0)$$

4.4 Models

The empirical test used a panel data set that considered nine years, from 1997 to 2005, for the firms in the printer industry. The panel regressions were analyzed using fixed effects (FE) because this study was based on within-firm changes in variables. All variables were used in terms of natural logs. Capturing the effects of independent variables on two different dependent variables in light of the trait had by each independent variable requires caution. Therefore, we designed different models for each independent variable. First, we designed two models to confirm the effect of a firm's collaborations on exploitation and exploration, respectively. In both models, we included collaboration experience, which is measured by degree centrality in the collaboration network (DEGREE), and collaboration status, which is measured by the ratio of the collaborated patents to the total patents (COLLABORATION_RATIO), as dependent variables. Model 1 used exploitation (EXPLOITATION) as an independent variable, and Model 2 used exploration (EXPLORATION) as an independent variable.

Second, we designed models for the firm's quantitative innovation performance, which was measured by the number of patents that the firm owned. In Model 3, we included the network density of the firm's collaboration network (DENSITY), the average market size of the technology in which the firm invested (MARKET_POSITIONING), and the number of technology classes in which the firm invested (CLASS_IN). These were our control variables. In Model 4, we introduced collaboration status (COLLABORATION_RATIO). Because degree centrality in the collaboration network could be directly related to the number of patents, we used the ratio of the collaborated patents to the total patents to test the relationship between the collaboration and the firm's quantitative innovation performance. In Model 5, we included exploitation (EXPLOITATION) in the regression model. Finally, in Model 6, we elaborated on all the independent variables including exploration (EXPLORATION) simultaneously.

To capture the effect on the firm's qualitative innovation performance, we used the average number of citations over five years. In Model 7, we included our control variables as in Model 3. In Model 8, we introduced collaboration experience (DEGREE). Unlike the number of patents, the average number of citations received was not directly related to degree centrality. Therefore, the regressions related to the firm's qualitative innovation performance used degree centrality in the collaboration network. Model 9 included exploitation (EXPLOITATION) and the square term for exploitation (EXPLOITATION^2). In Model 10, we elaborated on all independent variables including exploration (EXPLORATION), and the square term for exploration (EXPLORATION^2) at the same time.

To check the robustness of our analysis, we conducted additional regressions. We tested the same independent variables in Model 10 with different dependent variables. Model 11 and Model 12 used the number of average citations over three and 10 years after the grant as dependent variables.

5. RESULTS

5.1 Descriptive Statistics and Correlations

Table 2 presents the descriptive statistics for all variables by year. The mean of degree centrality in the firm collaboration network (DEGREE) steadily decreased from 0.0259 in the year 1997 to 0.0072 in the year 2005. Otherwise, the average market size of the technologies in which the firm invested (MARKET_POSITIONING) steadily increased from 342.5193 in the year 1997 to 2078.0307 in the year 2005. The rest of variables did not show specific patterns by year.

Table 3 presents the correlations for all variables. The average market size of the technologies in which the firm invested (MARKET_POSITIONING) and the average number of the technology classes in which the firm invested (CLASS_IN) have a high degree of correlation with our dependent variables. Therefore, we needed to control for cross-firm variation in the completeness of firms and in the technology diversity within the firms. A more competitive company may be able to more easily enter a highly competitive market or may already be in place.

