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Nonlinear Effect of Technological Diversification on the Corporate Patent Performance

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Abstract: Technological diversification has positive influence on corporate performance, however, previous studies have only presumed as a linear relationship. As business environment nowadays has became more dynamic and uncertain, it is important to explore the possible non-linear relationship between the technological diversification and its consequents. This study uses panel negative binomial fixed effect model to explore the nonlinear relationships between technological diversification and corporate patent performance. The result indicates that technological diversification has nonlinear effect of which an inverted U-shape on the corporate patent performance. Technological diversification is positively related with corporate patent performance when the value of technological diversification is below the critical point and vice-versa. This finding has important implication for corporate management.

Key words: Technological diversification, herfindahl-hirschman index, entropy

INTRODUCTION

The purpose of technological diversification is to reduce the production costs through economy of scale, economy of scope and business synergy. Therefore, company uses technological diversification to promote its growth (Kodama, 1986; Granstrand and Oskarsson, 1994; Suzuki and Kodama, 2004; Watanabe *et al*., 2004). In addition, technological diversification helps companies to have their competitive advantages in the market (Leten *et al*., 2007; Garcia-Vega, 2006). Granstrand and Oskarsson (1994) defined technological diversification as a company which applies its technological competence to wide technological field. Miller (2006) thought that technological diversification should extend its own knowledge more wide and connect it with the knowledge context with the company.

Although, previous studies extensively addressed that technological diversification have positive influence upon the corporate performance (Kodama, 1986; Granstrand and Oskarsson, 1994; Suzuki and Kodama, 2004; Watanabe *et al*., 2004), they did not explore the influence is linear or nonlinear. Under the dynamic and uncertain business environment nowadays, traditional models of business management are not often effective. Because of the complexity and uncertainty, the relationships between the managerial factors and their consequents are perhaps dynamic, not linear or monotonic. Because there is no research examines the nonlinear influence of technological diversification upon corporate patent performance. Hence, this study attempts to fill this research gap.

Technological diversification can accumulate more technological capabilities. Thus, when a company increases the scope of technology and builds the products more dedicate systematic, it is easier for its core products to make better profit and performance in market. Company takes technological diversification as its strategy in market, it can gain profit through economy of scale, economy of scope and diversified risk. On contrary, company extended its technology activities to heterogeneous fields, it may lead the company to increase the cost due to management in different fields.

Technological diversification has some risks. For example, if the company diversifies its investment, it may lead the business to use the resources inefficiently and reduce its performance. When a company diversified its investment in unrelated technological diversification, it may increase its complexity in technology, thus it may produce higher cost in integration, communication and supervision (Katila, 2002; Leten *et al*., 2007).

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Technological diversification can take the perspectives of organization learning, accumulate its professional knowledge and experience gradually and then expend this knowledge into the similar market to making profit (Breschi *et al*., 2003). However, excess technological diversification increases not only the coordination cost, the management expenses in information processing but also dilutes the resources in many fields. In the end, the performance may work not as good as expected. Therefore, highly technological diversification comes with many limitations, such as increasing transaction costs and information processing costs (Katila, 2002; Leten *et al*., 2007). Hence, this study proposed the hypothesis 1.

Hypothesis 1: Technological diversification (DT) has an inverted U-shaped relationship with patent performance.

MATERIALS AND METHODS

Sample and data collection: This study explored the influence of technological diversification on the firm's patent performance. The unit of analysis in this study is "firm" level. This research was conducted in the firms of the chemical industry and pharmaceutical industry in US. The sample of this study was collected from the Standard and Poor's compustat database with a Global Industry Classification System (GICS) code equal to 151010 and 352020. The sample consists of 71 US chemical companies and 84 US pharmaceutical companies in this study. The panel data containing patent data and financial data of the sample spanned the period from 1996 to 2007. The financial data of this study were obtained from the compustat database. The compustat database contains financial data of publicly traded companies in US. The patent data of this study was gathered from the United States Patent and Trademark Office (USPTO). These patent data of this study had sufficient information about names of assignees, technical fields and the issued dates and so on.

