Firm's innovation and performance

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(企業のイノベーションと成果)

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Contents

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Junghyun Song

Introduction

The relationship between a firm's innovative behavior and performance is now a significant issue in corporate economics. Firms are individual entities that produce products, undertake business and conduct innovative research and development (R&D) to consolidate their future performance. Increasing product complexity and range mean that firms now need to acquire more technical knowledge. However, not all firms are innovative. Some firms have a strong and robust competitive advantage in their technological knowledge and performance, and are thus competitive leaders. In contrast, other firms have a limited technological advantage, frequently resulting in their market exit or bankruptcy.

Diversified firms can generate economies of scope by efficiently exploiting resource allocation across multiple businesses. However, some researchers point out that firm diversification can have downsides, ultimately resulting in diseconomies of scope. Japan has large diversified firms, and there is some question on how the diversification activity affects a firm's performance.

Japanese firms are known for having intense technological knowledge and performance, particularly in high-tech manufacturing industries. Japanese firms are frequently characterized by large, robust ownership structures in contrast with the situation in other countries. There has been some investigation of the structure of such Japanese manufacturing industries; however, there is a lack of empirical analysis.

Many researchers use technology patent data as an innovative measure; however, there is a discordance when researchers attempt to use patent data for the economic analyses of goods and services, or for analysis at an individual firm or industry level. To resolve this issue, there is a need to establish a concordance between the patent and goods technology category and the standard industrial classification services category. However, currently there is no concordance in Japanese industries.

This paper focuses on the relationship between a firm's innovative behavior and performance in Japanese manufacturing. The main purpose of this research is to empirically establish how a firm's innovative behavior affects its performance. I focus on three main areas in my examination of innovation in Japanese manufacturing industries.

1. The effects of business diversification and technology diversification on performance

The purpose of this study is to analyze how both business diversification and technology diversification affect firm performance in Japan's electronics industry. Diversification direction (vertical integration) is investigated to estimate its effects on profitability. Surveyed firms were selected using Japanese stock exchange data and patent application data were collected for individual firms to identify existing technological knowledge. An analysis of selected firms over a ten year period was completed using defined variables; moreover, a series of model scenarios were prepared and undertaken to test the study hypotheses. Empirical results show that business diversification has negative effects on firm performance, the effect being particularly evident for non-manufacturing diversification. In contrast, the results reveal that technology diversification has positive effects on firm performance. This result strongly supports the importance of possessing technical diversity for firm performance. These findings contribute to a comprehensive understanding of diversification behavior.

2. Ownership, learning and innovation

This study considers organizational learning within governance groups in Japan's automotive industry. The main objective of this paper is to examine the existence of the spillover effect within the governance structure. Using data on firms' patent applications and financial status, I measure multiple spillover effects models to determine whether a member's level of technological knowledge is affected by that of other members within the governance group. My results show that the technological knowledge of other group members has a positive effect on a firm's knowledge growth and that technologically close knowledge has a greater positive effect than technologically distant knowledge. Furthermore, by comparing regression coefficients, the effect of a cooperative relationship with subsidiaries is greater than that with a subsidiaries' parent company. This explains why the Japanese automotive industry tends to form significant downstream organization governance alliances or associations (referred to in this paper as governance relationships) to accelerate technological performance. My results show that a governance relationship assists technology diffusion and that cooperation within the ownership relationship is an efficient structure to enrich organizational learning.

3. Linking patent data with industrial data and Japanese industrial technology profiles

This study had two primary objectives: to make a concordance between Japan Standard Industrial Classification (JSIC) and International Patent Classification (IPC) in Japanese manufacturing industries, and to measure the descriptive analyses of patenting behavior. The paper then describes the relevant technological competencies between the concordance and each firm's and each industry's attributes. Moreover, by examining the technological profiles, I produce a competency contribution matrix between each integrated technology field by my concordance, and by identified firms in each industry. Researchers can use patent data as an economic parameter by using this JSIC and IPC concordance. It is also a valuable tool to understand technology profiles, proximity and R&D activities among the industries.

The first area focuses on the internal strategies of firms, particularly within economics. The second area examines the effect of the governance group, an effect outside of the firm's control. Area three considers the concordance between technology and industrial fields to identify linkages between industrial behavior and patenting activity in Japanese manufacturing industries. I use these areas to establish the impact of the technology activity of individual firms in Japanese manufacturing industries. Two sources were used to extract the relevant data: financial reports and patents data. This research thus measured several empirical analyses to explain the relationship between a firm's innovative behavior and its performance.

I hope that this study will contribute towards the understanding of the impact of firms' innovation on Japanese manufacturing industries.

1. The Effects of Business Diversification and Technology Diversification on Performance: Empirical analysis of the Japanese Electronic Equipment Industry

1–1. Introduction

The impact of a firm's diversification strategy on its economic performance is a significant issue in strategic management research. Chandler (1962) argued that diversification was the future of corporation growth. He maintained that expansion into other businesses necessitates the acquisition of knowhow and structures to attain efficiency. A number of subsequent studies examined the positive effects of a diversification strategy (Williamson, 1971; Teece, 1982; Grant et al., 1988; Robins and Wiersema, 1995; Tanriverdi and Venkatraman, 2005). Other studies insisted that diversity has a negative effect (Baysinger and Hoskisson, 1989; Berger and Ofek, 1995; Geringer et al., 2000; Fukui and Ushijima, 2007). The impact of diversification strategies on the economic performance of corporations is a significant issue for management economics. A number of subsequent studies have attempted to clarify this issue; however, questions remain as to why firms diversify and as to the effects of diversification. In reviewing earlier studies on diversification strategy, Montgomery (1994) observed different and inconsistent findings.

Particularly in recent years, electronic equipment requires a range of complex technologies to combine its various technical parts. Increasingly sophisticated consumer demands and competition have placed pressure on the electronics industry to continually update their products. As more complex components are required the electronics industry needs to access more technologies. I thus conclude that Japan's electronics industry is an optimal one for examining the effects of diversification.

To establish the effects of business diversification and technology diversification on firms this paper focuses on the Japanese electronics industry, including firms possessing significant technology knowledge and businesses acumen such as Sony, Sharp, Panasonic, and Toshiba. Large firms tend to diversify into different business and technology fields. Leading medium-size companies, also possessing high levels of technology and know-how, contribute to, and support, Japan's electronic equipment industry. Some small and medium companies are more specialized in products and knowledge than relatively larger companies. Japan's firms had to reconsider their business strategies subsequent to the 1990s depression. In general Japanese firms were too diversified before the collapse of the bubble economy. To cope with the depressed economy, firm managers had to reconstruct their diversified businesses. Miyajima and Inagaki (2003) showed that Japanese firms decreased business diversification activities after the mid-1990s. In contrast, while business diversification decreased technology diversification became widespread (Gambardella and Torrisi, 1998). The effects of business diversification and technology diversification should be examined to identify their differences.

I outline the relationships that diversity and profitability have on the economic strategies of the Japanese electronics industry. The main purpose of this research is to comprehensively analyze how both business and technology diversification affect firm performance. To examine the effect of diversification, I measure the results of both business and technology diversification using two indices: concentration and the number of diversifications. By estimating both business and technology diversification, this paper can describe the effects of and draw a comparison between the diversifications. I also consider how vertical integration affects profitability. By measuring business diversification, technology diversification, and the direction of diversity, this paper comprehensively explains how diversification activities affect firm performance.

1–2. Theory and Hypotheses

In the study of diversification strategy, the resource-based theory is essential to explaining why diversification generates economies of scope. Diversified firms can allocate resources between business sectors, thus making better decisions on resource allocation than undiversified firms. Williamson (1971) argued that internal transactions and efficient resource allocation generates firm profitability. From this I conclude that the flexibility of resource allocation enjoyed by diversified companies has a positive impact on profitability. Similarly, Grant et al. (1988) asserted that diversified firms can make better resource allocation decisions, bringing better performance. Robins and Wiersema (1995) constructed an empirical model based on a resource-based approach for multi-business firms. They observed that highly interrelated business portfolios had positive effects on firm performance.

Efficient resource allocation can be accomplished if the corporation possesses sufficient, and related, common resources. When diversified, a firm shares common resources across multi-business sectors: the firm can attain economies of scope from cost savings. Diversifying into a knowledge-related business can lead to the exploitation of common resources across the businesses. Breschi et al. (2003) demonstrated that knowledge-relatedness is a major feature of a firm’s technology innovation. Similarly, Tanriverdi and Venkatraman (2005) empirically showed that having related knowledge resources across business sectors improves firm performance. Moreover, transaction cost theory suggests that managers should consider alternatives when a firm is in a position to exploit its resources. Teece (1982) argued that firms diversify to avoid high transaction costs, particularly in markets with specialized assets. Silverman (1999) showed that transaction costs affect a firm’s diversification decisions.

The studies discussed above examined the positive effects of business diversification, showing that firms can generate economies of scope by efficiently exploiting resource allocation across multiple businesses. The resource-based theory approach illustrates the advantages of economies of scope to be gained by diversification strategies. This study examines a hypothesis that business diversification has a positive effect on profitability.

Hypothesis 1a: Business diversification has a positive effect on firm performance.

Firm diversification can also have negative effects. Diversified firms must undertake ongoing expenditure in each individual business unit. Hence, large diversified firms can have poor opportunities if firms do not invest enough specific assets. Diversified firms do not benefit from economies of scale when it comes to capital assets as they must undertake separate asset financing for each business unit: this can be considered a weakness. The increased requirements for specific capital assets have reduced the advantage of large diversified firms. Baysinger and Hoskisson (1989) indicated that diversification has a negative effect on a firm's R&D intensity.

A number of studies focused on the relationship between diversification discount and firm value (Berger and Ofek, 1995; Campa and Kedia, 2002; Graham et al., 2002; Mansi and Reeb, 2002; Lee et al., 2008). In investigating the effect of the diversification discount on performance, Grant et al. (1988) found that product diversity led to declining profitability when a firm encountered limits to complexity. Geringer et al. (2000) empirically showed that product diversity has weak effects on firm performance. Similarly, Gemba and Kodama (2001) indicated that a firm's profitability diminished as it diversified into unrelated fields. Fukui and Ushijima (2007) noted the negative relationship between business diversification and performance in large Japanese firms.

Hence, I can conclude that the effects of business diversification on performance are not clear. While having a positive economies of scope impact, business diversification may also yield a negative effect on performance. Therefore, on the basis of the diseconomies of scope theory, this study also examines the hypothesis that business diversification decreases firm profitability.

Hypothesis 1b: Business diversification has a negative effect on firm performance.

The increasing complexities in product technologies have led to a diversity of technical knowledge. The more complex the products a firm manufactures, the greater the variety of technology required. From a resource-based theory perspective, diversified firms can create economies of scope by exploiting technical knowledge across their businesses (Robins and Wiersema, 1995; Gambardella and Torrisi, 1998; Miller, 2006). Some researchers have pointed out the increasing importance of technology diversification over business diversification. Patel and Pavitt (1997), and Brusoni et al. (2001) showed that multi-technology firms need to have detailed technical knowledge levels on the items they produce. Pavitt (1998) argued that specialized technology understandings have impacts on the products made.

Gambardella and Torrisi (1998) showed that firms are tending towards reduced product diversity, but an increased technical base diversity. Piscitello (2004) showed technology-based coherence to be more prevalent than product-based coherence.

Moreover, the combination of knowledge from different technical fields is an important technology opportunity resource. Gambardella and Torrisi (1998) showed that the accumulation of technology capability in different fields is essential to create complex products. Suzuki and Kodama (2004) found that technology diversity has contributed to product diversification and sales growth. They showed that taking advantage of technology economies of scope is necessary for a technology-based firm. Garcia-Vega (2006) and Miller (2006) maintained that a combination of knowledge was the source of technology opportunities. Cantner and Plotnikova (2009) showed a positive relationship between future product portfolios and technology diversification in the pharmaceutical and biotechnology industries. Technology diversification enables firms to create not only new products, but also new technologies. Miller et al. (2007) found that the use of interdivisional knowledge positively affects technical development.

Based on the above discussion, this study considers technology diversification as an essential factor in firm performance. I establish the hypothesis that technical variety positively affects firm profitability.

Hypothesis 2: Technology diversification has a positive effect on firm performance.

Firms do not diversify randomly. Firm managers assess the direction of diversification most appropriate to their situation. In the context of a make-or-buy decision, vertical integration is another essential consideration for diversification. Determining the boundaries of the firm is critical for firm performance, and in general, vertical integration is an essential source of boundary determination. To maintain stability of resource supply, vertical integration may be needed, particularly when the resource market is unstable. Technology interdependencies among vertical stages can also yield positive results. Brusoni et al. (2001) maintained that highly specialized technical knowledge was necessary to maximize the effectiveness of vertical integration. When corporations consider undertaking diversification by vertical integration, transaction and contracting costs are significant (Klein et al., 1978; Monteverde and Teece, 1982). Williamson (1971) argued that firm's internalize in vertical ways to avoid market failure.

The economies of vertical integration suggest it is the main strategy for enhanced performance (Hill and Hoskisson, 1987; Fukui and Ushijima, 2007). Gemba and Kodama (2001) noted the diversity direction of Japan's manufacturing industries. They found that diversifying into downstream businesses contributed to an increase in profitability. Arocena (2008) empirically found that economies of scope exist in vertical integrations. Similarly, Rothaermel et al. (2006), and Forbes and Lederman (2010) indicated that vertically integrated firms have high performance levels. Acemoglu et al. (2010) found that the downstream technology intensity is positively correlated with the likelihood of integration.

Based on the above discussion I observe that firms are willing to diversify into vertical integration for enhanced performance. Therefore, I hypothesize that diversifying into vertical integration positively affects firm performance.

Hypothesis 3: Diversifying towards vertical integration has a positive effect on performance.

