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Examining the Relationship between Earnings and Patent Filings among Pharmaceutical Companies in Asia

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ABSTRACT

Asian pharmaceutical firms often take over a decade to develop new patentable technology, with costs running into billions of dollars. It is a widely held belief that the resulting patents determine the future viability of the firm. The purpose of this study is to examine the number of patent filings and the number of jurisdictional patent filings on the earnings of the firm. We find that a significant relationship exists between the number of patent filings and profitability, but no such relationship exists between the jurisdictional filings and profitability.

Keywords: Pharmaceutical, Patent Filing, Asian Health Care
JEL Classifications: F, G, M

1. INTRODUCTION

Due to a limited patent life, pharmaceutical companies must continue to innovate and develop new products in order to maintain the firm's profitability (Moro et al., 2016). In the Asian markets, patenting indicates a firm's future viability and profitability (Maresch et al., 2016). Specifically, patents reflect continuing innovations that drive the future success of the firm (Reaiche et al., 2016). The purpose of this study is to examine the number of patent filings and their impact on the profitability of Asian pharmaceutical companies.

During the study of patent applications and total factor productivity, Guo (2015) concluded that a more frequent filing of patent applications indicates the presence of an increase in innovation. Kumar and Sundarraj (2016) noted that when companies file patent applications consistently, these companies may protect themselves during challenging financial times. Patents, however, are expensive to acquire, and they can take up to 5 years to produce a positive effect on the bottom line (Agostini et al., 2015).

Rising innovation costs are causing organizations to evaluate the effectiveness of the innovation process and to seek more budgetary control (Dunk, 2011). There is a lack of comprehensive studies examining frequency of patent application filings and a lack of clarity regarding the jurisdictions in which to seek patent protection to foster the best financial performance. The purpose of this quantitative research study was to explore the relationship between frequency and jurisdictional range of patent application filings and financial performance in the pharmaceutical industry. The study may add to the body of knowledge related to the management of patents, specifically for companies that are overseeing research and development (R&D) budgets and global patent portfolios in the pharmaceutical industry. Understanding the extent of relationships among frequency and jurisdictional range of patent applications and financial performance may help companies to develop an effective approach to filing patent applications across the world.

The Asian pharmaceutical industry is characterized by an inherent risk that existing drug patents will expire or be successfully challenged by generic competitors. The development of new drugs

Table 1: Descriptive statistics – Financial metrics

Variable	n	Min	Max	M	SD
Revenue	96	100,000	9,530,460,000	359,929,113	1,432,443,245
Net profit margin	96	-12,208	1	-253	1,301
Market cap	96	18,335,942	84,990,760,740	2,975,702,787	9,875,744,837

Min: Minimum limit, Max: Maximum limit, M: Mean. SD: Standard deviation

Table 2: Skewness and kurtosis coefficients – financial metrics

Variable	n	Skewness		Kurtosis	
	Statistic	Statistic	SD Error	Statistic	SD Error
Revenue	96	5.707	0.246	33.995	0.488
Net profit margin	96	–8.484	0.246	77.229	0.488
Market cap	96	6.662	0.246	51.609	0.488

SD: Standard deviation. Skewness indicated the symmetry of the distribution. Kurtosis indicated the sharpness of the peak of the distribution

Table 3: Descriptive statistics - patent metrics

Variable	n	Min	Max	M	SD
Patent frequency	96	0	49	2.78	5.61
# Jurisdictions	96	1	2	1.55	0.50

Min: Minimum limit, Max: Maximum limit, M: Mean, SD: Standard deviation

Table 4: Skewness and kurtosis coefficients - patent metrics

Variable	n	Skewness		Kurtosis	
	Statistic	Statistic	SD Error	Statistic	SD Error
Patent frequency	96	6.331	0.246	49.353	0.488
# of Jurisdictions	96	–0.213	0.246	–1.997	0.488

SD: Standard deviation. Skewness indicated the symmetry of the distribution. Kurtosis indicated the sharpness of the peak of the distribution

Table 5: Kolmogorov-Smirnov statistics

Variable	Statistic	df	Sig.
Patent frequency	0.310	96	0.000
# of Jurisdictions	0.367	96	0.000
Revenue	0.425	96	0.000
Net margin	0.423	96	0.000
Market cap	0.382	96	0.000

df: The degree of freedom or n; Sig.: Statistical significance

Table 6: Durbin-Watson test

Dependent variable	Durbin-Watson
Revenue	1.441
Net profit margin	1.594
Market capitalization	1.710

Predictors (independent variables): Normalized jurisdictional range, normalized patent frequency

often takes over a decade and costs often run into the billions of dollars. Large pharmaceutical companies spend more than 15% of revenue on R&D (First Research, 2019).