This study was mainly conducted in the chemical industry and pharmaceutical industry in United States. The chemical industry is crucial to the modern world economy, converting raw materials (oil, natural gas, air, water, metals and minerals) into more than more than 70,000 different products. Polymers and plastics, polyethylene, polypropylene, polyvinyl chloride, polyethylene terephthalate, polystyrene and polycarbonate comprise about 80% of the industry's worldwide outputs. Chemicals are used to make a wide variety of consumer goods, as well as thousands inputs to agriculture, manufacturing, construction and service industries. The chemical industry itself consumes 26% of its own outputs. Its major industrial customers include rubber and plastics, textiles, apparel, petroleum refining, pulp and paper and metal companies. The output of the chemical industry is nearly $2 trillion dollars and the EU and U.S. are two major producing areas in the world. In the U.S. there are 170 major chemical companies. They operate internationally with more than 2,800 facilities outside the U.S. and 1,700 foreign subsidiaries or affiliates. The U.S. chemical output is over $400 billion dollars per year during the past years. The U.S. chemical industry earns large trade surpluses and employs more than a million people in the United States. The chemical industry is the second largest consumer of energy in manufacturing and spends over $5 billion dollars annually. In Europe, especially Germany, output of the chemical, plastics and rubber sectors are huge. They generate about 3.2 million jobs in more than 60,000 companies. Since 2000 the chemical industry creates 2/3 of the entire manufacturing trade surplus of the EU. Besides, the chemical industry accounts for 12% of the EU manufacturing industry's added value. The chemical industry is chosen because it is technologically based and so places heavy emphasis on research and development. Besides, US is one of the important countries for the chemical industry in the world. Therefore, this research selects the chemical industry of US as the research sample.

There are several characteristics for the pharmaceutical industry. First, it is the leading high research and development (R and D) intensive industry in United States and thereby has both the highest R and D to sales ratio among all major industries in United States. Second, patent protection is very strong in this industry and pharmaceutical companies generally recognize they are in races with other firms to develop innovative new products. Finally, there is sufficient data in the pharmaceutical industry and it is possible to obtain finance and patent information of these pharmaceutical companies easily. In addition, success in the U.S. pharmaceutical industry is dependent upon the ability to continually develop new pharmaceutical products by investing in R and D. New products are especially important in this industry for two reasons. First, the treatment of diseases is continually changing, which makes old products obsolete. Second, patent can allow pharmaceutical companies to make their products have high economic margins.

Measurement

Patent performance: Numerous studies used patent citations as an indicator to measure the importance or value of patents. Because, patent citations can provide the information of the technological abilities of companies and show the impact and value of their patents (Jaffe *et al*., 1993; Narin, 1994; Stolpe, 2002; Zhang *et al*., 2012; Chang *et al*., 2012). The dependent variable of this study is patent performance. Therefore, this study used patent citations and patent counts to assess the patent performance of companies.

Technological diversification: This study used Herfindahl-Hirschman Index (HHI) of patents (Quintana-Garcia and Benavides-Velasco, 2008; Garcia-Vega, 2006; Chiu *et al*., 2008, 2010; Leten *et al*., 2007; Lai *et al*., 2010) and entropy of patents (Watts and Porter, 2003; Kodama, 1986; Gemba and Kodama, 2001) to measure the level of a firm's technological diversification. Technological diversification is calculated as follows:

$$TD_{HHI} = 1 - \sum_{j=1}^{J} \left(\frac{N_j}{N} \right)^2 \quad (1)$$

For a set of N patents falling into J classes, with N_j patents in each class ($N_j > 0$, j = 1, ..., J):

$$TD_{entropy} = \sum_{i=1}^{N} P_i \ln\left(\frac{1}{P_i} \right) \quad (2)$$

where, P_i = Proportion of technological field in United States Patent Classification (USPC) subclasses i, for a corporation with N different USPC subclasses.

Control variable: This study included a number of control variables in the empirical model that may influence a firm's innovation performance: Firm size and firm R and D spending. Numbers of studies discussed firm size significantly affect innovation performance (Cockburn and Henderson, 2001; Acs and Audretsch, 1987, 1988; Audretsch and Acs, 1991; Cohen and Klepper, 1996; Zhang *et al*., 2012; Chang *et al*., 2012). Firm size can demonstrate the economies and diseconomies of scale. Therefore, to control size effect, firm size is measured by the logarithm of sales in this study. R and D expenditures is argued to be an important predictor of innovation performance (Narin *et al*., 1987; Griliches, 1990; Trajtenberg, 1990; Schoenecker and Swanson, 2002; Brouwer and Kleinknecht, 1999; Hall and Bagchi-Sen, 2002; Pakes and Griliches, 1980; Cincera, 1997; Crepon and Duguet, 1997; Montalvo, 1997; Zhang *et al*., 2012; Chang *et al*., 2012). Hence, this study controlled for R and D expenditures by using the logarithm of annual research and development expenditure as a proxy.

Statistical method: The dependent variable is measured by the patent citations, which is take non-negative integer values. While the linear regression model has often been applied to count outcomes, this can result in inefficient, inconsistent and biased estimates. Thus, count data model would be appropriate to deal with this type of dependent variable (Hausman *et al*., 1984). The panel data of this study containing patent data and financial data spanning the period of a decade from 1996 to 2007. Panel data combining the characteristics of time series and cross sections may have firm-specific effects, period specific effects, or both. In order to analyze the panel data, this study applied panel negative binomial regression fixed effect model to verify the hypotheses in the research framework.