Figure 1–1. Theoretical map between diversification strategy and performance

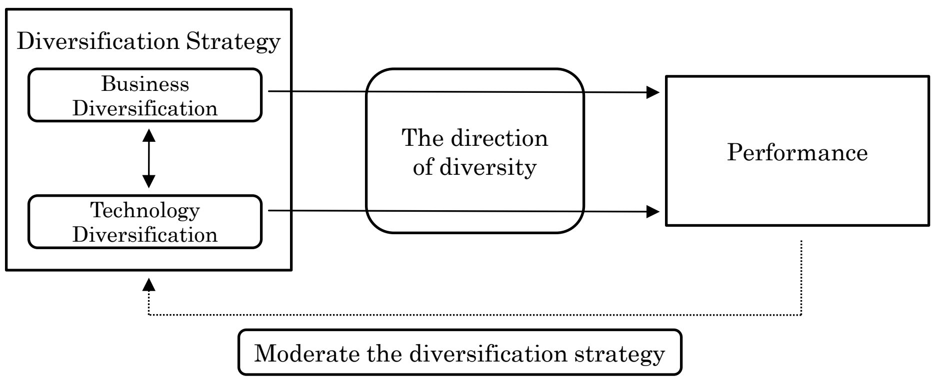

Figure 1–1 provides a theoretical map of business diversification, technology diversification and performance strategies. The map illustrates how different diversification strategies affect the economic objectives. A firm manager can strategically consider diversification based on two strategies: business diversification and technology diversification. Diversified businesses may be motivated by acquiring a variety of technical opportunities. To conduct many businesses, firms need to have technical variety. Further, having high levels of technical opportunities enhances the business portfolio.

The effect of business diversity and technology diversity on firm performance can appear similar: however, they can impact in different ways. Business diversification can have positive effects on firm performance by exploiting common resources and efficient resource allocation. Whereas, technology diversification can generate a positive effect by its technical opportunities mix. Furthermore, the direction of diversification—such as vertical integration—is a determining factor of the diversification strategy. Finally, firms tend to modify their diversification strategy to attain best performance.

1–3. Data and Methods

This study extracted financial data from the Development Bank of Japan (DBJ)[1]. The target companies are listed on the first and second section of the Tokyo, Osaka, and Nagoya stock exchanges in Japan. The study includes data from companies from the old JASDAQ security exchange, the market of the high-growth and emerging stocks (Mothers), and the Nippon New Market Hercules stock exchange. The patents application data for each target company was collected using the Institute of Intellectual Property (IIP) database[2]. Japanese company annual reports have been obliged to clarify their business segment data since 1998, hence, this research examines the ten year period from 1998 to 2008. A sample of 265 electronic firms was selected using unbalanced panel data.

Dependent Variable

A lot of research has used ROA (return on assets) as a variable of firm profitability (Grant et al., 1988; Robins and Wiersema, 1995; Degryse and Ongena, 2001; Gedajlovic and Shapiro, 2002; Fukui and Ushijima, 2007). As ROA is one of the most widely employed measures of financial performance, for this study I regarded the **ROA** as firm profitability. To establish how business diversification, technology diversification, direction of diversity and other control factors affects firm profitability, I set up explanatory variables described below.

Explanatory Variables

This research examined business diversification by extracting data from corporations' annual reports. Each business segment is identified by a four-digit Japan Standard Industrial Classification (JSIC) code in order to specify what they make. To establish the business diversification index, I defined two aspects of the business diversification activity: business concentration and business diversification. I used the Herfindahl index to measure the concentration of sales among the business segments. This paper measured the sales of each firm in the business sectors using the Herfindahl **Business Concentration** index. If a firm concentrates its sales in one business sector, its business concentration index would be close to 1. If a firm distributes its sales among many businesses, its business concentration index would be close to 0.

I focused on comparing the number of business segments to firm size. **Business Diversification** is measured by the number of businesses per total sales. While business concentration measures the concentration of sales among the businesses, business diversification considers the breadth of business diversity. The bigger the firm size, the more the firm may diversify its business. Previous research

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[1] http://www.dbj.jp/ricf/en/databank/
[2] http://www.iip.or.jp/patentdb/index.html, see Goto and Motohashi (2007)

emphasized the importance of firm size to diversification (Wolf, 1977; Goto, 1981; Castaldi et al., 2006). To establish an adequate index of business diversification normalized by firm size, it is necessary to control firm size. Hence, business diversification is a proxy variable of firm size.

To clarify the firm's patent activity, this research collected patent application data from the IIP patent data base. Not all innovations are patented: however, patent data has been used as a major indicator of innovative technology capabilities (Scherer, 1965; Pakes, 1986; Levin et al., 1987; Trajtenberg, 1990; Hitt et al., 1991; Hall et al., 2000; 2001; Silverman, 1999; Harhoff et al., 2003; Tokumaru, 2006). Therefore, this research draws on patent application data to explain a firm's technical knowledge. I defined two aspects of technology diversification: technology concentration and technology diversification. I used the Herfindahl index of firm patents to measure **Technology Concentration** using subclasses of the International Patent Classification (IPC). I also measured **Technology Diversification** as the number of subclasses in the IPC divided by total sales. This index indicates the breadth of technical variety to firm size.

Not all patents are useful. Harhoff et al. (2003) point out that many patents are economically worthless, and Reitzig (2003) revealed that most patents have both relevant and redundant characteristics. Trajtenberg (1990) and Hall et al. (2000; 2001) showed that using citation-weighted counts to measure patent quality is more suitable than using simple counts. Therefore, this study examined both simple count models and citation-weighted models of Citation Count (CC), to determine the worth of patent application data. To re-scale the citation intensities of year and field interaction effects, I introduced the "fixed-effects" approach method of Hall et al. (2001). This method measures patent citation value as normalized by average cited tendencies for technology fields and year trends.

To ascertain the effects of vertical integration on performance, this study used an input-output (IO) table. First, I matched IO industry codes to the JSIC four-digit classification code. From IO table, top 10 upstream sectors were chosen for each industry according to amount of its purchase. Similarly, top 10 downstream sectors were chosen according to amount of its sales. I then specified top sale business segment as a main segment, and other business segment as sub segments in each firm's business segment data. If the sub segment was specified by the related upstream—or downstream—10 industries of the main segment, I input the **Upstream**—or **Downstream—dummy** variable. I used these variables to estimate how vertical integration affects firm performance.

Some manufacturing firms in Japan diversify into a non-manufacturing business—such as real estate, finance, hotel and resort industries. Resource-based knowledge coherence is less relevant to non-manufacturing industries than to manufacturing industries. Firm managers hardly exploit manufacturing's Research and Development (R&D) knowledge into non-manufacturing businesses. In the above theories, lack of knowledge concerning the non-manufacturing business diversified may have different effect with manufacturing business. As the electronic equipment industry is studied here, I controlled diversification into a non-manufacturing industry. To control the effect of non-manufacturing business, I examined each business segment name and description in its financial annual report to identify the non-manufacturing businesses. This research established a **Non-manufacturing dummy** for firms diversified into a non-manufacturing industry sector such as banking, real estate, hotel, transport, and service.

To control a firm's technical quantitative knowledge, this study calculated **Patent intensity:** measured by the patent stock divided by total sales. Because technology knowledge is cumulative knowledge, and recent knowledge is more valuable than past knowledge, this research used the patent stock as sum of five-year patents application with a fixed 20% annual depreciation rate. Firms conduct R&D investment to enrich technology opportunities not only to exploit prior technology capabilities but to also acquiring new technology. Throughout the R&D investment process technology knowledge is an intangible fixed asset: firms thus attempt to achieve optimal levels of R&D investments dependent on their own technical opportunities, market demands and product innovations. Researchers have focused on the relationship between R&D investment and the diversification activity (Hitt et al., 1991; Hoskisson and Johnson, 1992; Silverman, 1999; Garcia-Vega, 2006; Miller, 2006). Therefore, this research controls the effect of **R&D intensity** measured by R&D expenditures divided by total sales. To control firm size, I established **Firm size** as the log of the number of employees. Because leverage can affect a firm's performance (Tallman and Lee, 1996; Miller, 2006), this study included a **Leverage** variable measured by long-term debt per total assets. Moreover, year dummies are included to regulate the effect of time factors.

The main model of regressions and correlation matrix is as follows.

$$
\begin{aligned}
\mathrm{ROA}_{it} = {} & \mathrm{Business\ Concentration}_{it} + \mathrm{Business\ diversification}_{it} + \mathrm{Technology\ Concentration}_{it} + \\
& \mathrm{Technology\ diversification}_{it} + \mathrm{Upstream\ dummy}_{it} + \mathrm{Downstream\ dummy}_{it} + \\
& \mathrm{Non\ manufacturing\ dummy}_{it} + \mathrm{Patent\ Intensity}_{it} + \mathrm{R\&}D\ \mathrm{Intensity}_{it} + \mathrm{Firm\ Size}_{it} + \\
& \mathrm{Leverage}_{it} + \mathrm{Year\ Dummy}_{it} + \varepsilon_{it}
\end{aligned}
$$

Table 1−1 shows the descriptive statistics and correlation matrix across the variables.

Table 1–1. Descriptive statistics and correlation matrix

Variable	Mean	S.D.	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1 ROA	0.048	0.054	1													
2 Business Concentration	0.757	0.259	0.191 ***	1												
3 Business Diversification	0.077	0.187	-0.068 ***	-0.045 *	1											
4 Technology Concentration	0.360	0.275	0.073 ***	0.254 ***	0.198 ***	1										
5 Technology Diversification	0.275	0.465	-0.007	0.056 **	0.383 ***	-0.160 ***	1									
6 Technology Diversification (CC)	0.081	0.320	-0.015	0.040 *	0.421 ***	-0.079 ***	0.889 ***	1								
7 Upstream Dummy	0.045	0.207	-0.087 ***	-0.244 ***	-0.038	-0.163 ***	-0.019	-0.005	1							
8 Downstream Dummy	0.031	0.172	0.033	-0.148 ***	0.007	-0.052 **	0.002	0.002	-0.039	1						
9 Non-manufacturing Dummy	0.251	0.434	-0.012	-0.422 ***	0.183 ***	-0.052 **	0.061 **	0.026	0.138 ***	0.175 ***	1					
10 Patent Intensity	3.079	11.026	0.027	0.043 *	0.019	-0.094 ***	0.763 ***	0.740 ***	0.012	-0.002	-0.004	1				
11 Patent Intensity (CC)	2.991	11.158	0.020	0.047 **	0.072 ***	-0.083 ***	0.731 ***	0.744 ***	0.017	-0.005	-0.012	0.977 ***	1			
12 R&D Intensity	0.044	0.033	-0.077 ***	0.044 *	0.055 **	-0.044 *	0.109 ***	0.051 **	-0.018	0.081 ***	-0.019	0.069 ***	0.053 **	1		
13 Firm Size	6.582	1.167	-0.091 ***	-0.354 ***	-0.390 ***	-0.457 ***	-0.262 ***	-0.133 ***	0.249 ***	0.069 ***	0.042 *	-0.061 **	-0.064 ***	0.019	1	
14 Leverage	0.047	0.061	-0.293 ***	-0.112 ***	0.144 ***	0.029	0.039	0.056 **	0.031	0.034	0.035	-0.026	-0.015	-0.078 ***	-0.087 ***	1

Note: CC means citation count value of patents number. ***: Statistically significant at the 1% level. **: Statistically significant at the 5% level. *: Statistically significant at the 10% level.

1–4. Analyses and Results

Multiple regression analysis was used to analyze the effects of each concentration and diversification on profitability. To control each firm's unobserved effects, I used fixed-effects estimation. Hausman's evaluation test was used to examine each model, showing that a fixed-effect is preferable to a random-effect in all models. Model 1 examines the concentration effect of diversification, and Model 2 tests the effect of diversification side. Model 3 includes interaction term between both diversification indices, and Model 4 estimates both concentration and diversification indices. Table 1–2 shows the regression results of the simple count for patent variables, and Table 1–3 indicates the citation count results of Table 1–2.

Table 1–2. Regression results of simple count for patent variables

	Model 1	Model 2	Model 3	Model 4
Business Concentration	0.0389 **			0.0359 **
	(0.0168)			(0.0161)
Business Diversification		–0.0651 ***	–0.4477 ***	–0.4496 ***
		(0.0192)	(0.0381)	(0.0381)
Technology Concentration	–0.0034			0.0030
	(0.0054)			(0.0054)
Technology Diversification		0.0131 ***	0.0078 *	0.0081 *
		(0.0042)	(0.0040)	(0.0042)
Business Diversification ×			0.0412 ***	0.0410 ***
Technology Diversification			(0.0036)	(0.0036)
Upstream Dummy	–0.0029	–0.0054	–0.005	–0.0028
	(0.0340)	(0.0339)	(0.0324)	(0.0324)
Downstream Dummy	0.0167	0.0167	0.0207 **	0.0219 **
	(0.0108)	(0.0108)	(0.0103)	(0.0103)
Non-Manufacturing Dummy	–0.0140 *	–0.0178 ***	–0.0021	0.0035
	(0.0073)	(0.0069)	(0.0067)	(0.0072)
Patent Intensity	–0.0001	–0.0005 ***	–0.0004 **	–0.0004 **
	(0.0001)	(0.0002)	(0.0002)	(0.0002)
R&D Intensity	–1.0244 ***	–1.0076 ***	–0.9022 ***	–0.8949 ***
	(0.0648)	(0.0651)	(0.0630)	(0.0631)
Firm Size	0.0043	0.0038	–0.0018	–0.0019
	(0.0035)	(0.0035)	(0.0034)	(0.0034)
Leverage	–0.1512 ***	–0.1496 ***	–0.1407 ***	–0.1408 ***
	(0.0255)	(0.0255)	(0.0244)	(0.0244)
Constant	0.0500 *	0.0857 ***	0.1390 ***	0.1098 ***
	(0.0273)	(0.0238)	(0.0232)	(0.0265)
Firm fixed-effects	Included	Included	Included	Included
Year Dummies (1998–2007)	Included	Included	Included	Included
Number of observations	1733	1733	1733	1733
R-Square (Within)	0.3029	0.3075	0.3652	0.3674

Note: Numbers in parentheses are standard errors. Year time dummies are abbreviated on tables. ***: Statistically significant at the 1% level. **: Statistically significant at the 5% level. *: Statistically significant at the 10% level.