Patents are a product of R&D from drug development (Hsu et al., 2013). However, not every innovation is subject to patent protection, and companies sometimes choose not to file a patent application even for innovations that might be patentable (Grupp and Schmoch, 1999). Nevertheless, an increase in patent application filings correlates positively to an increase in innovation, enhances productivity (Hsu et al., 2013), protects higher income (Moro et al., 2016), and contributes to economic growth (Guo, 2015).

Table 7: Pearson correlation statistics

Independent variable	Revenue	Net profit margin	Market capitalization
Patent frequency	0.375**	0.260*	0.266**
Jurisdictional range	0.170	–0.025	0.084

**Correlation is significant at the 0.01 level (2-tailed); *Correlation is significant at the 0.05 level (2-tailed)

Table 8: Multiple regression model analyses

Model	Dependent variable	Independent variables
1	Revenue	Patent frequency Jurisdictional range
2	Net profit margin	Patent frequency Jurisdictional range
3	Market capitalization	Patent frequency Jurisdictional range

Dependent variable financial performance is measured by revenue, net profit margin, and market capitalization

Table 9: Regression analysis results model 1: Revenue

Independent variable	P-value	R-squared	Correlation (r)
Patent frequency	0.001	0.141	0.375
Jurisdictional range	0.660	0.141	0.170

n=94, confidence level=95%

2. GLOBAL PHARMACEUTICAL INDUSTRY

According to MarketLine (2019), global pharmaceuticals is a $1,112 billion industry that has been growing at a compound annual growth rate of 4.5%. The pharmaceutical industry has been one of the most profitable sectors in the United States for years (IBIS World, 2019). The United States constitutes 35% of the global pharmaceuticals market value and is the largest filer of patent applications in the pharmaceutical industry, as illustrated by the patent search results in Figure 1 from the online database Lens.org using a classification code A61K. The Asia-Pacific region accounts for 29% of the global pharmaceuticals market value, and Europe for 26% (Line, 2019).

The global pharmaceutical industry is dominated by a small number of multinational corporations, various generics companies, and small biotech firms that are focused on a limited number of new products (Line, 2019). IBIS World (2019) analyzed the industry by dividing it into the following segments:

Table 10: Coefficients: Revenue

Model		Unstandardized coefficients		Standardized coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	238,926,967	689,479,110		0.347	0.730
	nPatentF	1,069,993,471	31,047,326	0.390	3.446	0.001
	nJurisdi	123,007,907	462,827,178	–0.030	–0.266	0.791

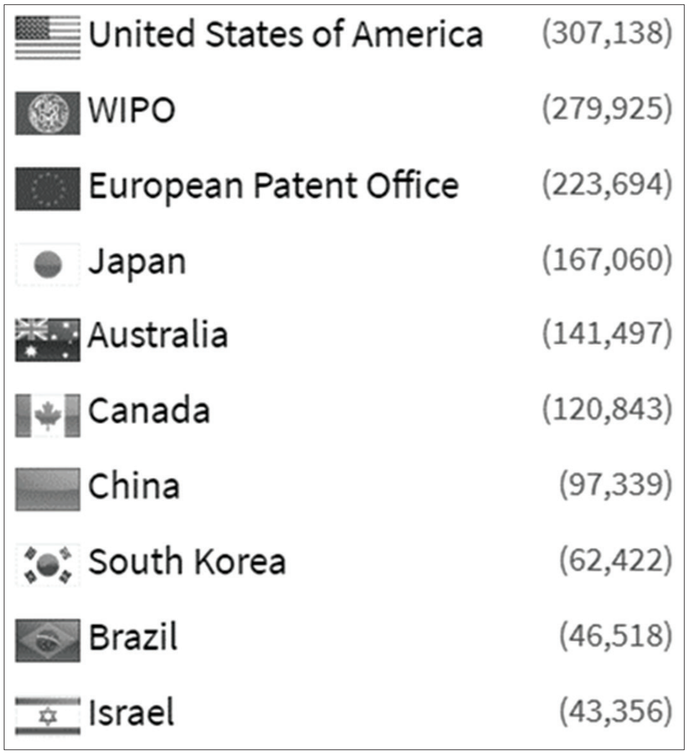
Dependent variable: nRevenue

Table 11: Regression analysis results model 2: Net profit margin

Independent variable	P-value	R-squared	Correlation (r)
Patent frequency	0.002	0.102	0.260
Jurisdictional range	0.065	0.102	–0.025

n=94, confidence level=95%

Figure 1: Jurisdictional breakout of patent application filings in the pharmaceutical industry



- Diabetes prescriptions
- Oncology prescriptions
- Autoimmune prescriptions
- Respiratory prescriptions
- Mental health and nervous system prescriptions
- Other prescriptions.