YEAR		MARKETSIZE	CLASS_IN	DEGREE	COLLABORATION _RATIO	EXPLORATION	EXPLOITATION	PATENTCOUNT	AVG.THREE	AVG.FIVE	AVG.TEN
1997	Mean	342.5193	8.9146	0.0259	0.3705	0.0763	0.2164	46.0488	4.5762	9.5297	20.3128
	SD	262.1748	20.2790	0.0308	0.4814	0.2230	0.3874	153.5607	4.9155	10.8160	24.0642
1998	Mean	553.1864	8.6583	0.0213	0.3908	0.0374	0.1792	55.5750	3.6855	7.4972	16.0814
	SD	459.5518	22.7786	0.0290	0.4794	0.1415	0.3634	223.8562	4.1482	9.2004	21.3794
1999	Mean	768.2393	7.7725	0.0146	0.3884	0.0326	0.1171	56.7844	3.6431	7.5705	17.4813
	SD	620.9381	23.0752	0.0233	0.4789	0.1365	0.3015	271.0987	4.2583	9.1784	24.6599
2000	Mean	993.8539	8.1907	0.0137	0.3738	0.0649	0.1362	65.2887	3.9544	8.2458	20.9532
	SD	807.8225	24.7842	0.0233	0.4751	0.2025	0.3135	334.1772	4.8359	10.2929	33.8246
2001	Mean	1253.3036	8.1593	0.0114	0.3945	0.0543	0.1227	71.8407	3.6823	7.8278	21.3506
	SD	1024.5199	25.9473	0.0216	0.4674	0.1837	0.3004	394.9321	4.6313	10.2079	35.2397
2002	Mean	1424.7718	7.7744	0.0101	0.4054	0.0300	0.1279	73.7970	3.6719	7.7960	20.6344
	SD	1259.8123	26.0946	0.0206	0.4763	0.1453	0.3223	442.1094	5.3712	11.2229	35.3598
2003	Mean	1653.5170	7.2771	0.0090	0.3890	0.0251	0.1150	74.7198	3.3371	7.3123	19.8865
	SD	1528.4990	26.1169	0.0204	0.4741	0.1268	0.3060	485.1295	5.0371	10.7273	34.3345
2004	Mean	1910.3765	6.7479	0.0084	0.3670	0.0346	0.0915	75.9328	2.9842	6.5203	18.1157
	SD	1845.0067	26.5756	0.0196	0.4686	0.1551	0.2718	526.2698	4.6609	9.9616	32.2506
2005	Mean	2078.0307	6.3652	0.0072	0.3871	0.0175	0.0707	73.9436	2.8706	6.3015	17.4405
	SD	1996.4798	26.4300	0.0181	0.4773	0.1234	0.2526	549.4285	4.4495	9.3339	30.0539

Table 2 Descriptive statistics

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) MARKETSIZE	1.0000									
(2) CLASS_IN	0.6737	1.0000								
(3) DEGREE	-0.1981	0.0702	1.0000							
(4) COLLABORATION RATIO	0.3018	0.2868	0.3303	1.0000						
(5) EXPLORATION	0.1750	0.5276	0.2733	0.1096	1.0000					
(6) EXPLOITATION_3	0.1967	0.5568	0.2570	0.0918	0.6749	1.0000				
(7) PATENTCOUNT	0.5625	0.9265	0.2108	0.2499	0.6101	0.6860	1.0000			
(8) AVG.THREE	0.5882	0.5380	-0.0819	0.2582	0.1489	0.1881	0.4517	1.0000		
(9) AVG.FIVE	0.7194	0.5874	-0.1570	0.2519	0.1393	0.1649	0.4780	0.8824	1.0000	
(10) AVG.TEN	0.7241	0.5990	-0.2092	0.2493	0.1246	0.1491	0.4796	0.8306	0.9458	1.0000

Table 3 Correlation

5.2 A firm's collaborations and technology boundary spanning

Dependent variable	The effect of collaboration on technology boundary spanning	
	Exploitation	Exploration
	MODEL 1	MODEL 2
DEGREE	0.2733***	0.2689***
	(0.0434)	(0.0559)
COLLABORATION_RATIO	0.0466	0.1007**
	(0.0282)	(0.0364)
R^2	0.0273	0.0205
Adjusted R^2	-0.2253	-0.2339
F-statistic	22.1148	16.4485

Table 4 A firm's collaborations and technology boundary spanning

Model 1 reports the results for the panel regressions of the exploitation, and Model 2 reports the results for the panel regressions of exploration. Both models used fixed effects (FE). In Model 1, degree centrality in the collaboration network (DEGREE) has positive effects on exploitation. This variable appears positive and statistically significant. The coefficient for the ratio of collaborated patents to total patents (COLLABORATION_RATIO) has a positive value, but it is not statistically significant. Therefore, hypothesis 1a is partially supported. In Model 2, both degree centrality in the collaboration network (DEGREE) and the ratio of collaborated patents to total patents (COLLABORATION_RATIO) have positive effects on exploitation. These variables appear positive and statistically significant. Therefore, hypothesis 1b is fully supported.

5.3 The Firm's Quantitative Innovation Performance

The models in Table 5 report the results for the panel regressions of the firm's quantitative innovation performance using fixed effects (FE). The dependent variable is the number of patents. These regressions include up to 408 firms with 2134 firm-years. Model 3 in Table 5 presents the results for the control variables. The results in Table 5 show that the network density of the firm collaboration network (DENSITY) has a negative impact on the firm's quantitative innovation performance. This variable demonstrates a negative and statistically significant coefficient in Model 3 through Model 6. The average market size of the technology in which the firm invests (MARKET_POSITIONING) also has a negative effect on the firm's quantitative innovation performance. This variable exhibits negative and statistically significant coefficients in all regressions in Table 5. Otherwise, the number of the technology classes in which the firm invests (CLASS_IN) has a positive impact on the firm's quantitative innovation performance. This variable appears positive and statistically significant in all regression models in Table 5.