Table 1–3. Regression results of citation count for patent variables

	Model 5	Model 6	Model 7	Model 8
Business Concentration	0.0390 **			0.0386 **
	(0.0168)			(0.0161)
Business Diversification		–0.0818 ***	–0.4035 ***	–0.4055 ***
		(0.0194)	(0.0359)	(0.0359)
Technology Concentration	–0.0036			–0.0018
	(0.0054)			(0.0052)
Technology Diversification (CC)		0.0257 ***	0.0130 **	0.0127 **
		(0.0052)	(0.0052)	(0.0052)
Business Diversification ×			0.0365 ***	0.0363 ***
Technology Diversification (CC)			(0.0035)	(0.0035)
Upstream Dummy	–0.0028	–0.0060	–0.0058	–0.0028
	(0.0340)	(0.0337)	(0.0325)	(0.0325)
Downstream Dummy	0.0168	0.0166	0.0203 **	0.0216 **
	(0.0108)	(0.0107)	(0.0103)	(0.0103)
Non-Manufacturing Dummy	–0.014 *	–0.0180 ***	–0.0043	0.0019
	(0.0073)	(0.0068)	(0.0067)	(0.0072)
Patent Intensity (CC)	–0.0002	–0.0008 ***	–0.0005 ***	–0.0005 ***
	(0.0001)	(0.0002)	(0.0002)	(0.0002)
R&D Intensity	–1.0237 ***	–1.0010 ***	–0.9067 ***	–0.9015 ***
	(0.0648)	(0.0647)	(0.0631)	(0.0631)
Firm Size	0.0040	0.0028	–0.0019	–0.0020
	(0.0035)	(0.0035)	(0.0034)	(0.0034)
Leverage	–0.1510 ***	–0.1488 ***	–0.1408 ***	–0.1418 ***
	(0.0255)	(0.0253)	(0.0244)	(0.0244)
Constant	0.0519 *	0.0944 ***	0.1388 ***	0.1093 ***
	(0.0273)	(0.0237)	(0.0233)	(0.0265)
Firm fixed-effects	Included	Included	Included	Included
Year Dummies (1998–2007)	Included	Included	Included	Included
Number of observations	1733	1733	1733	1733
R-Square (Within)	0.3037	0.3149	0.3633	0.3659

Note: Numbers in parentheses are standard errors. CC means citation count value of patents number. Year time dummies are abbreviated on tables. ***: Statistically significant at the 1% level. **: Statistically significant at the 5% level. *: Statistically significant at the 10% level.

The results of Table 1–2 (simple count), and Table 1–3 (citation count), show highly similar and consistent results for each explanatory variable. All empirical results are consistent and stable for both simple and citation count models.

Model 1, 4, 5, and 8 show business concentration has a positive and statistically significant relationship with ROA when considered with all the control variables. This result implies that specialized firms performed better than diversified firms. Furthermore, business diversification is significantly negative in all models. The results of business concentration and business diversification measures coherently indicate that diseconomies of scope exist in diversified businesses (Hypothesis 1a is rejected, Hypothesis 1b is supported).

Technology concentration exhibits no significant results. However, technology diversification has a positive effect on ROA, in contrast to business diversification. This result indicates that technology variety is a positive factor of profitability in all specifications (Hypothesis 2 is supported). Taken in comparison with the business diversification results, it is proven that business and technology diversifications have different effects on firm profitability. The positive and statistically significant relationship between technological variety and firm performance is found in not only model 2, 3, 4 (simple count), but also model 6, 7, and 8(citation count).

To test the combined effects between business and technology diversifications, Models 3, 4, 7, and 8 of this study examine their interaction variables. The interaction term's effect of both diversifications has a positive relationship with ROA. Looking at the combined effects, the study found the results for each diversification's coefficients to be significantly consistent. Further, the synergy effect between the diversifications is verified. In relation to the total coefficient effect of each diversification: the effect of business diversification on performance is positively dependent on technology diversification, and the effect of technology diversification on performance is positively dependent on business diversification. Specialized firms, or firms with small amounts of business diversification, have small positive technology diversification effects. Largely business diversified firms can acquire more profits by diversifying into technology fields. Large levels of business diversification positively affect the technology diversification effect on performance.

The vertical integration of the upstream dummy shows no significant results in any models. However, Models 3, 4, 7, and 8 show that the downstream dummy has a possibility of positive effects on performance (Hypothesis 3 is partly supported). These results coherently support the results of Gemba and Kodama (2001) and Acemoglu et al. (2010), indicating that downstream diversification generates positive effects. Moreover, Models 1, 2, 5, and 6 show that the non-manufacturing business dummy has a negative relationship with firm performance. R&D intensity has a negative effect on performance. Unexpected R&D investment can have a negative impact on profitability. Large sunk costs are essential for the electronics industry to be competitive. Hence, a firm's R&D investment would be larger than the optimal level, because R&D is a negative factor. Leverage is also a negative factor of firm profitability in all the empirical models included in the study.

1–5. Discussion

This study comprehensively examines how business diversification and technology diversification affect firm performance. Empirical results significantly represented the negative effects of business diversity. Firms that diversify their businesses are less profitable than specialized firms. Further, the number of businesses a firm is involved in per firm size has a negative effect on performance. This result can be explained by the diseconomies of scope, particularly in cases of non-manufacturing business diversification. From a specific investment viewpoint, there is more profitability in specialized businesses than in diversified firms. One reason for diversification failure is the increased requirements for specific investment and knowledge that diversification brings. The electronics industry is characterized by intense competition and firms need to concentrate on their main business, investing in specific assets to effectively compete. This can explain the study results that show excessive business diversification to have a negative effect on firm profitability.

From a technology strategy viewpoint, technology diversification has positive effects on firm profitability, strongly supporting the importance of technical variety for enhanced performance. Moreover, firms possessing diverse technology knowledge can improve profitability by undergoing business diversification. This result is robust and consistent in both the simple count patent model and the citation count model. The empirical results of the relationships between technology diversification and ROA explain why firms have to acquire many fields of technology, also supporting the results of Miller (2006). To assimilate more profit, a firm needs to acquire a wider spread of technology, unlike in business diversification. This research indicates that having expertise in a variety of technical fields is a key factor for the electronics industry, as it requires a broad range of parts and technologies. This empirical result strongly supports previous research highlighting the importance of technology variety (Robins and Wiersema, 1995; Gambardella and Torrisi, 1998; Suzuki and Kodama, 2004; Garcia-Vega, 2006; Miller 2006; Miller et al., 2007; Cantner and Plotnikova, 2009).

The results of this research show that downstream diversification has positive effects on performance. This result can explain the existence of downstream vertical economies in the electronics industry. These results all point to a conclusion that firms must consider the direction of vertical integration to enrich their profitability.

After the depression of the 1990s, Japanese firms needed to develop new strategies for survival. Large business diversification is resulted in diseconomies of scope, therefore, firms reconstructed their businesses diversification strategies (Miyajima and Inagaki, 2003) towards technology diversity. The complexity of products has dramatically increased in the electronics industry, particularly in the last few decades. As products require a greater combination of parts, the more diversity of technology knowledge from different technologies is needed. The study results reveal the negative effects of business diversification and the positive effects of technology diversification, coherently supporting why firms have reduced their product diversity while increasing their technical variety (Gambardella and Torrisi, 1998).

Throughout these empirical results, I found different effects of business and technology diversification on performance. Overall, these results suggest that to precisely establish the effect of diversification researchers should consider not only the business elements impacting on a firm, but also the technology elements and the direction of the diversification.

2. Ownership, Learning and Innovation: An Empirical Analysis of the Japanese Automotive Industry

2–1. Introduction

Partnership relations and technology transfers are keys objectives of business network research in recent decades (Peters and Becker, 1997-98; Ahmadjian and Lincoln, 2001; Kohtamäki, 2010; Kotabe, 2003). Partnership structures, such as ownership and governance groups in the automotive industry, not only preserve sustainable supply chains but also enable collaborations and generate learning and innovation among members. Previous research has shown that groups of firms can enrich their technological capacity via their members' cooperative innovation. Asanuma (1989), Attewell (1992) and Sako (1996) found that the organizational learning effect is a major incentive for construction organizations to integrate their internal absorptive capacities. Furthermore, Ahmadjian and Lincoln (2001) showed the learning effect experienced in alliances is a significant reason why the governance relationship is valuable in the automotive industry; also, Kotabe et al. (2003) indicated that technological transfers are positively related to a supplier's performance. Although these earlier studies consider organizational learning (using interview and questionnaire data techniques), there is very little quantitative analysis to date. Accordingly, this research examines organizational learning within a governance relationship using firms' financial and patent application data.

The automotive industry has an extensive and complex structure to enable the manufacture of automotive vehicles as final products. In manufacturing of this kind, a number of elements come into play: design, research and development (R&D), materials and parts. Automotive manufacturers often organize long-term governance groups to maintain their governance relationship and supply chain stability. Such groups are common, particularly in Japan, and are composed of successful companies such as Toyota, Honda, and Nissan. These companies create governance groups with a significant production capacity that makes millions of cars annually. The intensive and long-term governance relationship is often considered a characteristic of the Japanese automotive industry (Asanuma, 1989; Ahmadjian and Lincoln, 2001; Kotabe, 2003), and has enabled groups to enrich their productivity. Moreover, the value chain governance structure generally offers lower transaction costs and is a further reason why Japanese automotive firms have achieved a competitive advantage (Dyer, 1996). Such governance also acts to lower internal transaction costs (Williamson, 1971; 1985; Dyer, 1996), and to avoid supply stoppages (Asanuma, 1989) and contract hazards (Ahmadjian and Lincoln, 2001). The automotive industry has needed significant levels of new and complex technology to conduct its vehicle assembling process in the last decade. Manufacturing firms must now invest heavily in R&D to acquire the necessary technology capacity for the relevant complex and varied systems. These technology requirements not only concern a vehicle's primary components (e.g., engine combustion systems and power trains), but also its safety equipment, drive assistant systems and the electronic control systems that are increasingly common; modern electronic technology can provide greater efficiency (Henderson and Clark, 1990). The need for such complex parts requires a variety of technological knowledge: in the context of studies in this area, the transfer of technological information and R&D spillover are important in the organization of the automotive industry (Peters and Becker, 1997-98). The automotive industry requires high levels of specific investment and long-term contracts, hence its governance relationship is more important than in other manufacturing industries. Specific asset requirements in the automotive industry have forced firms to create long-term and sustainable organizations (Williamson, 1985).

The relationship between organizational learning and the diffusion of knowledge is a significant issue in strategic management research. The main objective of this paper is to examine the existence of the spillover effect within the governance structure to clarify why firms construct ownership relations. Generally speaking, the automotive industry in Japan is characterized as having extensive and robust ownership relationships in contrast to the situation in the United States or Europe. Long-term and stable contracts, and close asset and management relationships are common features of the Japanese automotive industry. Earlier studies used questionnaire data to examine relationship effects; in contrast I used quantitative data to measure the spillover effect in a governance relationship. This empirical method provides direct and ample evidence of organizational spillover effects.

I examined a hypothesis that a member's technology depends on not only its own technological capacity, but also on the technological capacity of other members within the group governance. I defined ownership relationships for Japanese automotive firms based on their annual reports. Thus, it is an appropriate industry to estimate the effects of ownership structures. Furthermore, firms' patent application data were collected to measure technology knowledge. I used patent data to determine a firm's technological capacity and how the effect of organizational learning affects technological capacity. Panel data were used to analyze 103 firms between from 1991 to 2008, and a series of linear regression model scenarios were conducted to clarify the hypotheses. The empirical results show that the technical knowledge of other group members has a positive effect on a firm's knowledge growth. Moreover, a spillover effect regarding technology distance was considered, and the results show that technologically close knowledge has a greater positive effect than technologically distant knowledge. These results indicate that the governance relationship is an important boundary of technology flow and that cooperation within the ownership relationship is an efficient structure to enrich organizational learning.

2–2. Hypotheses

I consider the governance relationship to be a valuable structure for exploiting the existing technical knowledge of other members. Group members can exploit the technical knowledge of other members and also benefit from the ownership relation. Group members are willing to cooperate both in terms of technical knowledge and business know-how to enhance the group's overall performance. Hence, firms can enjoy the technology spillover effects of the internal governance structure. This technology transfer has easier and more efficient spillover effects than firms experience outside the ownership relation. Cohen and Levinthal (1990) found that an organization's absorptive capacity depends on the absorptive capacities of its individual members. By sharing and exploiting the technological capacity and know-how of other members, each member's innovation affects the technology and know-how of others. A mutual interdependence in terms of spillover can easily occur in the automotive industry, as the assembly of a complete vehicle requires an extensive construction system. By the transfer of technical knowledge within an alliance, members can enrich their innovative opportunities. Therefore, I propose the following hypothesis:

Hypothesis 1: The technology capacity of the parent company and subsidiaries has a positive effect on a firm's technological performance.

When researching the spillover effect of a firm's ownership relationships each firm's absorptive capacity is considered. A firm's prior knowledge is required to help absorb further technology information. Firms can only internalize technology capacity if there is a high level of technology capacity with the group. The theory of innovation flow states that the learning effect (i.e., exploiting each member's absorptive capacity) is a major incentive to establish a group (Asanuma, 1989; Attewell, 1992; Sako, 1996; Kotabe et al., 2003). In other words, absorptive capacity is an essential factor to exploit prior technology and to create new technology innovation (Cohen and Levinthal, 1989; 1990, Ahmadjian and Lincoln, 2001).

However, not all external technology capacity has the same effect on a firm's internal technological performance. Firms can easily assimilate the technology spillover effect within its existing technology fields. I thus believe that previously acquired technology is a valuable measure of technological distance. In other words, technology capacity from distant technology fields may have a reduced spillover effect even if there are extensive technological opportunities within the group. As a result, I consider that the technologically close knowledge of a parent company or subsidiary may have a greater effect on spillover than technologically distant knowledge. Thus, technology spillover from a technologically close field has a greater positive effect than technologically distant fields.

