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Full Length Research Paper

Patenting patterns of global information technology (IT) firms and their business performance

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This paper defines patenting patterns of 169 global IT firms and compares the types in terms of their patent activities. Based on a framework of multiple patenting indicators representing a firm's patent quantity, patent quality, and patent technology concentration, four different types of patenting patterns are defined and analyzed the difference among the patterns in financial performances. The results show that these patterns classified by the firms' patenting characteristics can be distinguished also by their business performance. There are significant differences among the patenting patterns in total revenue, R&D expenditure, annual revenue growth, and revenue per employee.

Key words: Patenting pattern, business performance, patent quality, patent quantity, technology concentration.

INTRODUCTION

The importance of intellectual property has been increasing fast in the era of knowledge economy. Patent, as a major intellectual property, is regarded as an essential source of technical and commercial knowledge (Park et al., 2005), and widely adopted in researches as a major indicator of research and development activities.

Many researchers have discussed the relationship between patents and corporate performance on the firm level in the empirical studies. Scherer (1965) found positive relationship between patents granted and sales growth in 365 firms from the Fortune 500 list. Research results of Comanor and Sherer (1969) indicates larger influence of patent applications on sales as well as positive relationship between patent applications and sales in 57 firms of the pharmaceutical industry. Griliches (1990) emphasized that there is quite a strong relationship between R&D expenditures and the number of patents and patents are a good indicator of differences in inventive activity across different firms.

In the research by Austin (1993, 1995) using 550 patents granted of 20 biotechnology firms in the U.S, positive influence of patents granted on the market value and stronger influence of key patents on market value were found. On the other hand, Ernst (1995, 2001) used different patenting indicators and found that the rate of valid patents and highly cited patents are positively related to economic performance. In addition, he showed that patent applications lead to sales increase with a time lag of 2 to 3 years after the priority year in 50 German firms in mechanical engineering industry. Breitzman and Thomas (2002) suggested that patent analysis can be used for several aspects of merger and acquisition activities including targeting, due-diligence compatibility and valuation.

Chen and Chang (2010) examined the relationships between patent quality indicators and corporate market value in the US pharmaceutical industry, and their research showed that relative patent position and patent citations were positively associated with corporate market value. The study of Chang et al. (2012) explored the relationships between the patent performance and corporate performance in the pharmaceutical company.

These researches indicate strong relationship between patents and business performance. Most of all, they mainly focus the causal relationships between patent indicators and business performance indicators without considering the whole aspects of patenting activities. In addition, the research data was country-specific and industry-specific, or small sized.

The purpose of this research is to define patterns of firm's patenting activities using patent indicators, and to analyze the patterns in terms of business performances in information technology (IT) industry. The sample firms are 169 global competitive IT companies. Therefore, the country-specific problem can be removed, and previous research results can be validated and extended by this study about IT industry. In addition, this research handles large scaled patent data, 186,607 patents granted by United State Patent and Trademark Office (USPTO), and measures several patenting indicators considering three patent dimensions, such as patent quantity, patent quality, and patent technology concentration.

This paper is organized as follows. Subsequently, the paper provides explanation of patent indicators that previous researches defined, as background. Data collection and measurement are then described and the research methodology and analysis are presented thereafter. Finally, research results, a few final remarks and some prospects for possible future study are discussed.

BACKGROUND: PATENT INDICATORS

In this study, several patenting indicators are used to cluster the IT firms' patenting patterns. These indicators can explain a firm's patenting activities in terms of patent quantity, patent quality, and patent technology concentration.

Count of patents granted

One of the most useful measures as patent information is the number of patents granted to specific firm over a given time period (Hirschey and Richardson 2004). A granted patent is believed to be of higher technological capacity than the mere patent application (Basberg, 1987). In addition, patent counts are highly correlated with contemporaneous research and development expenditures, and close association with citation-based patent indexes (Trajtenberg, 1990).

Citation frequency

The highly cited patents are patents of more than average technological impact and tend to be important, seminal inventions. Therefore, citation frequency is used as indicators of technical quality of patent (Karki, 1997). The number of citations received by a patent in subsequent patent can also be viewed as a sign for an economically important invention (Albert et al., 1991; Ernst, 1998; Narin and Noma, 1987).

The firm market values are correlated with the portion of eventual citations that cannot be predicted based upon past citations. That means stock prices are correlated with future citations that cannot be predicted on the basis of current patent data (Hall et al., 2000).