In Model 4, we introduce the ratio of collaborated patents to total patents (COLLABORATION_ RATIO) as an independent variable. The result indicates it has a positive effect on the firm's quantitative innovation performance. This variable exhibits positive and statistically significant coefficients in Model 4 through Model 6. Therefore, hypothesis 2a is supported. In Model 5, we include independent variables related to exploitation (EXPLOITATION). Exploitation (EXPLOITATION) has a positive effect on the firm's quantitative innovation performance. This appears constant and statistically significant in both Model 5 and Model 6, thus hypothesis 3a is supported. In Model 4, we include the independent variable related to Exploration (EXPLORATION). It has a negative effect on the firm's quantitative innovation performance. As a result, hypothesis 4a is supported.

	Dependent Variable: Quantitative Innovation Performance (Patent Count)			
	MODEL3	MODEL4	MODEL5	MODEL6
DENSITY	-0.1093 ***	-0.1117 ***	-0.1045 ***	-0.1058 ***
	(0.0101)	(0.0101)	(0.0096)	(0.0096)
MARKET_ POSITIONING	-0.1533 ***	-0.1572 ***	-0.1234 ***	-0.1405 ***
	(0.0127)	(0.0128)	(0.0123)	(0.0125)
CLASS_IN	0.9941 ***	0.9896 ***	0.9293 ***	0.9553 ***
	(0.0148)	(0.0149)	(0.0146)	(0.0150)
COLLABORATION_ RATIO		0.0130 *	0.0134 **	0.0142 **
		(0.0054)	(0.0051)	(0.0051)
EXPLOITATION			0.0666 ***	0.0681 ***
			(0.0045)	(0.0047)
EXPLORATION				-0.0219 ***
				(0.0041)
R^2	0.8813	0.8818	0.8946	0.8951
Adjusted R^2	0.8492	0.8496	0.8659	0.8664
F-statistic	4154.14	3126.13	2845.18	2381.90

Table 5 Regressions for Quantitative innovation performance

5.4 The Firm's Qualitative Innovation Performance

	Dependent Variable:			
	Qualitative Innovation Performance (Average citation received over 5 years)			
	MODEL7	MODEL8	MODEL9	MODEL10
DENSITY	-0.0368 *	-0.0610 ***	-0.0599 ***	-0.0573***
	(0.0170)	(0.0173)	(0.0174)	(0.0174)
MARKET_ POSITIONING	0.6125 ***	0.5869 ***	0.5788 ***	0.5786 ***
	(0.0214)	(0.0217)	(0.0221)	(0.0223)
CLASS_IN	0.2369 ***	0.2712 ***	0.2840 ***	0.2851 ***
	(0.0249)	(0.0254)	(0.0265)	(0.0270)
DEGREE		-0.0944 ***	-0.0967 ***	-0.0941 ***
		(0.0162)	(0.0163)	(0.0163)
EXPLOITATION			-0.0443 *	-0.0755 *
			(0.0189)	(0.0328)
$EXPLOITATION^2$			0.0394 *	0.0610 *
			(0.0186)	(0.0292)
EXPLORATION				0.0279
				(0.0169)
$EXPLORATION^2$				-0.0300 **
				(0.0110)
R^2	0.7351	0.7403	0.7412	0.7426
Adjusted R^2	0.6633	0.6697	0.6704	0.6719
F-statistic	1552.08	1195.23	799.407	603.449

Table 6 Qualitative innovation performance regression

Models in Table 6 report the results for the panel regressions for the firm's qualitative innovation performance using fixed effects (FE). The dependent variable is the number of citations received over five years after a grant. These regressions also include up to 408 firms with 2134 firm years. Model 7 presents the results for the control variables. The results in Model 7 show that the network density of the firm collaboration network (DENSITY) has a negative impact on the firm's qualitative innovation performance. This variable shows negative and statistically significant results in Model 8, Model 9 and Model 10. The average market size of the technology in which the firm invests (MARKET_POSITIONING) has a positive impact on the firm's qualitative innovation performance. This variable exhibits positive and statistically significant coefficients in all regressions in the models.