Hypothesis 2: The spillover effect from technologically close sectors has a greater positive effect than technologically distant sectors.

Joint patent activity is a further important indicator of information diffusion. Some researchers point out that R&D alliances are an important strategy that affects firm performance. Group members can acquire and share technological know-how and information via cooperative R&D relationships. In relation to internal exchange of information, joint patent activity among group members is tangible evidence of R&D partnership. In other words, joint patent experience among the members represents cooperative R&D activity frequency among the companies. I believe that cooperative research is an essential factor of the governance structure, and therefore, propose the following hypothesis that joint patenting activity is a positive factor for a firm's technological performance.

Hypothesis 3: Joint patents within an internal ownership structure have a positive effect on a firm's technological innovation.

Finally, this paper makes a comparative analysis between the spillover effect within and outside of an ownership group. The diffusion of technological knowledge is frequently hampered by transfer barriers. Members of the ownership group can easily exploit other members' technological capacity; meanwhile, there is restricted cooperative spillover for external firms because they have no cooperative relationships with the group. Outside of the organization, competitive, rival relationships can hamper the knowledge transfer (Attewell, 1992); such relationships among rivals mean that cooperation is difficult. However, group members are generally willing to cooperate with each other when they share the same objective: the profitability of the group. Within the organization, they can easily transfer the knowledge to each other, resulting in spillover innovation and information flow among members. In other words, the border of the group restricts technology spillover and information flow. If the governance group is an optimal structure for technological information flow, the group's spillover has a greater positive effect internally than externally. Hence, I expect here that the border of the ownership group is a critical element of information flow.

Hypothesis 4: The spillover effect within the ownership group has a greater effect on a firm's technological performance than a spillover effect from outside the group.

2–3. Data and Variables

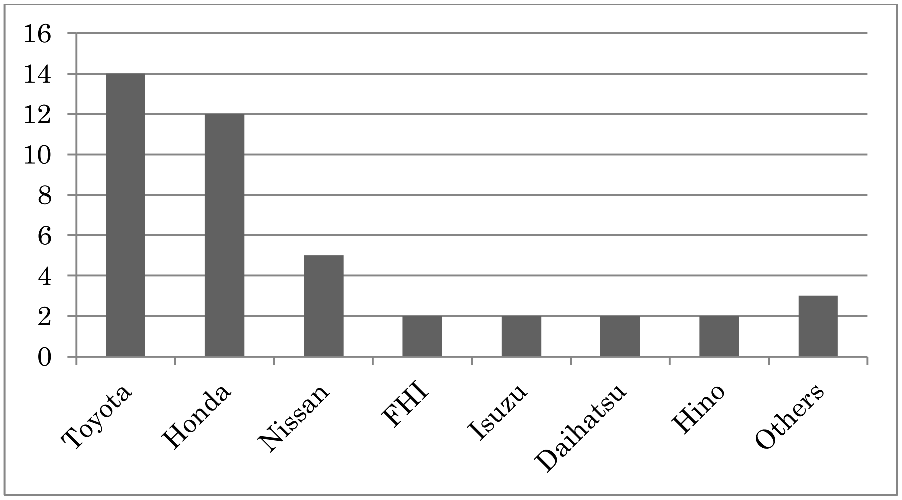
To collect the financial status of each sample firm, we obtained financial data from the Development Bank of Japan (DBJ).[3] Targeted firms were those that engage in automotive manufacturing as their main business, and are listed in the first and second sections of the Tokyo, Osaka and Nagoya stock exchanges in Japan. Companies that produce complete automotive vehicles, such as Toyota, Honda, Nissan, Mitsubishi, Mazda, Suzuki, Daihatsu, Fuji Heavy Industries (FHI), Isuzu, UD Trucks and Hino, are very large and have very different characteristics than other companies. These vehicle manufacturers not only assemble entire cars but are also responsible for the design of all their vehicles. As they are responsible for design covering the many aspects of the vehicle manufacturing progress, these manufacturers also have more patents than auto-parts makers. This heterogeneity can be seen in the mean number of patent applications for vehicle manufacturers and parts makers: vehicle manufacturers average ten times the number of patents (1,171) than parts manufacturers (113) each year. These particular size and patent activity features set vehicle manufacturers apart from firms that only produce auto-parts. Hence, these 11 vehicle manufacturers were excluded from the sample companies, but were included as parent companies. As a result, 103 samples from the automotive industry were selected using unbalanced panel data. This research examines an 18-year period, 1991–2008.

To identify the ownership structure, I looked at the affiliate companies listed in each firms' annual reports. Affiliate companies identified in the annual reports were used to define the parent company and subsidiaries of each firm.[4] A parent company and subsidiary relationship shows the ownership structure that involves both a capital and a technology alliance relationship. Figure 2–1 shows the sample firms that are also a parent company of a vehicle manufacturing company. Toyota has the largest number of subsidiaries (14), followed by Honda (12). Some sample firms also have a parent company.

[3] http://www.dbj.jp/ricf/en/databank/

[4] Not all subsidiaries are listed in the section on affiliate companies. Larger companies in the Japanese manufacturing industry can have more than 1,000 subsidiaries, thus, only relatively large and important subsidiaries are included.

Figure 2–1. Number of vehicle manufacturer subsidiaries per parent company in the sample firms



To clarify the firm's technological capacity, this research takes a firm's technological capacity to be the number of patents it has been granted. The use of patent data is a common technique to determine technology levels, because patent data have been used in many studies as a major indicator of innovative technology capabilities (Scherer, 1965; Pakes, 1986; Levin et al., 1987; Trajtenberg, 1990; Hitt et al., 1991; Hall et al., 2000; 2001; Silverman, 1999; Harhoff et al., 2003; Tokumaru, 2006). Patent application data for each sample company were collected from the Institute of Intellectual Property (IIP) database.[5] Data regarding patent applications for the sample firms, parent company and subsidiaries was extracted to measure the level of technological knowledge for each group. Each patent application was compiled together with each target firm's group to measure the technological knowledge of that group.

Dependent Variable

This paper considers the sample firms' technological performance as a dependent variable. The firm is willing to make an application for patents to assure its own technology, thus an analysis of patent data is a good measure of a firm's technology. Hence, the number of its patents is taken as a proxy variable of a firm's technological performance. We set a target ***firm's number of patent applications*** as a dependent variable, representing technological performance.

Not all patents are valuable. Harhoff et al. (2003) pointed out that many patents are economically worthless, and Reitzig (2003) revealed that most patents have both relevant and redundant characteristics. Many researchers have used triadic counts to measure the value of each patent (Haroff et al., 1999; Jensen et al., 2005; Bacchiocchi and Montobbio, 2007). This study examines both simple counts (SC) and triadic

[5] http://www.iip.or.jp/patentdb/index.html, see Goto and Motohashi (2007).

counts (TC) to determine the value of patent application data. For TC variables, I counted the number of patents a firm applied for in Japan, the United States and with the European Patents Office (EPO). Briefly, the SC patent numbers provide a quantitative value and the TC numbers focuses on the qualitative value of each patent. Thus, the average mean value of the sample firms' number of patents (applied for in Japan, the United States and with the EPO) per year (25.9) is approximately one fifth that of the SCs (126.9). These SC and TC numbers are also calculated in each explanatory variable below to consider the value of patents.

Explanatory variables

I calculated the previous patent applications of each firm's parent company and subsidiaries to measure technological spillover capacity within the governance group, because I assume that prior technological capacity of each parent company and subsidiaries affects the future technological performance of a sample firm. As technology knowledge is cumulative, and recent knowledge is more valuable than old, I assume that prior technological knowledge from four years ago until last year can affect technological performance. This research used patent stock as the sum of a four-year period of patent applications with a fixed 20% annual depreciation rate. As a result, **Parent company patents** is calculated by looking at a parent company's patent stock (i.e., the number of patents owned) and **Subsidiaries patents** is a subsidiary's patent stock variable.

I then considered the spillover effect model of technological distance. I distinguished between sectors that are technologically close and those that are technologically distant. Technological distance was determined using subclasses from the International Patent Classification (IPC) of the patents that classifies patents based on technology sector. I assume that firms can easily assimilate technological capacity in areas where they already possess some know-how and skills; in contrast, it is more difficult for firms to exploit technological capacity in areas where they have scant prior know-how. Patents in the same technological sector as those already owned by a sample firm can be easily exploited for technology flow from other member's prior technology. Thus, we judge each technology sector's technological distance in terms of whether or not a firm already has patent applications in the same IPC subclass.

I assigned a sample firm a close technological sector when it had a patent application in that IPC subclass and a distant technological sector when it did not hold a patent application in that IPC subclass. I measured **same subclass patents** for each parent company and its subsidiaries; a match was made if a target firm's patent application shared the same IPC as the patents of its parent company and subsidiaries. This variable determines technological knowledge from a close sector. I also defined **different subclass patents** for each parent company and its subsidiaries, calculated by a parent company's patents minus the parent company and subsidiaries' IPC-matched patents. In summary, the sum of parent company and subsidiaries IPC-matched and IPC-unmatched patents is equal to the parent company patents and the subsidiaries patents. I assume that same subclass patents have a relatively close technological distance compared with different subclass patents (as stated in hypothesis 2). These same and different subclass variables are also stock variables like parent company patents and subsidiaries' patents.

Table 2–1. Same and different subclass patents for sample firms

	Total patents	Same subclass (% of total)	Different subclass (% of total)
Parent	2241.7	642.3 (29%)	1599.4 (71%)
Subsidiaries	40.8	29.5 (72%)	11.3 (28%)

Table 2–1 shows the annual average results for same and different patents of the parent companies and subsidiaries of the sample firms. As shown, 29% of parent company patents are in the same IPC categories as the firms' patents, and 72% of subsidiaries patents are matched. Hence, even though there is large pool of technological knowledge in parent companies, a greater technological similarity is found with subsidiaries.

To consider the effect of cooperative research on technological performance, I measured the number of joint patents between parent companies and subsidiaries. I regard the number of joint patents to represent the internal cooperative R&D activity frequency within an organization; hence, a patent application that is jointly applied for with a parent company and subsidiaries can be calculated. **Joint with parent company** is measured by the number of joint patent stock with the parent company. **Joint with subsidiaries** is the number of joint patent stock with subsidiaries. These values imply the frequency of joint R&D activity, proving hypothesis 3 that tests whether joint patents have a positive effect on a firm's technological performance.

Next, I considered the spillover effects from outside of the governance group. Unless it occurs in the same automotive industry field, the technological spillover effect varies depending on whether or not the relationship is within an alliance group. Within the same industry, another firm's knowledge may have a positive effect, however, when the firm is a rival, an external spillover effect may have a negative effect on future technological performance. In the strongly competitive market of the automotive industry, patent applications from the outside—particularly from a rival firm—may reduce a firm's future technological innovation. We considered **Out-group patents**, measured by the number of patent stock from outside the group (i.e., for the entire automotive industry sample). This variable can be implied to represent all outside groups in the automotive industry to test hypothesis 4.

To control each target firm's technical knowledge, this study also considered R&D behavior. R&D investment is a significant tool for enriching technology opportunities, not only through exploiting prior technology capabilities but also to acquire and assimilate new technology from outside the firm.

Therefore, this paper controlled for the effect of **R&D intensity,** measured by R&D expenditure divided by total sales. Moreover, each firm's log of total sales was used as **Firm size** to control for firm size. **Year dummies** were included to regulate the effect of year time factors.

Figure 2–2. Mean value of patents of sample firms, parent companies and subsidiaries

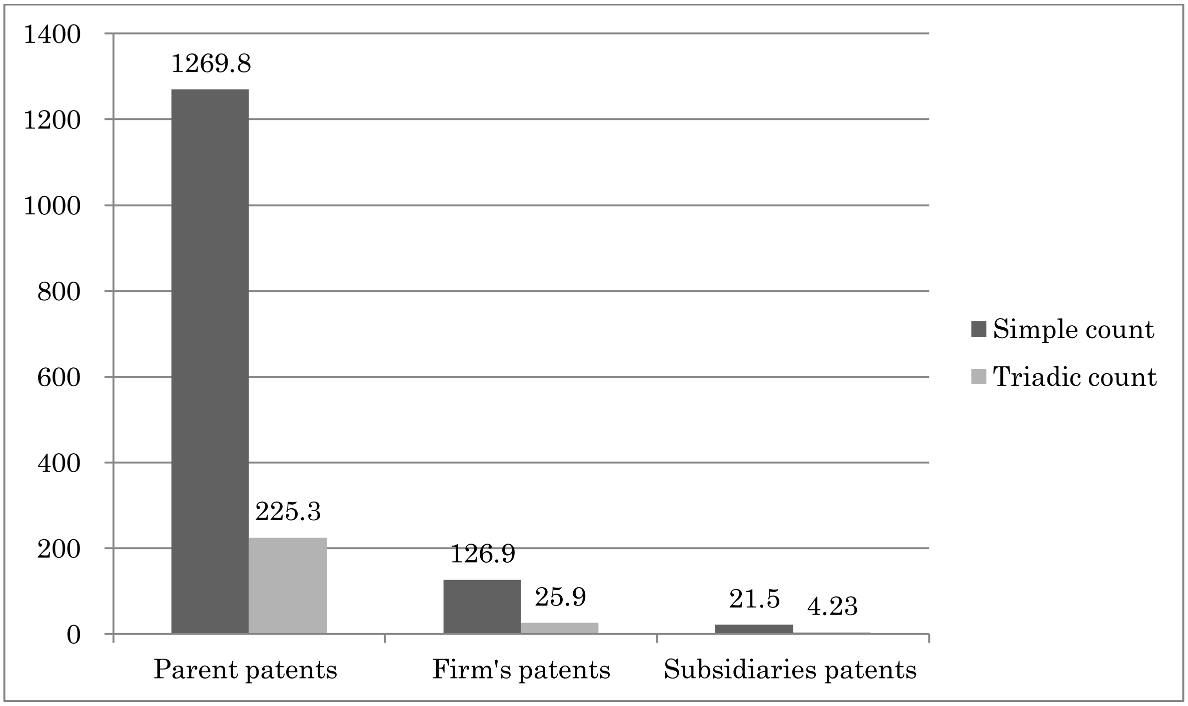


Figure 2–2 indicates the mean value of the patent application of each firm, parent company and subsidiaries. Parent company patents show a large technological pool, especially for vehicle manufacturing companies. In contrast, subsidiaries have a relatively small number of patents compared with the sample firms and the firms' parent companies. This trend is found with both SCs and TCs, with the SC value being approximately five times that of the TC for firms and parent companies and four times that of subsidiaries. Table 2–2 shows the descriptive statistics and correlation matrixes across the variables used in the linear regression models.