The key buyers in the pharmaceuticals market are pharmacies, hospitals, health insurance providers, and government health care programs. Major suppliers in the pharmaceutical industry are manufacturers of active pharmaceutical ingredients, which is a sub-sector of the chemical industry. Many leading pharmaceutical companies invest in chemical manufacturing, while others produce their own chemicals to improve the company's profitability (Line, 2019).

Agostini et al. (2015) indicated that the impact of patent filings on the companies' financial performance is industry-dependent, requiring an industry-specific analysis. Many industries rely on a constant flow of new products, making a continual investment in R&D that much more important (Chang et al., 2015a). Pharmaceutical companies compete to develop and commercialize more effective medicine for a variety of medical conditions, such as cardiovascular diseases, cancer, and diabetes. Global spending on medicine is increasing as a result of economic growth and the rising costs of specialty drugs (First Research, 2019).

3. DATA AND METHODS

This paper focuses on filings in Asia's two largest markets, China and Japan. Ninety-Six patent filings are examined against corporate earnings growth. Ordinary least squares (OLS) is used to determine the impact on profitability. The study's population consists of companies that have filings in China or Japan and are traded on NASDAQ. The OLS is represented by the following equation:

$$Y=\beta_0+\beta_1X_1+\beta_2X_2$$

Financial performance data, including revenue, net profit margin, and market capitalization, were pulled from Quandl for each year between 2013 and 2017. The data were entered into IBM SPSS Statistics 24 and analyzed using SPSS data analysis techniques.

4. DESCRIPTIVE ANALYSIS AND RESULTS

Aggregate descriptive statistics were generated for each of the metrics - financial and patent application counts - as illustrated in Tables 1-4. Table 1 shows revenue ranges from \$100,000 to \$9,530,460,000 with a mean of \$344,035,416 and standard deviation of \$1,360,546,714. The revenue range was very broad because, as First Research (2019) indicated, it takes more than 10 years to develop new drugs, and even longer to generate sales.

Most companies had a negative net profit margin ranging from (\$12,208) to positive \$1 with a mean of (\$253) and a standard deviation of \$1,301. This was not surprising as many pharmaceutical companies spend more than 15% of revenue on R&D (First Research, 2019). Market capitalization ranged from \$18,335,942 to \$84,990,760,740 with a mean of \$2,975,702,787 and standard deviation of \$9,875,744,837, revealing that the sample consisted of small and large companies.

Statistical methods included skewness and kurtosis. Skewness indicated the symmetry of the distribution. Kurtosis indicated the

Table 12: Coefficients: Net profit margin

Model		Unstandardized coefficients		Standardized coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	723	640		1.129	0.262
	nPatentF	92	29	0.371	3.204	0.002
	nJurisdi	–802	430	–0.216	–1.866	0.065

Dependent variable: nProfitMargin

Table 13: Regression analysis results model 3: Market capitalization

Independent variable	P-value	R-squared	Correlation (r)
Patent Frequency	0.012	0.074	0.266
Jurisdictional Range	0.547	0.074	0.084

n=94, confidence level=95%

sharpness of the peak of the distribution. In a normal distribution, the values of skewness and kurtosis are zero (Tabachnick and Fidell, 2013). Table 2 showed that variables had a skewness of greater than 5 and kurtosis of greater than 33, signifying that distribution was not normal.

Positive skewness suggests that data values are clustered to the left-hand side of a graph. Negative skewness indicates clustering of the values at the high end or the right-hand side of a histogram. According to Table 2, revenue and market capitalization had positive skewness, denoting that most values were clustered on the left-hand side of the graph and having mostly low values.

According to Table 3, patent frequency had a mean of 2.78, with a standard deviation of 5.61. Jurisdictional range had a mean of 1.55, with a standard deviation of 0.50. Most companies in the study did not file many patent applications. Frequency of the patent application filings depended on the size and the maturity of an organization. Several large and well-known pharmaceutical companies that were captured in the study filed a relatively large number of patent applications, while most of the smaller pharmaceutical companies filed a relatively small number of patent applications.

According to Table 4, jurisdictional range had negative skewness and kurtosis. Negative kurtosis values indicate that the distribution is flat.

The Kolmogorov-Smirnov statistic is used to assess the normality of distribution. The Kolmogorov-Smirnov test is appropriate only for continuous distributions of random samples. This study met the continuous distribution requirement, and the Kolmogorov-Smirnov statistic was used rather than other available statistical methods. The Kolmogorov-Smirnov test in Table 5 indicated the non-normality of the data. The Sig. value (i.e., P-value) of less than 0.05 indicated non-normality, and all variables had the P = 0.000.