Technical impact index (TII)

This index means a firm's portion of highly cited patents in a specific period. TII is the percent of patents, which are in the most highly cited 10% of all patents in a particular period and the expected value of the TII has been normalized to equal 1 (Karki, 1997).

Current impact index (CII)

The CII is a simple count of the number of citations generated by a company's most recent 5 years of patents, divided by the expected number of citations based upon the average number of citations for all companies in a specific industry. Thus, the CII measures how often a company's patent is cited in subsequent patent applications relative to the typical pace of patent citations (Hirschey and Richardson, 2001). A CII is 1.3, for example, means that a given company's patents are cited 30% more often than average. Just as citation frequency, high CII implicates high technological value or economic value of the patent (Deng et al., 1999).

For this study, the measurement for this index is modified a little. The 169 firms' patents are used in order to analyze past 10 years' accumulated innovative activity and current business performance in this research. Hence, instead of five-year citation frequency, ten-year citation frequency is used to calculate the CII.

Technology strength

That is the number of patents multiplied by the current impact index (Karki, 1997). In this study, this index is calculated by multiplying CII by the number of company patents granted.

Patent concentration

This indicator illustrates the frequency distribution of patents over patent classes. Some companies might patent in only few patent classes in order to concentrate their technological activities, whereas other companies might patent in a variety of technological fields (Ernst, 1995). In order to compute patent concentration ratio in this research, first, the number of patent classes in each firm is counted as patent technology scope. Then, the number of patent in each patent class is counted for each firm. Next, each patent class's distribution ratio is computed by dividing the number of patent in each patent class into the firm's total patent number. Finally, the concentration ratio is drawn from averaging the distribution ratios for each firm.

DATA COLLECTION AND MEASUREMENTS

For this research US patent data was collected from the supplement CD-ROM of Jaffe and Tranjtenberg (2002). In order to select a homogeneous group of companies, ‘EB300: The Rankings’ listed by Electronic Business in 2004 was used. Target firms were the firms in the ‘EB300: Rankings’ list of companies and these companies are worldwide IT companies. In addition, financial values in the ’EB300: Rankings’ was utilized for the target firms’ economic performances.

The target firms can be divided into two groups such as patenting group and non-patenting group. In order to classify them, company names in the ‘EB300: The Rankings’ list and company names of patent assignee were compared. The 169 patenting firms were drawn from the job of matching company names and were selected as the sample firms.

There are total 186,607 patents granted by USPTO from 1990 to 1999 for the 169 patenting firms. Table 1 shows the basic characteristics of the sample firms’ patenting activity, such as number of patent, number of most highly cited 10% patents, number of patent classes, average citation frequency, and patenting time.

In this research, firms’ patenting characteristics are considered in three dimensions such as patent quantity, patent quality, and patent technology concentration. As described in the previous session, the number of patents and technology strength reflects patent quantity, citation frequency and CII represent patent quality, and patent technology concentration is drawn from the number of patent classes.

Using the firms’ patent information, patent indicators of each firm, including technology impact index (TII), citation impact index (CII), technology strength, and patent technology concentration, were measured. Table 2 summarizes the patent indicator measurements for the sample firms.

Methodology and analysis

This part of the study explains data analysis. First, in order to define firms’ patenting patterns, clustering analysis is conducted with patent indicators. Next, discriminant analysis is used to validate the clusters. Finally, financial performance differences among the clusters are analyzed using one-way analysis of variance (ANOVA) and Duncan multiple range test as post-hoc test.

Cluster analysis: Classification of the sample firms in terms of patenting characteristics

Cluster analysis was conducted using the SPSS software. In order to classify the firms, four patenting indicators were used. The independent variables for clustering are TII, CII, technology strength, and patent concentration ratio. Before clustering, values of technology strength were normalized and patent concentration ratio was applied by logarithmic transformation. Using the K-means clustering method with the four variables, the solution of four clusters was gained. The four clusters about patenting patterns were summarized in Table 3.

Cluster 1: The companies in cluster 1 have greatly large number of patents, the very high portion of the most highly cited 10% of all patents, and the very long-term patenting history. In addition, they have wide variety of patent technology classes, so their patent technology concentration is dispersed.

Ernst (2003) defined a small group characterized by high patenting activities as well as by high patenting quality as ‘key inventors’ in the inventor portfolio. Companies in cluster 1 can be called as the key inventors. International business machines (IBM), Toshiba, Hitachi, Motorola etc. are included in cluster 1. It is possible to imply that a small group in IT industry has large scaled patents with relatively high quality ranging over various patent technologies.