Table 2–2. Descriptive statistics and correlation matrixes

Variable	Mean	S.D.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1 Firm's patents (SC)	126.86	363.08	1																			
2 Firm's patents(TC)	25.95	99.86	0.966 ***	1																		
3 Parent patents (SC)	2241.67	3559.11	0.315 ***	0.306 ***	1																	
4 Parent IPC matched patents (SC)	642.30	1732.60	0.636 ***	0.603 ***	0.724 ***	1																
5 Parent IPC unmatched patents (SC)	1599.37	2596.26	0.008	0.017	0.888 ***	0.325 ***	1															
6 Parent patents (TC)	390.19	716.33	0.233 ***	0.236 ***	0.861 ***	0.575 ***	0.796 ***	1														
7 Parent IPC matched patents (TC)	105.14	289.93	0.597 ***	0.577 ***	0.711 ***	0.955 ***	0.337 ***	0.671 ***	1													
8 Parent IPC unmatched patents (TC)	285.04	564.53	-0.011	0.003	0.727 ***	0.239 ***	0.837 ***	0.925 ***	0.337 ***	1												
9 Subsidiaries patents (SC)	40.80	155.70	0.587 ***	0.577 ***	0.278 ***	0.613 ***	-0.029	0.198 ***	0.560 ***	-0.036	1											
10 Subsidiaries IPC matched patents (SC)	29.49	131.53	0.633 ***	0.627 ***	0.280 ***	0.640 ***	-0.043	0.199 ***	0.586 ***	-0.048 *	0.984 ***	1										
11 Subsidiaries IPC unmatched patents (SC)	11.31	35.06	0.232 ***	0.213 ***	0.183 ***	0.323 ***	0.036	0.134 ***	0.289 ***	0.022	0.748 ***	0.619 ***	1									
12 Subsidiaries patents (TC)	8.19	39.83	0.466 ***	0.464 ***	0.244 ***	0.554 ***	-0.036	0.181 ***	0.512 ***	-0.034	0.922 ***	0.923 ***	0.631 ***	1								
13 Subsidiaries IPC matched patents (TC)	7.14	39.16	0.470 ***	0.470 ***	0.256 ***	0.566 ***	-0.027	0.192 ***	0.525 ***	-0.026	0.913 ***	0.924 ***	0.588 ***	0.996 ***	1							
14 Subsidiaries IPC unmatched patents (TC)	1.05	3.66	0.037	0.022	-0.082 ***	-0.021	-0.099 ***	-0.089 ***	-0.045	-0.090 ***	0.267 ***	0.160 ***	0.585 ***	0.229 ***	0.139 ***	1						
15 Joint patents with parent	44932.23	9642.07	0.546 ***	0.500 ***	0.269 ***	0.480 ***	0.049 *	0.229 ***	0.483 ***	0.042	0.335 ***	0.358 ***	0.147 ***	0.310 ***	0.317 ***	-0.020	1					
16 Joint patents with subsidiaries	8194.86	2996.53	0.776 ***	0.780 ***	0.289 ***	0.651 ***	-0.038	0.209 ***	0.603 ***	-0.045	0.883 ***	0.923 ***	0.460 ***	0.793 ***	0.800 ***	0.080 ***	0.400 ***	1				
17 Other patents (SC)	14.63	75.39	-0.119 ***	-0.111 ***	-0.104 ***	-0.118 ***	-0.063 **	-0.001	-0.073 **	0.037	-0.096 ***	-0.101 ***	-0.046	-0.071 **	-0.075 ***	0.025	-0.051 *	-0.107 ***	1			
18 Other patents (TC)	1.82	8.38	-0.047	-0.036	0.027	0.013	0.028	0.121 ***	0.068 **	0.118 ***	-0.035	-0.039	-0.012	-0.020	-0.021	0.004	0.021	-0.035	0.918 ***	1		
19 R&D intensity	0.02	0.03	0.342 ***	0.354 ***	0.256 ***	0.295 ***	0.154 ***	0.313 ***	0.341 ***	0.222 ***	0.206 ***	0.215 ***	0.112 ***	0.191 ***	0.195 ***	-0.008	0.212 ***	0.256 ***	0.103 ***	0.225 ***	1	
20 Firm size	7.80	0.48	0.508 ***	0.446 ***	0.467 ***	0.550 ***	0.274 ***	0.348 ***	0.515 ***	0.177 ***	0.443 ***	0.420 ***	0.390 ***	0.383 ***	0.367 ***	0.239 ***	0.324 ***	0.411 ***	-0.056 *	-0.015	0.213 ***	1

Note: ***: Statistically significant at the 1% level. **: Statistically significant at the 5% level. *: Statistically significant at the 10% level.

2–4. Analyses and Results

Multiple regression analyses were measured to determine the spillover effects of a governance structure. As the firms are listed companies of a relatively large size and most have patent applications (only three of the 103 total firms had no patents), zero is seldom a dependent value. Thus, I believe that a linear regression model of panel data is an adequate model in this research. To control each firm's inherent differences, I used a fixed effect model for the linear regressions. Hausman's evaluation test was conducted in each model, and showed that a fixed effect is preferable to a random effect in most models.

Table 2–3. Regression results for parent companies' patents and subsidiaries' patents

	Model 1		Model 2	
	Y: Firm's patents (SC)		Y: Firm's patents (TC)	
Parent patents (SC)	0.0003			
	(0.0019)			
Subsidiaries patents (SC)	0.177	***		
	(0.048)			
Parent patents (TC)			0.005	*
			(0.003)	
Subsidiaries patents (TC)			0.199	***
			(0.045)	
Out-group patents (SC)	-0.0013	**		
	(0.0005)			
Out-group patents (TC)			-0.002	*
			(0.001)	
R&D Intensity	326.813	**	109.445	***
	(141.956)		(41.833)	
Firm Size	227.782	***	39.642	***
	(37.356)		(10.984)	
Constant	-1612.745	***	-275.719	***
	(294.477)		(89.209)	
Firm fixed-effects	Included		Included	
Year Dummies (1991–2007)	Included		Included	
Number of observations	1208		1208	
R-Square (Within)	0.1263		0.1229	

Note: Numbers in parentheses are standard errors. Year time dummies are abbreviated in the tables. SC: simple count; TC: triadic count of patent numbers. ***: Statistically significant at the 1% level. **: Statistically significant at the 5% level. *: Statistically significant at the 10% level.

In model 1, the spillover effect from the parent company is positive but not significant. However, the subsidiaries spillover effects have a very positive and significant relationship with a firm's technological performance on 0.177 coefficient at the 1 percent level. The out-group patents effect is negative factor for firm's technological innovation at the 5 percent level. Model 2 considers each patent's value weight by TC; these results are more interesting and empirically significant than model 1. The spillover effect from both parent company and subsidiaries' knowledge has a positive effect on a firm's technological performance (hypothesis 1 is supported). This result implies that the members of an ownership group have a positive effect on future technological performance, supporting the existence of organizational learning. A comparison of parent company and subsidiaries' coefficients shows that the effect of subsidiaries is greater than the effect of the parent company (0.199 > 0.005).

A spillover effect from outside the group has a negative effect on a firm's technological performance in both model 1 (−0.0013) and model 2 (−0.002). This result can be interpreted as suggesting that a rival's technological capabilities may reduce a firm's future research potential. Further, R&D intensity is shown to have a positive effect on technological performance in both models. This result implies that a large R&D investment may enhance a firm's technological know-how. Moreover, firm size positively affects a firm's technological performance, showing that a large firm can increase its technology levels.

Table 2–4. Regression results of Same and Different subclass patents

	Model 3 Y: Firm's patents (SC)		Model 4 Y: Firm's patents (TC)	
Parent Same patents (SC)	0.020	***		
	(0.003)			
Parent Different patents (SC)	-0.011	***		
	(0.002)			
Subsidiaries Same patents (SC)	0.004			
	(0.070)			
Subsidiaries Different patents (SC)	0.185			
	(0.189)			
Parent Same patents (TC)			0.019	***
			(0.005)	
Parent Different patents (TC)			-0.001	
			(0.003)	
Subsidiaries Same patents (TC)			0.128	***
			(0.050)	
Subsidiaries Different patents (TC)			-0.347	
			(0.496)	
Out-group patents (SC)	-0.001			
	(0.001)			
Out-group patents (TC)			-0.001	
			(0.001)	
R&D Intensity	288.330	**	101.341	**
	(138.560)		(41.740)	
Firm Size	189.362	***	32.662	***
	(36.761)		(11.145)	
Constant	-1327.720	***	-225.380	**
	(296.480)		(90.159)	
Firm fixed-effects	Included		Included	
Year Dummies (1991–2007)	Included		Included	
Number of observations	1208		1208	
R-Square (Within)	0.1718		0.1316	

Note: Numbers in parentheses are standard errors. Year time dummies are abbreviated on tables. SC: simple count; TC: triadic count of patents number. ***: Statistically significant at the 1% level. **: Statistically significant at the 5% level. *: Statistically significant at the 10% level.

Models 3 and 4 are technological distance models where the spillover effect from ownership is categorized as same subclass or different subclass. Considering both effects, my empirical results show that spillover from same subclass patents has a greater significant positive effect on technological performance rather than different subclass fields. This result implies that in a technologically close sector is easier to exploit another member's technological capacity (thus, hypothesis 2 is supported). In model 3, the spillover effect from the parent company of IPC-unmatched patents has a negative and significant relationship. The prior technological capacity of a parent company may reduce a firm's future technological performance. These effects are more clear and significant in model 4 that considers the value of patents by triadic count. In model 4, both parent company and subsidiaries same subclass patents show positive effects and are statistically significant at the 1% level. In contrast, different subclass patents have no significant effects on a firm's technological performance in model 4. This also implies that the degree of technological distance, either IPC-matched or not, is a valuable model in this research. Out-group patents are statistically insignificant in both models 3 and 4, indicating that the spillover effect from outside the group is less important and significant than from inside of the group. Moreover, R&D intensity and firm size have a positive relationship in both models.

Table 2–5. Regression results for joint patents

	Model 5 Y: Firm's patents (SC)		Model 6 Y: Firm's patents (TC)	
Joint with parent	0.300	***	0.063	***
	(0.056)		(0.016)	
Joint with subsidiaries	3.464	***	2.276	***
	(0.831)		(0.238)	
Out-group patents (SC)	-0.0012	**		
	(0.0005)			
Out-group patents (TC)			-0.002	**
			(0.001)	
R&D Intensity	289.298	**	95.308	**
	(139.115)		(39.818)	
Firm Size	195.243	***	29.438	***
	(36.688)		(10.485)	
Constant	-1368.636	***	-191.746	**
	(297.537)		(85.648)	
Firm fixed-effects	Included		Included	
Year Dummies (1991–2007)	Included		Included	
Number of observations	1208		1208	
R-Square (Within)	0.1598		0.1963	

Note: Numbers in parentheses are standard errors. Year time dummies are abbreviated on tables. SC: simple count; TC: triadic count of patents number. ***: Statistically significant at the 1% level. **: Statistically significant at the 5% level. *: Statistically significant at the 10% level.

Models 5 and 6 explain the spillover effect using the joint patent variables of the governance group. The results show that the experience of a joint patent with both the parent company and subsidiaries has a positive effect on a firm's performance in both models. These results imply that a joint R&D partnership accelerates knowledge regarding technology in the governance group. Moreover, the coefficient effect of joint patents with subsidiaries is higher than the effect with the parent company (3.4 > 0.3), although the mean value is smaller than for the parent company (14.6 for a joint patent with a parent company and 1.8 for a joint patent with a subsidiary). Thus, a firm's joint R&D relationship with subsidiaries has a greater positive and more intense effect than with the parent company.

2–5. Discussion

This paper empirically examined the spillover effects of ownership structure in the Japanese automotive industry. By using firms' patent application and financial data, this research measured multiple regression models of spillover effects via empirical analyses. The results show that there is a positive spillover effect on a firm's technological performance within the governance group structure. There is also a concrete spillover effect in organizations, supporting the fact that firms construct organizational and alliance groups to help with the transfer of technological knowledge. As the governance relationship is a long-term and sustainable alliance structure, it also creates a positive partnership for future technological performance. Moreover, the fact that the effect of subsidiaries is greater than that of the parent company is interesting and significant. As shown in table 2–1, subsidiaries have a relatively small degree of technological knowledge; however, they enjoy a greater degree of technological similarity with the vehicle manufacturing firms than the parent companies. Furthermore, comparing coefficients, the effect of a cooperative relationship with subsidiaries is greater than that with the firm's parent company. This result explains why the Japanese automotive industry characteristically enjoys large, typically downstream, governance relationship to accelerate technological performance. Cooperation with the parent company may also be important, however, the relationships with subsidiaries appear more valuable. Hence, firms are more likely to construct larger and more robust governance relationships in a downstream direction in the Japanese automotive industry.