Moreover, the number of the technology classes in which the firm invests (CLASS_IN) also has a positive impact on the firm's qualitative innovation performance. This variable appears positive and statistically significant in all regression models in Table 6.

In Model 8, we introduce degree centrality in the firm collaboration network (DEGREE) as an independent variable. The results indicate that it has a negative effect on the firm's qualitative innovation performance. This variable exhibits negative and statistically significant coefficients in Model 8, Model 9, and Model 10. Therefore, hypothesis 2b is supported. In Model 9, we include independent variables related to exploitation (EXPLOITATION). We expected exploitation activities to have negative effects on the firm's qualitative innovation performance. However, the results exhibit that the square term of exploitation (EXPLOITATION^2) has a positive effect on the firm's qualitative innovation performance, which means the relationship between the exploitation activities and the firm's qualitative innovation performance is curvilinear (U-shape). Thus, hypothesis 3b is not supported. In Model 10, we include independent variables related to exploration (EXPLORATION). The square term of exploration (EXPLORATION^2) has a negative effect on the firm's qualitative innovation performance, thus the relationship between exploration activities and the firm's qualitative innovation performance is curvilinear (inverted U-shape). As a result, hypothesis 4c is supported.

5.5 Robustness check

To check the robustness of our analysis, we tested the same independent variables in Model 10 with different dependent variables. In Model 11, we used the average number of citations received over three years after a grant. There was no change in the results for the control variables or in the degree centrality in the firm's collaboration network (DEGREE). However, the coefficients for the independent variables related to exploitation (EXPLOITATION) and exploration (EXPLORATION) were not statistically significant. It could be interpreted that more than a certain period of time is required for exploitation and exploration to take effect.

In Model 12, we used the average number of citations received over 10 years after a grant. Unlike the results in Model 10 and Model 11, the coefficient of the network density of the firm collaboration network (DENSITY) had a positive value. This could be interpreted in terms of the fact that collaborative industry climates have negative effects on the firm's qualitative innovation performance in the short run, but its effect is ambiguous in the long run. The results related to collaboration and technology boundary spanning was the same in Model 10.

In addition, we conducted comparisons between fixed effects models and random effects models. Model 13 is the random effects model (RE) of Model 6, and Model 14 is the random effects model (RE) of Model 10. Because the p-value of the Hausman test for both models is lower than 0.05, our main models were analyzed with fixed effects models. However, we compared the results of random effects models to check the robustness of our results.

The results of Model 13 were the same as in Model 6. However, there are few differences between the results of Model 10 and Model 14. The results indicated that only the square term of exploration had a statistically significant effect on the firm's qualitative innovation, which supports hypothesis 4c.

	Dependent Variable: Qualitative Innovation Performance (Average citation received)		
	MODEL10 (5 years)	MODEL11 (3 years)	MODEL12 (10 years)
DENSITY	-0.0573***	-0.1566 ***	0.0291
	(0.0174)	(0.0197)	(0.0167)
MARKET_ POSITIONING	0.5786 ***	0.4426 ***	0.6092 ***
	(0.0223)	(0.0253)	(0.0215)
CLASS_IN	0.2851 ***	0.2979 ***	0.2817 ***
	(0.0270)	(0.0306)	(0.0260)
DEGREE	-0.0941 ***	-0.0752 ***	-0.0670 ***
	(0.0163)	(0.0184)	(0.0157)
EXPLOITATION	-0.0755 *	-0.0533	-0.0899 **
	(0.0328)	(0.0372)	(0.0316)
EXPLOITATION^2	0.0610 *	0.0405	0.0729 **
	(0.0292)	(0.0331)	(0.0282)
EXPLORATION	0.0279	0.0107	0.0249
	(0.0169)	(0.0192)	(0.0163)
EXPLORATION^2	-0.0300 **	-0.0158	-0.0274 **
	(0.0110)	(0.0125)	(0.0106)
R^2	0.8951	0.6233	0.7667
Adjusted R^2	0.8664	0.5197	0.7025
F-statistic	2381.90	345.988	687.133