RESULTS

The descriptive statistics of this study were showed in Table 1. The average number of patent counts was 407.66 with a standard deviation of 1293.35. Table 1 showed that patent counts showed positive correlations with all the variables. Specifically, the correlation coefficients with the firm size, R and D expenditures, TD_{HHI} and $TD_{entropy}$ were 0.69, 0.43, 0.38 and 0.56 with a statistical significance of positive correlation ($p<0.01$). The average number of patent citations was 690.21with a standard deviation of 2280.44. Table 1 showed that patent citations showed positive correlations with all the variables. Specifically, the correlation coefficients with the firm size, R and D expenditures, TD_{HHI} and $TD_{entropy}$ were 0.62, 0.36, 0.36 and 0.54 with a statistical significance of positive correlation ($p<0.01$).

This study used the negative binomial fixed effect model to verify the hypotheses in the research framework. This study showed the results of the negative binomial fixed effect model in Table 2. The results illustrated in Table 2 support the hypothesis in this study that there is an inverted U-shaped relationship between technological diversification and corporate patent performance. Technological diversification does positively affect corporate patent performance (coefficient = 0.42, z = 13.43, $p<0.01$ in the Model 1; coefficient = 0.87, z = 45.40, $p<0.01$ in the Model 2; coefficient = 0.44, z = 9.51, $p<0.01$ in the Model 3; coefficient = 0.95, z = 28.02, $p<0.01$ in the Model 4), whereas its square term has a negative impact on performance (coefficient = -0.15, z = -8.43, $p<0.01$ in the Model 1; coefficient = -0.02, z = 4.79, $p<0.01$ in the Model 2; coefficient = -0.20, z = -7.39, $p<0.01$ in the Model 3; coefficient = -0.06, z = -5.83, $p<0.01$ in the Model 4), indicating an inverted U-shaped relationship between technological diversification and corporate

Table 1: Means, standard deviations and correlations coefficient between variables

Variables	Mean	SD	1	2	3	4	5
Patent counts	407.66	1293.35	1				
Patent citations	690.21	2280.44	0.96**	1			
Firm size	2850.84	7167.24	0.69**	0.62**	1		
R and D expenditures	253.31	916.04	0.43**	0.36**	0.83**	1	
TD_{HHI}	0.54	0.41	0.38**	0.36**	0.30**	0.20**	1
$TD_{entropy}$	3.30	2.60	0.56**	0.54**	0.51**	0.36**	0.83**

***: p<0.01, SD: Standard deviation, TD_{HHI}: Herfindahl-hirschman index of patents to measure the level of a firm's technological diversification, $Td_{entrophy}$: Entropy of patents to measure the level of a firm's technological diversification

Table 2: Results of negative binomial regression fixed-effect model

	Patent counts		Patent citations	
Variables	Model 1	Model 2	Model 3	Model 4
Intercept	0.72**(7.58)	-1.35**(-12.72)	-0.71**(-6.51)	-3.27(-21.38)
Control variables				
Firm size	0.09**(4.97)	0.04**(3.60)	0.15**(7.10)	0.01(0.24)
R and D expenditures	0.01(0.35)	-0.01(-1.14)	0.06(1.68)	-0.13**(-5.31)
Independent variables				
TD_{HHI}	0.42**(13.43)		0.44**(9.51)	
TD^2_{HHI}	-0.15**(-8.43)		-0.20**(-7.39)	
$TD_{entrophy}$		0.87**(45.40)		0.95**(28.02)
$TD^2_{enthropy}$		-0.02**(-4.79)		-0.06**(-5.83)
Log Likelihood	-4955.36	-4079.99	-4694.73	-4255.41
Chi-Square	326.41	2520.90	285.26	1178.70
No. of groups	1319	1370	1163	1166
No. of observations	133	142	115	116

No. in parentheses are z values, *: p<0.05, **: p<0.01,TD_{HHI}: Herfindahl-hirschman index of patents, to measure the level of a firm's technological diversification, TD^2_{HHI}: Entropy of patents to measure the level of a firm's technological diversification, $Td_{entrppy}$: Square of technological diversification that measured by the entropy of patents, $TD^2_{entropy}$: Square of technological diversification that measured by herfindahl-hirschman Index of patents

patent performance. Therefore, the result showed a positive and significant impact of the linear term and a negative and significant impact of the squared term. Therefore, the hypothesis, H1, was significantly supported in this study.