Same and different subclass models empirically show that technological distance and similarity affects the technological spillover effects. Firms can easily exploit another member's technological capacity if they share expertise in that particular field. Although not all of our empirical results are useful and meaningful, we found that technologically close sectors have a greater positive effect than more distant sectors. This result indicates that technologically close knowledge can have a direct effect, and it supports the theory of technological distance on information flow. Some models show that IPC-unmatched parent patents have a negative effect on a firm's technological performance. The case of substitute relationship of R&D investment may represent this result. In other words, a substitute relationship within the governance group may also occur. If R&D investment is concentrated on an upstream firm, for example the parent company, the firm's capacity for R&D may be diminished. Moreover, if the group concentrates its R&D investments upstream, investments by subsidiaries may be diminished. Thus, this result may answer the question: how does the technological capacity of the parent company and subsidiaries affect a firm's technological performance? From a group entrepreneurial perspective, R&D investment may be more efficient when concentrated on a parent's capacity. This is particularly the case in the automotive industry where a large R&D investment toward the parent will be needed to design, manufacture, and assemble the car. Therefore, a substitute relationship may exist between the sample firms and their parent companies in terms of R&D investment.

This paper also measured the effect of joint patents within a group and showed that cooperative R&D among group members generates further technological knowledge. This result indicates that cooperative R&D within an alliance group is a key factor for technology innovation. Joint patents within the governance group indicate that there is a cooperative R&D partnership; hence, joint R&D alliance is another important determinant for a firm's technological performance.

Spillover effects from within the governance group have a greater positive effect than firms outside of the group structure. This result implies that internal spillover effects show a more positive and significant relationship with technological performance compared with external spillover effects. This result is interesting, particularly when compared with earlier research. For example, Cohen and Levinthal (1989) found that spillover effects from the same industry had a positive effect. However, when I looked at the industry's spillover effect in terms of firms within a governance group and outside the group, the effect was different for each category. Spillover effects from inside the group have a positive effect; however, the effect from outside the group may have a negative factor. This result also implies that a governance group is a better structure to exploit and assimilate in-group spillover effects compared with outside firms. This result strongly and empirically supports that firms and organizations are willing to apply patents to protect their technology innovations (Mansfield, 1986; Levin et al., 1987) because of strong competition within the automotive industry. The result also can be interpreted as a prime example of organizational learning, show that ownership structure is an important barrier to technology diffusion (Ahmadjian and Lincoln, 2001). In summary, a spillover effect from outside the group may have a negative consequence on a firm's technological capacity, while the effect from inside the group generates a positive impact. Moreover, this conclusion indicates that when measuring spillover effect, ownership and alliance structure must be considered carefully.

This paper has several limitations. First, not all innovations are patented. Hence, including other technological activities in addition to patent activity and R&D activities should be considered. Secondly, the study did not measure the governance structure of the entire supply chain in the automotive group. In addition to ownership governance, supply chain relationship may also have spillover effects for innovation activity. It is difficult to define the entire supply chain structure; moreover, several auto parts firms supply their products to many buyers. Thus, we leave these limitations as further challenge.

In recent decades, many researchers have attempted to discover why firms join a governance group. Some researchers have stated the in-group spillover effect as a reason (Attewell, 1992; Ahmadjian and Lincoln, 2001; Peters and Becker, 1997–98; Sako, 1996; Kotabe et al., 2003); however, a lack of empirical evidence existed to support such claims. In this empirical study, we have shed light on the spillover effects of governance structures, showing that a governance group is a valuable approach for encouraging technological innovation. The ownership group, a key feature of the Japanese automotive industry, represents a very efficient network structure that acts to extend technological diffusion. The extensive and stable structure is valuable not only for secure contracts, and a close asset and management relationship, but also for mutual technological learning among the group members. As a result, this study emphasizes the importance of technological flow inside the governance group. This result strongly supports and clarifies the effect of the ownership structure, thus indicating that this type of organization is a good measure of technology diffusion.

3. Linkage between technology and industry: Concordance between JSIC and IPC of the Japanese Manufacturing Industry

3–1. Introduction

The relationship between patenting and economic performance is a significant issue in strategic management research. Patent data has been used as an important indicator of technology capabilities to estimate technological knowledge (Scherer, 1965; Pakes, 1986; Levin et al., 1987; Griliches, 1990; Trajtenberg, 1990; Hitt et al., 1991; Hall et al., 2000, 2001; Silverman, 1999; Harhoff et al., 2003; Tokumaru, 2006). Patents data has a tangible and quantitative value and are usually given a proxy value when used to analyze technological activity. However, a discord arises when researchers attempt to use patent data for the economic analyses of goods and services or for analyses at an individual firm or industry level. It is difficult to use patent data for analysis at the firm or industry level. There is a fundamental discord between industrial classification and the International Patent Classification (IPC). Standard Industrial Classification explains what they make goods and supply services for: IPC centers on which technological features and knowledge are included in the patent. To analyze patent data as an economic parameter, researchers have to make a concordance between the technological industrial categories (Kortum and Putnam, 1997; Schmoch et al., 2003; Broekel, 2007; Lybbert and Zolas, 2014). To match patent data to disaggregate economic data (particularly firm level analysis), the concordance will help to enable more empirical research (Lybbert and Zolas, 2014).

Establishing a link between industrial categories and technological categories has been a significant issue in strategic management research when using patent activities as economic data for a proxy of innovation behavior (Schmoch et al., 2003; Broekel, 2007; Lybbert and Zolas, 2014). Several researchers have attempted to construct an IPC concordance between the industrial category and technological fields. Kortum and Putnam (1997) made a Yale Technology Concordance between the Canadian standard industrial classification and IPC. Verspagen et al. (1994) showed a one-to-one match concordance between IPC and International Standard Industrial Classification using European Patent Office data. Schmoch et al. (2003) constructed the DG Concordance that provides links between 625 IPC subclasses and 44 manufacturing fields. Broekel (2007) made a concordance between 31 technological fields and 22 manufacturing industries on the German Industry Classification. Lybbert and Zolas (2014) showed Algorithmic Links with Probabilities concordance that used the data mining approach of text matching.

Clearly, each country has its own industrial structure and patent activity meaning that researchers must consider the individual country concordance. Japanese manufacturing patents are different to those of other countries; hence, it is inappropriate to use another country's concordance for the economic analysis of Japanese industries. However, to date there is no concordance between Japanese industries and IPC. The absence of concordance in Japan may be a problem for researchers seeking to use patent data for the analysis of Japanese industry.

The main purpose of this paper is to make a concordance between Japan Standard Industrial Classification (JSIC) and IPC on Japanese manufacturing industries. Throughout this process we examine Japanese manufacturing patenting activities. We measure several descriptive analyses including technology profile and technological distance among the industries to explain the technological propensity and closeness among the Japanese manufacturing industries. By these means, we can determine the type and variety of linkages between industrial behavior and patenting activity.

3–2. Concordance between JSIC and IPC

The following conditions are set to construct the concordance between JSIC and IPC. The primary objective of this research is to establish a manufacturing industry concordance; therefore, only the manufacturing sector is considered. Each manufacturing industry is distinguished by a two-digit JSIC classification, and the firms listed on the first and second section of the Tokyo, Osaka, and Nagoya stock exchanges in Japan are considered. We aggregate all manufacturing firms into two-digit JSIC. The financial data were extracted from the Development Bank of Japan.[6] To measure patent activity, we also collected each firm's patents application data by using the Institute of Intellectual Property database.[7] We set the study period from 2006−2010: this covers the latest IPC version (8th Version).

We first collected each firm's patent applications for the relevant manufacturing industries. The leather tanning, leather products and fur skins industry (JSIC number: 20) in the study sample contained only one firm, and this firm had no patent applications during 2006−2010. Therefore, data from 23 industries was collected, ranging from food manufacturing (JSIC number: 9) to miscellaneous manufacturing (JSIC number: 32), and disregarding the leather industry (Table 3–1).

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[6] http://www.dbj.jp/ricf/en/databank/

[7] http://www.iip.or.jp/patentdb/index.html, see Goto and Motohashi (2007)

Table 3–1. Number of patent applications by JSIC manufacturing industry

JSIC no.	Industrial field	No. of firms	No. of patents
9	Food	115	3063
10	Beverages, tobacco and feed	15	856
11	Textile	71	9315
12	Lumber and wood	9	366
13	Furniture and fixtures	12	1332
14	Pulp and paper	28	4568
15	Printing	27	11012
16	Chemical	194	40493
17	Petroleum and coal	10	557
18	Plastic	38	8901
19	Rubber	18	11274
21	Ceramic, stone and clay	66	9921
22	Iron and steel	54	12229
23	Non-ferrous metal	44	16407
24	Fabricated metal	78	4409
25	General-purpose machinery	7	7436
26	Production machinery	162	35154
27	Business oriented machinery	68	84003
28	Electronic parts, devices and circuits	81	50555
29	Electrical machinery	79	71270
30	Information and communication electronics equipment	58	112298
31	Transportation equipment	118	91660
32	Miscellaneous	48	12682
	total	1400	599761

As shown in Table 3−1, information and communication electronics equipment has the highest number of patents (112,298), with the transportation equipment industry (91,660) in second place. Both of these industries include characteristics of high technology requirements, high profit, and large and remarkable sales share in the global market, all of which are supported by significant patenting knowledge. Machinery, electronic parts, and chemical industries have relatively high patent levels. These industries also have knowledge-based characteristics generating various technology patents. In contrast, the food, beverages, lumber, furniture and petroleum industries have relatively low levels of patent applications. These are resource-based industries that do not needed knowledge-based patents unlike machinery industries. Overall, we have ascertained that there is consistent patent activity throughout Japanese manufacturing industries.

Next, we matched 625 IPC subclasses and two-digit JSIC. Each top share of two-digit JSIC is linked with each subclass of IPC. Following measurements of Verspagen et al. (1994), Schmoch et al. (2003) and Borekel (2007), we linked the IPC subclasses to only one field of industry. Such one-to-one matches may cause the loss of secondary and tertiary information; however, it can provide direct and intuitive information (Schmoch et al., 2003). As a result, we made a concordance between 23 JSIC manufacturing industries and 596 IPC subclasses[8] (see Annex 1).

3–3. Concordance, technological diversity and R&D activity

In this section we analyze the relationship between technological diversity, firm size and research and development (R&D) by industrial categories. R&D investment is important not only to exploit prior technology capabilities but also to acquire and assimilate new technology. The combination of knowledge from different technical fields is increasing in significance. To produce complex products, manufacturing firms have to acquire a variety of technological knowledge; the more complex the products a firm manufactures the greater the variety of technology needed. There has been considerable research showing that a firm's technology variety is a key factor for its innovation activity (Robins and Wiersema, 1995; Gambardella and Torrisi, 1998; Brusoni et al., 2001; Piscitello, 2004; Garcia-Vega, 2006; Miller, 2006; Cantner and Plotnikova, 2009). Hence, we estimate the relationships between firm size, R&D and technology diversity by this concordance. Also, by conducting a comparative analysis between the diversity of concordance and the diversity of IPC-subclass, we consider the relevance of their diversity indexes.

We calculated each firm's technology diversity for each industry. We used the Herfindahl index to measure the distribution of patent applications among the industries of concordance. We defined technology concordance diversity as 1 minus Herfindahl index. When firms diversify into other technology fields, the value of technology diversity would increase.

$$\text{Concordance diversity} = 1 - \sum_{i=1}^{n} \left(\frac{P_i}{P}\right)^2$$

P_i: Number of patent applications in industry i

To compare with IPC-based technology diversity, we also measured the index of technology diversity based on a four-digit IPC subclass. By these terms, we can compare Concordance diversity and IPC diversity in the context of technology diversity. IPC diversity is calculated as follows;

$$\text{IPC diversity} = 1 - \sum_{i=1}^{n} \left(\frac{S_i}{S}\right)^2$$

S_i: Number of patent applications in subclass i

[8] We focus on and analyze the manufacturing sector only. As a result of constructing the concordance, 596 of the 625 subclasses are linked.

While Concordance diversity is measured by manufacturing industrial category, IPC diversity is based on the IPC technology sector. This variance is because of the differentiation between the industrial category and the technology category that depends on its research objectives. Table 3–4 shows the mean value of the technology diversity of each Concordance diversity and IPC diversity.

Table 3–2. Mean technology diversity value and correlation with firm size and R&D intensity

JSIC no.	Industrial field	Concordance diversity	IPC diversty	Corr. With Con. div. & IPC diversity	Corr. with Con. div. & firm size	Corr. with Con. div. & R&D intensity
9	Food	0.36	0.56	0.87 ***	0.31 ***	0.25 ***
10	Beverages, tobacco and feed	0.40	0.56	0.92 ***	0.48 **	0.69 ***
11	Textile	0.43	0.68	0.86 ***	0.39 ***	-0.02
12	Lumber and wood	0.40	0.32	0.93 ***	0.81 ***	-0.52 **
13	Furniture and fixtures	0.40	0.51	0.94 ***	0.48 **	0.09
14	Pulp and paper	0.38	0.52	0.96 ***	0.27 *	0.37 **
15	Printing	0.39	0.69	0.89 ***	0.88 ***	0.52 **
16	Chemical	0.35	0.62	0.73 ***	0.28 ***	-0.24 ***
17	Petroleum and coal	0.46	0.62	0.99 ***	0.32	0.03
18	Plastic	0.52	0.66	0.91 ***	0.41 ***	0.39 ***
19	Rubber	0.56	0.71	0.95 ***	0.52 ***	0.17
21	Ceramic, stone and clay	0.53	0.63	0.95 ***	0.48 ***	-0.01
22	Iron and steel	0.42	0.57	0.94 ***	0.51 ***	0.38 ***
23	Non-ferrous metal	0.57	0.71	0.95 ***	0.38 ***	0.06
24	Fabricated metal	0.41	0.54	0.90 ***	0.48 ***	0.06
25	General-purpose machinery	0.76	0.91	0.46 **	0.03	-0.69 ***
26	Production machinery	0.42	0.58	0.85 ***	0.38 ***	0.04
27	Business oriented machinery	0.41	0.60	0.90 ***	0.38 ***	0.05
28	Electronic parts and circuits	0.47	0.60	0.88 ***	0.29 ***	-0.05
29	Electrical machinery	0.47	0.63	0.89 ***	0.37 ***	0.05
30	IC equipment	0.35	0.67	0.62 ***	0.09	-0.12
31	Transportation equipment	0.33	0.67	0.63 ***	0.12 **	-0.02
32	Miscellaneous	0.39	0.47	0.92 ***	-0.02	-0.10

Note: ***: Statistically significant at the 1% level. **: Statistically significant at the 5% level. *: Statistically significant at the 10% level.