Cluster 2: The size of this cluster is largest and more than half of the sample firms are included in cluster 2. Patenting characteristics seems to be relatively similar to those of cluster 1. In every patenting indicator, cluster 2 follows cluster 1 as Table 3 shows. The differences between two clusters, however, are significant. Including Samsung electronics, Microsoft, Apple computers, EDS etc., many famous IT firms are classified into this cluster.

Cluster 3: Cluster 3 is the second largest group next to cluster 2. The companies in this cluster have a few patents of lower quality than average and short-term patenting history in a few several specific patent technology fields. It is possible to say that their entire patenting performance level is low.

Cluster 4: Patenting characteristics of cluster 4 seems similar to those of cluster 3 in the aspect of quantity, technology scope and patenting term history. In patenting quality and the scale of cluster, however, there is significant difference between two clusters, as summarized in Table 3. Even though the companies in this cluster have small number of patents and very short patenting history in narrow range of patent technology areas as those in cluster 3, the quality of their patent is better than any other cluster. It is possible to say that there is a very small group containing talents and potentials in patenting. Dell computer, Cisco systems, Qualcomm, and a few IT companies are included in this cluster.

Discriminant analysis: Validation of the clusters

In order to validate the previous clustering, a discriminant analysis with the cluster as the dependent variable and the four clustering variables as independent variables was conducted. The discriminant analysis results reported in Table 4, which are the correlations between the clustering variables and the discriminant functions, are useful in assessing which variables are important in distinguishing among clusters. Each of the three resulting canonical correlations (0.88, 0.79, 0.71) is significant ($p<.001$) using Wilks’ Lambda statistic. In addition, the results indicate that 95.9% of original clustered cases are correctly classified as displayed in Table 5.

ANOVA analysis: Assessment of difference among the clusters in terms of financial performance

In the following, the four different patenting clusters are compared according to financial performance. In this analysis, the five financial variables are used as the economic performance on the firm level. The five variables are as follows; total revenues, net income, R&D spending, revenue per employee, and five-year annual revenue growth.

In order to examine whether the features in terms of financial performance will differ among the four patenting clusters, one-way ANOVA was conducted. The results of ANOVA indicate that there are significant differences between the four clusters in total revenue, R&D spending, revenue per employee, and five-year annual revenue growth (%), except net income. Table 6 shows the results of ANOVA. According to the ANOVA results that there are significant differences between the four patenting clusters in thefour financial variables, except net income, a post-hoc test to analyze degree of the differences was followed.

The results of post-hoc test based on Duncan multiple range test ($p=0.05$) are as follows; There are no significant differences among cluster 2, 3 and 4 in total revenue, and R&D spending. This could imply that it is possible to integrate cluster 2, 3, and 4 in terms of total revenue, and R&D spending. In addition, it is found that there

Table 1. Basic statistics for each of the 169 sample firms.

Patent indicator	Mean	Std. deviation	Min	Max
Count of patents granted	1104.18	2280.39	1.00	14902.00
Count of most highly cited 10% patents	110.42	282.95	0.00	2419.00
Count of patent classes	55.70	59.32	1.00	247.00
Average citation frequency	3.29	2.51	0.00	17.42
Patenting time (years)	7.37	3.32	1.00	10.00

Table 2. Patent indicator statistics for each of the 169 sample firms.

Patent indicator	Mean	Std. deviation	Min	Max
Count of patents granted	1104.18	2280.39	1.00	14902.00
Average citation frequency	3.29	2.51	0.00	17.42
Technical impact index (TII)	0.59	1.52	0.00	12.96
Citation impact index (CII)	1.00	0.76	0.00	5.29
Technology strength	1276.00	3038.70	0.00	24371.43
Patent concentration	0.13	0.24	0.00	1.00

Table 3. Patenting characteristics summary of the patenting clusters.

Patent indicator	Cluster 1 (n=15)	Cluster 2 (n=89)	Cluster 3 (n=56)	Cluster 4 (n=9)	Duncan test*
Count of patents	7294.60	847.18	24.41	46.89	1<2>4,3
Average citation frequency	4.200	3.244	2.003	10.288	4>1,2>3
TII	4.5385	0 .3487	0.0075	.0524	1>2,4,3
CII	1.2765	0.9862	0.6088	3.1271	4>1,2>3
Technology strength	9401.64	811.48	159.78	17.12	1>2,4,3
Patent concentration	0.0057	.0206	0.2875	0.4927	4>3>1,2

Means with significant differences (p<.001) between clusters at as one-way ANOVA results. *Duncan test at significant level p=0.05.