Many statistical procedures, such as multiple regression, are sensitive to normality (Templeton, 2011). The diagnostics tests in this study showed that the dependent and independent variables had no linear relationship. Data had many significant outliers, and variables were not normally distributed. Templeton (2011) recommended transforming the data to improve the normality of variables.

To be able to analyze the relationship between the variables using a regression, data had to be transformed. A Two-Step approach was applied in IBM SPSS Statistics 24 to transform dependent and independent variables to improve the linearity of the data and to minimize variance (homoscedasticity). Step 1 involved selecting Rank Cases from the Transformation menu and creating a Fractional Rank. Step 2 consisted of computing variables by selecting Inverse DF as the Function Group and Idf. Normal as the Functions and Special Variables. New histograms and Normal Q-Q plots were generated after transformation to confirm normal distribution, linearity, and homoscedasticity.

Once normal distribution, linearity, homoscedasticity, and lack of significant outliers had been confirmed, independence of observations was checked using the Durbin-Watson statistics. The Durbin-Watson test checks the errors of adjacent observations and their correlation to each other. Because regressions must be run for each dependent variable separately, Table 6 presented the results for the Durbin-Watson test for each dependent variable: revenue, net profit margin, and market capitalization. The Durbin-Watson statistics can range from 0 to 4. The Durbin-Watson values for the three dependent variables were between 1.4 and 1.7, indicating that there was independence of residuals.

The final assumption that had to be checked to run a multiple regression was multicollinearity. Multicollinearity occurs when two or more independent variables are highly correlated with each other. When one independent variable predicts another independent variable, interpreting the regression results and identifying which variables contributed to the variance can be difficult.

Table 7 presented the outcomes of the correlation testing. No correlations were larger than 0.7, which is a threshold for multicollinearity. Collinearity statistics showed all Tolerance values greater than 0.1, and none of the VIF values greater than 10, indicating that the data set had no collinearity problems.

5. ANALYSIS OF HYPOTHESES

Three multiple linear regression models were used to predict a continuous dependent variable based on multiple independent variables, as displayed in Table 8.

Table 7 showed a significant positive correlation between patent frequency and revenue, r = 0.375, a significant positive correlation between patent frequency and net margin, r = 0.260, and a significant positive correlation between patent frequency and market capitalization, r = 0.266. Based on the results in

Table 14: Coefficients: Market capitalization

Model		Unstandardized coefficients		Standardized coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	4,419,973,766	4,934,467,793		0.896	0.373
	nPatentF	571,928,407	222,199,671	0.303	2.574	0.012
	nJurisdi	-2,004,549,189	3,312,364,034	–0.071	–0.605	0.547

Dependent variable: nMarketCap

Table 9, patent frequency had a P-value of 0.001, indicating with a confidence level of 95%, a statistically significant relationship between patent frequency and revenue. R-square was .141, meaning that 14.1% of variances in revenue could be explained by patent frequency. Using the values from Table 10, the regression equation for revenue is:

Y = 238,926,967 + 1,069,993,471 (Patent Frequency) + 123,007,907 (Jurisdictional Range)

Based on the results in Table 11, patent frequency had a P = 0.002, indicating with a confidence level of 95%, a statistically significant relationship between patent frequency and net profit margin. R-square was 0.102, meaning that 10.2% of variances in revenue could be explained by patent frequency. Using the values from Table 12, the regression equation for revenue is:

Y = 723 + 92 (Patent Frequency) - 802 (Jurisdictional Range)

Based on the results in Table 13, patent frequency had a P = 0.012, indicating with a confidence level of 95%, a statistically significant relationship between patent frequency and market capitalization. R-square was .074, meaning that 7.4% of variances in revenue could be explained by patent frequency. Using the values from Table 14, the regression equation for revenue is:

Y = 4,419,973,766 + 571,928,407 (Patent Frequency) - 2,004,549,189 (Jurisdictional Range)

6. CONCLUSION

For an Asian pharmaceutical firm, obtaining a patent can be costly both in terms of money spent and the amount of time it takes to procure a patent. Thus, it is of keen interest to these firms to examine the effect the number of patent filings and the number of jurisdictional filings have on earnings. We find that a significant relationship exits between the number of filings and earnings, but no significant relationship exists between the number of jurisdictional filings and earnings. The findings of this study may help organizations justify the decision to invest in R&D. The study also supports an establishment of an IP strategy to file patent applications frequently while control their jurisdictional breadth as an effective IP management process.

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