The general machinery industry is the most diversified: it needs a variety of technological knowledge to make general machinery products. In contrast, the food, pulp, industries transport, information machinery, and chemical industries have relatively lower diversity in their technology fields. Comparing both diversity indexes: IPC diversity has a relatively higher value compared with Concordance diversity, except for the lumber and wood industry. This result implies that the IPC diversity calculated by subclass category has a higher propensity than the Concordance diversity at the industrial level. In summary, Concordance diversity and IPC diversity have very similar values for every manufacturing industry. This homogeneity is also found in the correlation between Concordance diversity and IPC diversity that is positive and statistically significant in all manufacturing industries.

Table 4 also indicates correlations between Concordance diversity with IPC diversity, firm size, and R&D intensity. We measured firm size as the log of total sales, and R&D intensity as expenditure divided by total sales. As a result, firm size has a positive and significant relationship with technology diversity, except in the petroleum, general machinery and miscellaneous industries. This result strongly supports the belief that large firms tend to significantly diversify into a variety of fields, and that technology variety is a key factor for R&D activity. Correlations with R&D intensity differ across manufacturing industries. Food, beverage, pulp, printing, plastic and iron and steel industries have a positive relationship between technology diversity and R&D intensity, while lumber, chemical, and general-purpose machinery have negative relations. In summary, the relationship between technology diversity and R&D intensity may differ by industry characteristic.

3–4. Technological proximity among industries

Each industry and each firm has its own technological position that implies its technology tendencies. Industry technology characteristics can be defined by measuring the technological similarity of its patenting activities. Based on Jaffe's (1986; 1989) theory of technological position closeness, we calculated technological proximity among the industries of JSIC concordance. P_{ij}, the technological proximity between industry i and industry j can be defined as follows:

$$P_{ij} = \sum_{k=1}^{K} f_{ik} f_{jk} \Bigg/ \left(\sum_{k=1}^{K} f_{ik}^2\right)^{1/2} \left(\sum_{k=1}^{K} f_{jk}^2\right)^{1/2}$$

f_{ik}: The number of patent application in industry i of technological field k

Using this term, we calculated the technological closeness among the JSIC industries. Table 3–2 shows the technological proximity matrix among the JSIC industries. An underlined numeric value indicates that the technological proximity is less than 0.1; meaning that the technologies are very similar between the relevant industries. Several groups of close technological relevance (<0.1 proximity) emerged.

Table 3–3. Technological proximity between the industries of concordance

	Food.	Beve.	Text.	Lumb.	Furn.	Pulp.	Prin.	Chem.	Petr.	Plas.	Rubb.	Cera.	Iron.	Non-f.	Fabr.	Gene.	Prod.	Busi.	Elec.p.	Elec.m.	ICeq.	Tran.	Misc.
Food	0																						
beverages & tobacco & feed	0.18	0																					
Textile	0.26	0.08	0																				
Lumber & wood	0.46	0.24	0.26	0																			
Furniture & fixtures	0.58	0.31	0.30	0.19	0																		
Pulp & paper	0.43	0.21	0.26	0.36	0.45	0																	
Printing	0.38	0.10	0.19	0.30	0.37	0.21	0																
Chemical	0.27	0.17	0.10	0.47	0.59	0.37	0.32	0															
Petroleum & coal	0.32	0.12	0.12	0.27	0.36	0.30	0.22	0.24	0														
Plastic	0.24	0.06	0.05	0.21	0.32	0.23	0.11	0.09	0.12	0													
Rubber	0.38	0.16	0.15	0.28	0.28	0.32	0.24	0.31	0.19	0.15	0												
Ceramic & stone & clay	0.38	0.14	0.17	0.24	0.29	0.27	0.15	0.32	0.19	0.13	0.20	0											
Iron & steel	0.57	0.33	0.37	0.38	0.40	0.46	0.36	0.57	0.37	0.35	0.36	0.29	0										
Non-ferrous metal	0.43	0.16	0.19	0.26	0.23	0.28	0.09	0.39	0.22	0.14	0.20	0.12	0.26	0									
Fabricated metal	0.43	0.16	0.21	0.08	0.15	0.28	0.14	0.43	0.21	0.16	0.20	0.13	0.28	0.10	0								
General-purpose machinery	0.45	0.17	0.18	0.23	0.14	0.32	0.20	0.44	0.19	0.19	0.17	0.16	0.28	0.11	0.12	0							
Production machinery	0.57	0.25	0.26	0.34	0.27	0.44	0.31	0.56	0.21	0.30	0.24	0.26	0.40	0.22	0.21	0.13	0						
Business oriented machinery	0.61	0.28	0.40	0.49	0.54	0.41	0.11	0.57	0.41	0.30	0.42	0.29	0.52	0.19	0.30	0.34	0.47	0					
Electronic parts & circuits	0.55	0.24	0.32	0.39	0.42	0.35	0.07	0.50	0.33	0.22	0.34	0.21	0.43	0.09	0.19	0.25	0.36	0.07	0				
Electrical machinery	0.61	0.29	0.36	0.40	0.40	0.40	0.13	0.56	0.35	0.25	0.36	0.24	0.46	0.11	0.18	0.24	0.35	0.19	0.04	0			
IC equipment	0.84	0.50	0.60	0.66	0.68	0.59	0.23	0.77	0.58	0.44	0.60	0.44	0.70	0.25	0.36	0.50	0.58	0.27	0.10	0.07	0		
Transportation equipment	0.83	0.55	0.46	0.54	0.19	0.69	0.55	0.80	0.58	0.52	0.42	0.48	0.56	0.33	0.38	0.21	0.36	0.72	0.57	0.51	0.80	0	
Miscellaneous	0.75	0.50	0.56	0.57	0.64	0.59	0.46	0.75	0.56	0.51	0.56	0.49	0.67	0.46	0.46	0.52	0.63	0.55	0.48	0.51	0.66	0.86	0

Note: Underlined values indicate technological proximity is lower than 0.1

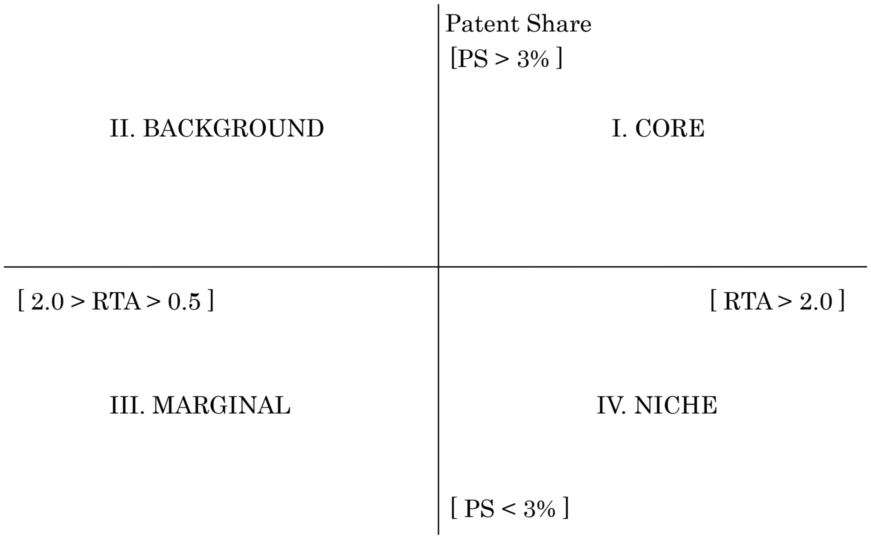
As shown in Table 3–3, these 11 technologically closed groups are 1) beverage and textile, 2) beverage and plastic, 3) textile and plastic, 4) lumber and fabricated metal, 5) printing and non-ferrous metal, 6) printing and electronic parts, 7) chemical and plastic, 8) non-ferrous metal and electronic parts, 9) business machinery and electronic parts, 10) electrical parts and electrical machinery, 11) electrical machinery and IC equipment.

Moreover, the plastic, rubber, ceramic and non-ferrous metal industries have a relatively close technological distance with other industries: this is reasonable as these materials form the basis for many industries. Furthermore, the electronic parts industry has a close technological relationship with four industries. Considering the fundamentals of this industry—making electronic parts—this result is reasonable. The food industry, in contrast, shows a relatively large technological distance with the metal and machinery industries.

3–5. Technical profiles of concordance

Each industry produces its own products; however, their technologies tend to cover many fields. Moreover, each industry has its own technological competencies with varying levels of competitive advantage (Patel and Pavitt, 1997). To estimate the technology profiles between technology fields and industries, we used Patel and Pavitt's (1997) technology profiles concept. They defined patent share (PS) and revealed technology advantage (RTA), and classified technological competencies into four fields (core, background, marginal and niche) by using PS and RTA levels. *"It is more useful to think in terms of* profiles of competencies, with varying levels of commitment and competitive advantage in a range of technological fields." (Patel and Pavitt, 1997, 146pp). We measured PS as shares of industry's total patents in each of the technology fields, and RTA as a firm's shares in total patenting in each of the 23 technological fields of the JSIC concordance, divided by the firm's aggregate share in all the fields. Figure 3–1 shows Patel and Pavitt's (1997) technological profiles classification.

Figure 3–1. A classification for firm's technological profiles[9]



[9] This figure is cited from Patel and Pavitt (1997), 146pp, Fig. 1.

Table 3–4. Firms' technological profile according to JSIC concordance

	Technological fields aggregated by JSIC concordance																						
	Food.	Beve.	Text.	Lumb.	Furn.	Pulp.	Prin.	Chem.	Petr.	Plas.	Rubb.	Cera.	Iron.	Non-f.	Fabr.	Gene.	Prod.	Busi.	Elec.p.	Elec.m	ICeq.	Tran.	Misc.
Food	****	****					***	***	*								*						
beverages & tobacco & feed	****	****			***	*	***	***			*						*	*		*			
Textile			****			*	*	****		*	*			*	*	*	****	*	*			*	
Lumber & wood			***	****	***		*	*		****		*	*		****		*			*			
Furniture & fixtures			***		****					****					****		*			*		***	
Pulp & paper		*	***		*	****	****	*		*		*				*		*					*
Printing		*			*	****	****	*		*			*			****	*	*	*		*		
Chemical	****	**	****	**		****	**	****	**	**		**	**	**			**	**	**				
Petroleum & coal	*							***	****	***	*	*	*		*	*	***			*			
Plastic			*		****		****	****		****	****	*	*	*	****	*	*	*	*	*			
Rubber			*					****		****	****	*		*		*	****					*	
Ceramic & stone & clay		*	****	*	****		*	*	****	****	*	****	****	*	*	****	*	*	*	*			
Iron & steel				****					****	**	*	**	****	****	*	****	*		*			*	
Non-ferrous metal								*		*	*	**	****	****		*	*	*	*	*	*	*	
Fabricated metal	*	****	*		****		****		*	****	*	***	***	*	****	*	*				*	*	
General-purpose machinery	*	*		*			*		****	*		*	*	*	****	****	***	*		*		*	
Production machinery		**									**	**	**	**	**	****	****					**	
Business oriented machinery				**		**												****			**		**
Electronic parts & circuits												**	**	**				**	****	**	**		
Electrical machinery				****	**					**		**			**	**		**	**	****	**	**	
IC equipment					**													**	**	**	****		
Transportation equipment										**			**	**			**			**		****	
Miscellaneous			*	****	****		*			*									*		*		****

Note: ****: core; ***: niche; **: background; *: marginal.

Table 3–3 shows the contribution of competencies in each of our technological fields of JSIC concordance to 23 JSIC manufacturing industries. By this means, we can estimate the technological pattern of each industry's patent activity (according to its technological competencies in JSIC concordance.) We can directly and easily establish which technology is linked with multiple industries, and vice versa. Noteworthy profiles are as follows:

1) The food, furniture and fixtures, rubber, production machinery, business oriented machinery, electronic parts, devices and circuits, information and communication electronics equipment, transportation equipment and miscellaneous industries have relatively lower competencies than the average. These industries concentrate on their own field of technology to achieve competitive advantage. These niche competencies are different to those of Patel and Pavitt (1997), who showed agricultural chemicals, bleaching and dyeing, power plant and nuclear energy as niche competencies.
2) The chemical industry has most background competencies with 11 technology fields. A variety of technology fields seem to provide background technological knowledge for the chemical industry. Chemical technology has core competencies with four industries, and niche competencies with three industries, particularly in the light-manufacturing and material industries. These wide and significant competencies are similar to those of Patel and Pavitt (1997).
3) The ceramic, stone and clay industry has the widest technology competence, and has the most core competencies (seven). This industry produces materials for a variety of industries; thus, many industries have technological competency with the ceramic, stone and clay industry as they use these materials.
4) Marginal and niche competencies are found mainly in the food, beverage, textile, lumber, furniture, and pulp industries. Generally speaking, these industries are niche industries with fewer firms and competition.
5) Plastic technology has the most core technology competencies in lumber, furniture, plastic, rubber, ceramic and non-ferrous metal industries. This result indicates that plastic technology is widely used in many industry fields. Like the chemical industry, these wide and significant competencies are similar to those of Patel and Pavitt (1997).
6) Plastic, iron and steel, non-ferrous metal, production machinery, and electrical machinery technologies are background competencies of the transport industry. These industries make transport components such as dash boards, steel, electronic wiring, working robots and electronic parts. To produce a complex product such as a car, firms require a variety of technological knowledge relating to its components. This relative competencies result differs to Patel and Pavitt (1997)'s research, reflecting the nature of Japanese manufacturing industries. Moreover, Japan's automotive industry

competencies are wider and more intensive than Patel and Pavitt's (1997) result for the vehicle and engines industry.

3–6. Discussion

This paper constructed a concordance between JSIC and IPC to use patent data at the industrial or firm disaggregate level. The concordance of a one-to-one match provides direct and intuitive information that includes the relevance and competencies between industrial category and technological fields. Moreover, this concordance may be a guideline for researchers using patenting data for analysis at a disaggregated level, such as at the firm or industrial level of Japanese manufacturing industries.