Table 4. Discriminant analysis results (1).

Canonical function	Eigen value	Canonical correlation	Wilks' Lambda	Chi-square (Sig.)	Canonical loading	Function 1	Function 2	Function 3
1	3.742	0.888	0.038	536.14 (0.000)	TII	-0.623(*)	0.585	-0.180
					CII	-0.044	0.314	0.925(*)
2	1.728	0.796	0.180	280.89 (0.000)	Tech. strength	-0.692(*)	0.630	-0.184
3	1.032	0.713	0.492	116.31 (0.000)	Patent concentration	0.852(*)	0.480	-0.173

(1) Right table: Pooled within-groups correlations between discriminating variables and standardized canonical discriminant functions. (2)* Largest absolute correlation between each variable and any discriminant function.

are two groups, such as cluster (1, 2) and cluster (3, 4), according to five-year annual revenue growth, and that there is no significant difference between cluster 1, 2, and 3 in revenue per employee. Table 7 displays the summary results of the Duncan multiple range test.

RESULTS AND DISCUSSION

Figure 1 displays the four clusters' position over patent quantity and patent quality. The size of a round reflects the number of companies in each cluster. The brightness of round color illustrates the patent technology concentration. The darker the color, the stronger the patent technology concentration is.

The positions of firm's patent pattern clusters imply as follows: First, considering patent quantity, the four patent patterns can be classified into two groups, such as cluster (1) characterized by very large number of patents

Table 5. Discriminant analysis results (2).

		Cluster	Predicted group membership 1	2	3	4	Total
Original	Count	1	13	2	0	0	15
		2	0	89	0	0	89
		3	0	4	52	0	56
		4	0	0	1	8	9
	Percent	1	86.7	13.3	0.0	0.0	100.0
		2	0.0	100.0	0.0	0.0	100.0
		3	0.0	7.1	92.9	0.0	100.0
		4	0.0	0.0	11.1	88.9	100.0

95.9% of original grouped cases correctly classified.

Table 6. Differences between clusters in financial performance – ANOVA results.

Finance performance variables	F	Sig.
Total revenues	10.518	0.000(*)
Net income	0.642	0.589
R&D spending	5.314	0.002(*)
Revenue per employee	5.325	0.002(*)
Five-year annual revenue growth	10.928	0.000(*)

*p < 0.001.

Table 7. Financial performance summary of the four patenting clusters – Duncan multiple test results.

Mean value	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Duncan Test*
Total revenues ($ millions)	42603.31	10952.28	6789.90	7644.50	1>2,4,3
R&D spending ($ millions)	25.41	8.38	5.24	9.56	1>4,2,3
Revenue per employee ($ thousands)	260.46	274.68	422.88	1149.75	4>3,2,1;
Five-year annual revenue growth (%)	0.0126	0.0192	0.1806	0.1876	4,3>2,1;

*Duncan test at significant level p=0.05.

and cluster (2, 3, 4). On the other hand, these two groups can be also distinguished by total revenue and R&D expenditure. The findings imply that companies with great large number of patents outperform in total revenue and R&D expenditure.

Second, with regards to patent quality, cluster (4) which has high quality but small number of patents can be discriminated by firm's revenue per employee. The difference between cluster 1, 2 and 3 is not significant in revenue per employee.

Finally, in terms of patent technology concentration, there is one homogeneous group, cluster (3, 4), and this group can be distinguished with other clusters by annual revenue growth rate. There are the unexpected results that this group's growth rate is greater than other two clusters. This result illustrates that companies focusing on specific technology areas outperform in annual revenue growth rate.

Four different patenting patterns of global IT firms are defined in terms of their patenting activities for 10 years in this study. The patterns are described with multiple patent indicators considering patent quantity, patent quality, and patent technology concentration, and the results indicate that there are significant differences among these patterns classified by firms' patenting characteristics in the firm's financial performance. Based on this study, causal relationships between firm's financial indicators and patenting patterns, such as annual revenue growth rate and degree of technology concentration, revenue per employee and patent quality will be analyzed in the future.