Table 7 Comparison with different time periods

	Comparison between fixed effects and random effects models			
	MODEL6 (FE)	MODEL13 (RE)	MODEL10 (FE)	MODEL14 (RE)
(Intercept)		-0.5795***		-0.2819
		(0.0527)		(0.0988)
DENSITY	-0.1058 ***	-0.1036 ***	-0.0573***	-0.0506 ***
	(0.0096)	(0.0096)	(0.0174)	(0.0174)
MARKET_ POSITIONING	-0.1405 ***	-0.1031 ***	0.5786 ***	0.5637 ***
	(0.0125)	(0.0107)	(0.0223)	(0.0206)
CLASS_IN	0.9553 ***	0.9117 ***	0.2851 ***	0.2913 ***
	(0.0150)	(0.0126)	(0.0270)	(0.0247)
DEGREE			-0.0941 ***	-0.0806 ***
			(0.0163)	(0.0150)
COLLABORATION _RATIO	0.0142 **	0.0128 *		
	(0.0051)	(0.0050)		
EXPLOITATION	0.0681 ***	0.0881***	-0.0755 *	-0.0620
	(0.0047)	(0.0048)	(0.0328)	(0.0335)
$EXPLOITATION^2$			0.0610 *	0.0472
			(0.0292)	(0.0298)
EXPLORATION	-0.0219 ***	-0.0231***	0.0279	0.0199
	(0.0041)	(0.0048)	(0.0169)	(0.0173)
$EXPLORATION^2$			-0.0300 **	-0.0257 *
			(0.0110)	(0.0112)
R^2	0.8951	0.8869	0.7426	0.6994
Adjusted R^2	0.8664	0.8866	0.6719	0.6982
F-statistic	2381.90	16660.1	603.449	4943.3

Table 8 Comparison between fixed effects and random effects

6. CONCLUSION AND DISCUSSION

The purpose of this study was to examine the relationship between the collaboration and innovation performance and the relationship between technology development tendencies and innovation performance. There are several important findings from our empirical analysis.

First, collaboration status has a significant positive effect on the firm's quantitative innovation performance. According to our results, the ratio of collaborated patents to the total number of patents has a positive impact on the number of patents that the firm owns. Thus, we confirm that collaboration could lead to the additional invention of patents. Second, collaboration experience has a significant negative impact on the firm's qualitative innovation performance. Our results demonstrate that degree centrality in the collaboration network has a positive effect on the average number of citations received. Therefore, our results imply that excessive collaboration could lead to a decrease in the quality of invention but an increase in the number of inventions.

At the same time, we suggest a new way to measure exploitation and exploration by using a multilayer network and confirming their effects on the firm's innovation performance. Our results show that exploitation has a positive impact on the firm's quantitative innovation performance while exploration has a negative effect on it. Moreover, our results show that the square term of exploration has a negative impact on the firm's qualitative innovation performance. Thus, we confirm the inverted U-shaped relationship between exploration activities and the firm's qualitative innovation performance. In contrast, exploitation activities have a U-shape relationship with the firm's qualitative innovation performance. Therefore, companies need to manage exploration and exploitation to improve both innovation performances when they expand their technology boundaries. Moreover, we confirm that collaborations have positive effects on both exploitation and exploration empirically.

This study contributes to innovation research for 2 main respects. First, the study suggests the perspectives to view collaboration to firm. Traditionally, many empirical studies confirm the positive effects of collaboration on firm's innovation performance. However, this study shows not only positive effects of collaboration but also negative effects by differentiate the innovation into qualitative and quantitative innovation. Therefore, firms should be careful in making collaboration decision.

Second, this study provides the direction for companies to exploration and exploitation. This study shows exploitation gives more inventions while exploration gives fewer inventions. This suggests that exploitation can lead to short-term innovation from more invention. In addition, an appropriate level of exploration can be helpful for firms by providing higher qualitative innovation performance. However, as inverted U-shape relationship shows, excessive exploration could lead to fetal failure. As a result, it is important for firms to balancing exploitation and exploration.

We admit that this research, limited to the sample of 10 years in the printer industry, may not be fully generalizable. If a wider range of samples with different industries were used, there might be more findings than in this study. Moreover, we didn't differentiate the inventions from collaborations and solitary works. If we differentiate them, we can find more detailed effects of collaboration.

In addition, although we used a multilayer network only to measure exploitation and exploration, it can be developed in many different directions. From the perspective of 'firm to class,' the firm's degree centrality related to the inter-layer edge can be interpreted in terms of the technology class on which the firm is working. The firm's betweenness centrality can be attributed to the role of the hub in fusing the technologies. On the contrary, in terms of 'class to firm', class's degree centrality can be attributed to the number of firms that are competing in the technology class. A class's betweenness centrality can be measured for collaboration in the technology class.

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