At the firm level analysis, we calculated each firm's technological diversity by using JSIC Concordance diversity. The Concordance diversity was similar to the IPC concordance based on subclass categories. However, considering that Concordance diversity is calculated by industrial category, we believe that Concordance diversity may be good proxy index for researchers trying to estimate the technological index at an industrial level. Additionally, we found that firm size has a positive relationship with technology diversity; moreover, R&D intensity has different relationships by industrial level. These results strongly support previous research showing that technology variety has a positive relationship with firm size and R&D activity.

Furthermore, we calculated the technological proximity among the industries. On this basis we identified industrial groups at a relatively close distance. Material industries have a relatively close technology distance with other industries. Thus, we can consider the technology relevance between manufacturing industries.

We also showed the technological profiles according to the JSIC concordance, by using Patel and Pavitt's (1997) technological profile theory. This theory highlights the relative competencies between the technological fields and industries. We showed that light-industries mainly have marginal and niche competencies. Material industries have a variety of technology field competencies. For example, to produce cars we showed that the transport equipment industry has technological competencies with parts-manufacturing industries. These results represent the actual manufacturing structure of the Japanese manufacturing industry.

This paper has some limitations. Similar to previous research, we focused only on one-to-one JSIC and IPC matches. This causes a loss of secondary or tertiary match information. The concordance of multiple matches is a matter for future research. For firm level analysis, we did not establish which technological diversity index was better − IPC diversity or Concordance diversity. This is a complex issue, because IPC diversity is measured by technological sector while Concordance diversity is based on the industry level.

However, the relevance and similarities between Concordance diversity and IPC diversity also implies that Concordance diversity can be a proxy value for IPC diversity, particularly in manufacturing industrial research.

Using patent data at an industrial level has long been a problem, particularly in the Japanese manufacturing industry. By using our JSIC and IPC concordance, researchers can adopt patent data as an economic parameter, or use it as a tool to understand technological profile or proximity among the industries. We believe this concordance between JSIC and IPC is a valuable tool for the empirical studies of Japanese manufacturing industries.

3–7. Annex

Concordance between JSIC and 596 subclass of IPC

JSIC	IPC	JSIC	IPC	JSIC	IPC	JSIC	IPC	JSIC	IPC	JSIC	IPC
9	A21D	13	E05G	16	C07C	19	B60C	24	E04G	26	B21K
9	A22C	14	A41B	16	C07D	19	B68F	24	E05D	26	B21L
9	A23B	14	A61F	16	C07F	19	C08C	24	E06B	26	B23D
9	A23C	14	A62B	16	C07H	19	D07B	24	E06C	26	B23G
9	A23D	14	B31C	16	C07J	19	E01C	24	F23B	26	B23H
9	A23G	14	B41M	16	C07K	19	F16L	24	F23D	26	B23Q
9	A23J	14	C13D	16	C08B	21	A47K	24	F23L	26	B24B
9	A23K	14	D21B	16	C08F	21	B03D	24	F23N	26	B24C
9	A23L	14	D21C	16	C08G	21	B09B	24	F24B	26	B24D
9	C12J	14	D21D	16	C08H	21	B28B	24	F24D	26	B25B
9	C13F	14	D21G	16	C08J	21	B28C	25	B31F	26	B25C
10	A01H	14	D21H	16	C08K	21	C03B	25	B41F	26	B25D
10	A24B	15	B31B	16	C08L	21	C03C	25	B63B	26	B25F
10	A24C	15	B42D	16	C09B	21	C04B	25	B63C	26	B25H
10	A24F	15	B44B	16	C09C	21	C05B	25	B63G	26	B26F
10	B67C	15	B44C	16	C09D	21	E03C	25	B63J	26	B27B
10	C12C	15	B44F	16	C09F	21	E03D	25	C10J	26	B27C
10	C12F	15	B65D	16	C09H	21	E21B	25	C10K	26	B27D
10	C12G	15	D06N	16	C09J	21	F23Q	25	E01D	26	B27F
10	C12H	15	G03H	16	C09K	21	H01T	25	E21D	26	B27G
11	A41C	16	A01M	16	C11B	22	B21B	25	F02C	26	B27L
11	A41D	16	A01N	16	C11C	22	B21C	25	F02K	26	B28D
11	A45B	16	A01P	16	C11D	22	B22D	25	F03D	26	B29C
11	A47G	16	A23F	16	C12N	22	C05D	25	F16T	26	B30B
11	B27N	16	A23P	16	C12P	22	C10B	25	F22B	26	B41K
11	B44D	16	A24D	16	C12S	22	C10C	25	F22D	26	B42B
11	B60V	16	A41G	16	C23F	22	C21B	25	F23C	26	B60B
11	C14B	16	A45D	16	D06L	22	C21C	25	F23G	26	B60F
11	C14C	16	A46B	16	D21J	22	C21D	25	F23H	26	B61B
11	D01B	16	A46D	16	F25J	22	C22C	25	F23J	26	B61J
11	D01F	16	A61K	16	F28G	22	C23C	25	F23M	26	B61K
11	D01G	16	A61P	16	F42B	22	C23G	25	F23R	26	B62B
11	D02G	16	A61Q	16	F42C	22	E02D	25	G21B	26	B65B
11	D02J	16	A62D	16	F42D	22	E04C	25	G21H	26	B65G
11	D03D	16	B01F	16	G03F	22	F16S	26	A01B	26	B66C
11	D04D	16	B01J	17	C09G	22	F17B	26	A01C	26	B66D
11	D04H	16	B29B	17	C10L	22	F27B	26	A01D	26	B67B
11	D06B	16	B32B	18	A42B	22	F27D	26	A01F	26	C02F
11	D06C	16	B41N	18	A44B	23	B22F	26	A01G	26	C10M
11	D06H	16	C01B	18	A45F	23	B23B	26	A21B	26	C23D
11	D06J	16	C01C	18	A63C	23	B23C	26	A21C	26	C25F
11	D06M	16	C01D	18	E01B	23	C05F	26	A23N	26	D02H
11	D06P	16	C01F	18	E01F	23	C22B	26	A41H	26	D03C
11	D06Q	16	C01G	18	E03F	23	C22F	26	B01D	26	D03J
11	D21F	16	C05C	18	E04B	23	C25C	26	B02B	26	D04B
11	F41H	16	C05G	18	E04D	23	C25D	26	B02C	26	E02B
12	B27K	16	C06B	18	E04F	23	C30B	26	B03B	26	E02F
13	A47B	16	C06C	18	F21P	23	E21C	26	B04B	26	F03C
13	A47F	16	C06D	19	A61D	23	H01B	26	B07B	26	F15B
13	B01L	16	C07B	19	B29D	24	A47H	26	B09C	26	F16C

JSIC	IPC	JSIC	IPC	JSIC	IPC	JSIC	IPC	JSIC	IPC	JSIC	IPC
26	F16D	28	B81B	29	G11C	30	G09B	31	B60P	31	F16B
26	F16G	28	B81C	29	G21C	30	G09C	31	B60Q	31	F16F
26	F16N	28	F16P	29	G21D	30	G09F	31	B60R	31	F16H
26	F26B	28	G04B	29	G21F	30	G09G	31	B60S	31	F16J
26	F28C	28	G04F	29	G21K	30	G10L	31	B60T	31	F16K
26	F41A	28	G04G	29	H01H	30	G11B	31	B60W	31	F17C
26	F41B	28	G06E	29	H01P	30	H01J	31	B61F	31	F21M
26	F41C	28	H01C	29	H02B	30	H01L	31	B61H	31	F21Q
26	G12B	28	H01F	29	H02H	30	H01Q	31	B62D	31	F21S
26	G21G	28	H01G	29	H02J	30	H01S	31	B62H	31	F28D
27	A01J	28	H01K	29	H02M	30	H03C	31	B62J	31	F28F
27	A61B	28	H03B	29	H05H	30	H03D	31	B62K	31	G01D
27	A61C	28	H03H	30	A47J	30	H03F	31	B62L	31	G01H
27	A61J	29	A61H	30	A47L	30	H03G	31	B62M	31	G01K
27	A61M	29	A61N	30	A61L	30	H03J	31	B63H	31	G01L
27	A63J	29	B07C	30	A62C	30	H03K	31	B64B	31	G01M
27	B26D	29	B08B	30	B03C	30	H03L	31	B64C	31	G05D
27	B27H	29	B26B	30	B04C	30	H03M	31	B64D	31	G05G
27	B31D	29	B27M	30	B06B	30	H04B	31	B64F	31	G08G
27	B41C	29	B60M	30	B21G	30	H04H	31	B65F	31	H01M
27	B41J	29	B61C	30	B82B	30	H04J	31	B66F	31	H01R
27	B41L	29	B61D	30	C40B	30	H04K	31	B68G	31	H02G
27	B42C	29	B61G	30	D01D	30	H04L	31	C13K	31	H02K
27	B65C	29	B61L	30	D06F	30	H04M	31	C25B	31	H02P
27	B65H	29	B64G	30	F01C	30	H04N	31	D01C	32	A01K
27	B67D	29	B66B	30	F16M	30	H04Q	31	D01H	32	A43B
27	C12M	29	C07G	30	F21K	30	H04R	31	D04C	32	A43D
27	C12Q	29	C10G	30	F21L	30	H04S	31	D04G	32	A45C
27	D05B	29	E03B	30	F23K	30	H04W	31	E01H	32	A47D
27	D05C	29	E21F	30	F24C	30	H05B	31	E04H	32	A63B
27	F03G	29	F01D	30	F24F	30	H05K	31	E05B	32	A63D
27	F25B	29	F03B	30	F24H	31	A47C	31	E05C	32	A63F
27	F25C	29	F03H	30	F24J	31	A61G	31	E05F	32	A63G
27	G01B	29	F15D	30	F25D	31	B05B	31	F01B	32	A63H
27	G01G	29	F17D	30	F41J	31	B21D	31	F01K	32	B42F
27	G01N	29	F21V	30	G01C	31	B21F	31	F01L	32	B43K
27	G02B	29	F22G	30	G01F	31	B21H	31	F01M	32	B43L
27	G02C	29	F28B	30	G01P	31	B21J	31	F01N	32	B43M
27	G03B	29	F41F	30	G02F	31	B22C	31	F01P	32	G04C
27	G03C	29	F41G	30	G04D	31	B23F	31	F02B	32	G10B
27	G03D	29	G01J	30	G05F	31	B23K	31	F02D	32	G10C
27	G03G	29	G01R	30	G06F	31	B23P	31	F02F	32	G10D
27	G06T	29	G01S	30	G06G	31	B25J	31	F02G	32	G10F
27	G07G	29	G01T	30	G06K	31	B60D	31	F02M	32	G10G
27	H02N	29	G01V	30	G06M	31	B60G	31	F02N	32	G10H
27	H05F	29	G01W	30	G06N	31	B60H	31	F02P	32	G10K
27	H05G	29	G05B	30	G06Q	31	B60J	31	F04B		
28	A44C	29	G07B	30	G07D	31	B60K	31	F04C		
28	B05C	29	G07C	30	G07F	31	B60L	31	F04D		
28	B05D	29	G08C	30	G08B	31	B60N	31	F04F		

Conclusion

This paper examined the relationship between innovation and performance of Japanese manufacturing industries. In recent decades, the relationship between a firm's innovative activity and performance has become a significant issue in corporate economics. However, there is a lack of previous empirical analyses, particularly for Japanese manufacturing industries.

This paper analyzed the innovative activity of the Japanese manufacturing industry in three ways. Chapter 1 focused on the firm's internal decision strategies relating to diversification. I examined how both business diversification and technology diversification affect firm performance in Japan's electronic equipment industry. Using individual firms' financial and patent application data, I completed multiple regression models of how diversification strategy affects a firm's performance. The empirical results show that business concentration and business diversification have negative effects on firm performance: this is particularly evident for non-manufacturing diversification. In contrast, technology diversification has positive effects on firm performance, showing the importance of technical diversity. Technically-diversified firms can enjoy more profit, signifying that a variety of technical fields is a key factor for the electronics industry, as it requires a broad range of parts and technologies.

Chapter 2 examined the firm's external methods of innovation, assimilated by firms' alliance relationships. I believe that the ownership structure of firms is a valuable arrangement to exploit the organizational learning effects of technology knowhow. Using data on firms' patent applications and financial status, I measured multiple regression models of spillover effects to determine whether a member's technological knowledge is affected by that of other members within the governance relationship. I clarified that the technological knowledge of other members has a positive effect on a firm's technological knowledge. I also proved a hypothesis that a technologically close sector has a greater positive effect than technologically distance sector, and that an internal spillover effect is more significant than one external to the ownership group. Throughout these results, I clarified the importance of technological diffusion inside the ownership structure. This result strongly clarifies the learning effect of the ownership structure, thus indicating that the organization is a good measurement of technology diffusion.

Finally, chapter 3 constructed a concordance between JSIC and IPC to exploit patent data as disaggregate economic data. One-to-one matched concordance has a limitation in that it loses information; however, it provides direct and intuitive information between the industrial category and technology fields. This concordance may solve the discordance problem when researchers try to use patent data for industrial level analysis. Moreover, I showed several descriptive analyses such as a correlation relationship with technological diversity and firm size, technological proximity and technological profile. These results represent the actual and beneficial features of manufacturing structures on the Japanese manufacturing industry.

Throughout this research, I observed how a Japanese manufacturing firm's innovation activity affects its performance. A firm should undertake a strategy of technology diversification to enhance its performance; business diversification did not show to be a useful tool for performance. In relation to a firm's external strategy, partnership relations such as ownership structure are valuable for technology flow. I also showed that technological distance is another important element of the technological spillover effect in chapter 2. Finally, I constructed a concordance between JSIC and IPC. By using this, researchers can appropriate patent data as economic parameters of the Japanese manufacturing industries.

I believe that this research can contribute to understanding the behavior of a firm's innovation in the Japanese manufacturing industries.

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