In this research, several limitations due to difficulties to

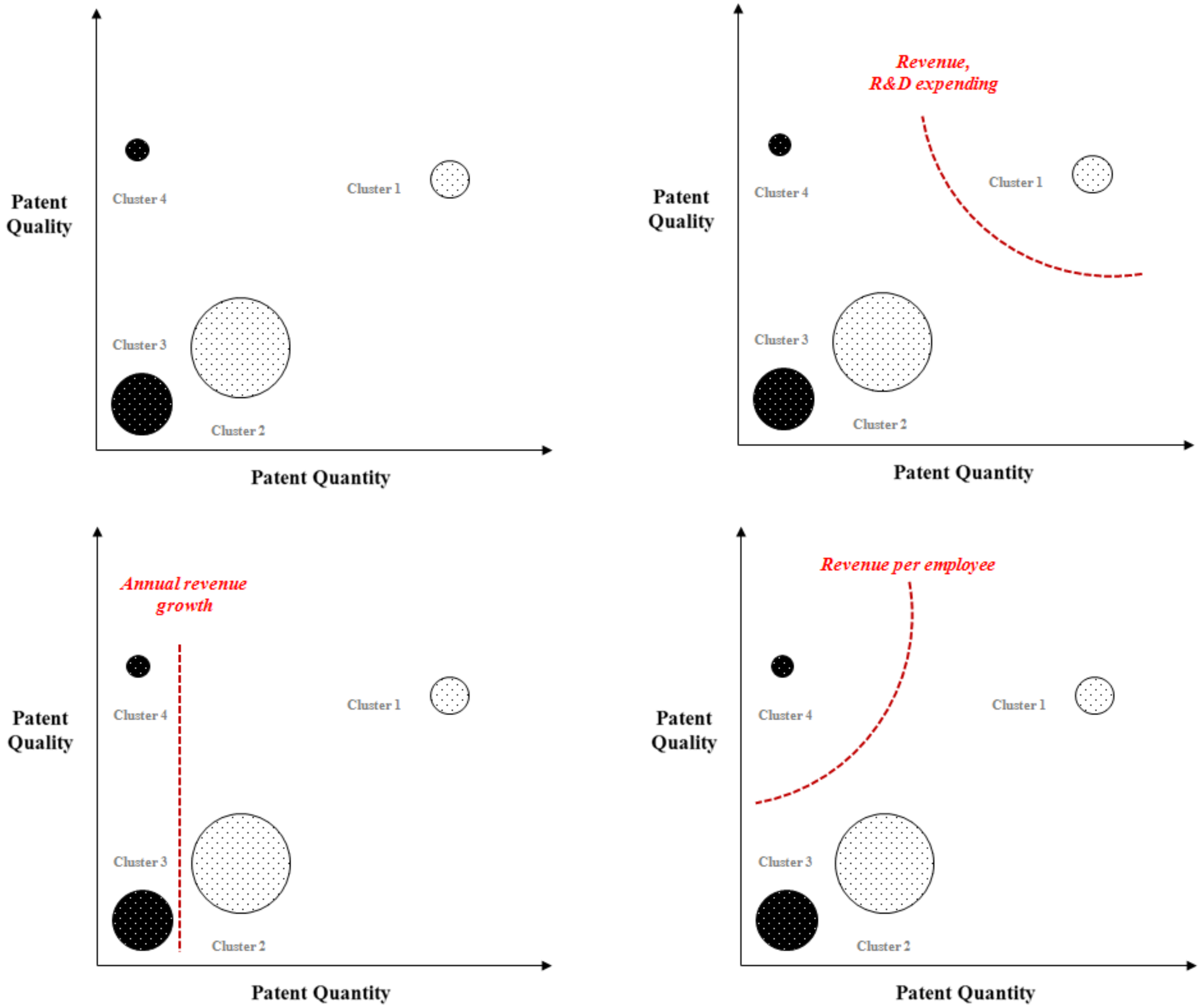

Figure 1. Quadrant of firm's patenting patterns. (1) Size of round: size of cluster, (2) Brightness of round: degree of patent technology concentration.

collect firms' information remain. First, even though the five financial variables are used to discriminate firm's patenting pattern in this research, there are several other factors indicating corporate performance, such as stock price, market share, competitiveness, reputation, etc. to be considered with firm's general characteristics. Second, this study deals with one-year financial performance. Time-series financial information can be used to analyze the impact of firm's patenting activities on business performance. Therefore, time-series financial data on firm level should be considered in future research.

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