Assuming away the effect of firm size and R and D expenditures, if any, the estimated regression equation for the model will be stated as:

$$\text{Model 1: Patent counts} = 0.72+0.42\ TD_{HHI} -0.15TD^2_{HHI} \quad (3)$$

$$\text{Model 2: Patent counts} = -1.35+0.87\ Td_{entropy} -0.15TD^2_{entropy} \quad (4)$$

$$\text{Model 3: Patent counts} = 0.71+0.44\ TD_{HHI} -0.20TD^2_{HHI} \quad (5)$$

$$\text{Model 4: Patent citations} = -3.72+0.95TD_{entropy} -0.06TD^2_{entropy} \quad (6)$$

To show how international diversification affects firm performance, a partial derivative of the curvilinear regression equation is taken with respect to technological diversification:

$$\text{Model 1: } \frac{\partial \text{Patent counts}}{\partial TD_{HHI}} = 0.42 - 0.30TD_{HHI} = 0 \quad (7)$$

This partial derivative will be positive negative if TD_{HHI}<0.12; it will become negative if TD_{HHI}>0.12 in the Eq. 7:

$$\text{Model 2: } \frac{\partial \text{Patent counts}}{\partial TD_{entropy}} = 0.87 - 0.04TD_{entropy} = 0 \quad (8)$$

This partial derivative will be positive negative if $TD_{entropy}$<0.83; it will become negative if $TD_{entropy}$>0.83 in the Eq. 8:

$$\text{Model 3: } \frac{\partial \text{Patent citations}}{\partial TD_{HHI}} = 0.44 - 0.40TD_{HHI} = 0 \quad (9)$$

This partial derivative will be positive negative if TD_{HHI}<0.04; it will become negative if TD_{HHI}<0.04 in the Eq. 9:

$$\text{Model 4: } \frac{\partial \text{Patent citations}}{\partial TD_{entropy}} = 0.95 - 0.12TD_{entropy} = 0 \quad (10)$$

This partial derivative will be positive negative if $TD_{entropy}$<0.83; it will become negative if $TD_{entropy}$<0.83 in the Eq. 10.

The critical point, implying the point where the marginal costs of technological diversification is equal to the marginal benefits of technological diversification, is 0.12 in the Model 1, 0.83 in the Model 2 and Model 4, while in the Model 3 it is 0.04.

The relationship between technological diversification and corporate patent performance is not linear and there exists an optimal value for technological diversification in the US chemical and pharmaceutical industry. If degree of technological diversification is below the optimal value, they are positively associated with corporate patent performance. However, if degree of technological diversification is beyond the optimal value, they are negatively associated with corporate patent performance.

DISCUSSION AND CONCLUSION

This study showed the outcome of technological diversification and it has an inverted U-shaped relationship with corporate patent performance which means that their relationship is not linear and there exists an optimal value for technological diversification. Although previous numbers studies confirmed that technological diversification have positive influence upon the corporate performance (Kodama, 1986; Granstrand and Oskarsson, 1994; Suzuki and Kodama, 2004; Watanabe *et al*., 2004).

However, Katila (2002) and Leten *et al.* (2007) argues that company dedicates itself into non-related technological diversification, it is facing the higher learning cost and it does not meet the advantages in economy of scale. In the meanwhile, the communication cost increasing gradually; therefore, it dilutes the corporate resources. Besides, when mangers are facing technological diversification, they have to deal with the heterogeneous technology and markets. It also increases the transaction costs in dealing with the processing of information management. Therefore, highly technological diversification comes with many limitations, such as increasing transaction costs and information processing costs.

There is a critical point in the nonlinearly inverted U-shaped relationship between technological diversification and corporate patent performance. Therefore, when technological diversification is below the critical value, the relationship between technological diversification and corporate patent performance is positive, the implication of the firms should diversify its patents or technological capabilities if it wants to enhance its patent performance. If pharmaceutical companies have broader technological competencies, they can take advantage of new technological opportunities more often and thereby the risk of missing new technological opportunities is less.

However, when technological diversification is beyond the critical value, the relationship between technological diversification and corporate patent performance is negative, the implication of the highly technological diversification increases the coordination, integration, communication and supervision cost (Leten *et al*., 2007; Katila and Ahuja, 2002). Besides, it dilutes the resources in many fields (Katila and Ahuja, 2002). Hence, when technological diversification is beyond the critical value, the relationship between technological diversification and corporate patent performance is negative.

This research was conducted in the US chemical and pharmaceutical industry. Future studies can undertake on other industries to explore the relevant topics and compare to this study. Finally, this study hoped that the research results can be beneficial to managers, researchers, or governments and contributed to relevant studies and future researches as reference.

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