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Applying Quantile Regression to Assess the Relationship between R&D, Technology Import and Patent Performance in Taiwan

Chung-Chu Chuang [1], Chung-Min Tsai [2], Hsiao-Chen Chang [2,*] and Yi-Hsien Wang [2]

[1] Department of Management Sciences, Tamkang University, New Taipei City 251, Taiwan; ccchuang@mail.tku.edu.tw
[2] Department of Banking and Finance, Chinese Culture University, Taipei 111, Taiwan; charming0723@gmail.com (C.-M.T.); wyx12@ulive.pccu.edu.tw (Y.-H.W.)
* Correspondence: zxz@ulive.pccu.edu.tw; Tel.: +886-0921-120-790

Abstract: Electronics companies are facing global economic and trade competition. As patents can form an endowment shield that protects the development of corporate capabilities, companies are actively increasing their number of patents and attaching importance to technological research and development and patent management to achieve differentiated strategic effects. As such, patent layout and research and development (R&D) investment have become important strategic weapons for Taiwanese manufacturers, with which to enter the international market or compete among enterprises. This study first utilized the principal components analysis method to define patents in terms of the number of patents and the times patents are cited, with R&D defined in terms of expenditure and intensity. Furthermore, this study used a quantile regression model to visualize the relationship between R&D, technological imports, and patent performance in Taiwanese listed electronics companies. The empirical results show that technological imports in the second time-lag period require patents, while the effect on patents varies alongside industry characteristics. In addition, the empirical results found that the total assets, number of employees, and number of patent inventors are also factors that significantly affect patents. This research proposes that Taiwan's listed electronics companies should expand their scale, increase their economic efficiency, maximize their resources, increase their patents, enhance their corporate value, boost their investor confidence, and improve their industry competitiveness.

Keywords: patent; R&D; technology import; quantile regression

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1. Introduction

The global economy has been dominated by the knowledge-based economy since the 1990s, which has driven the prosperity of the electronics industry. The development of the electronics industry has always relied upon knowledge intensity and inventions. To achieve a competitive edge, the electronics industry relies upon intangible assets and knowledge rather than tangible assets such as cash, land, plants, or equipment. Taiwan's manufacturing industry has been rapidly restructuring, while Taiwan's electronics industry has been growing rapidly, filling the gap left by the relocation of traditional industries and becoming the backbone of Taiwan's economy.

In 1996, the Organization for Economic Cooperation and Development (OECD 1996) released a report titled "The Knowledge-Based Economy", which highlights that knowledge is an important factor of production. The knowledge-based economy refers to an economic system based on the ownership, allocation, generation, and use of knowledge. The era of the knowledge-based economy pursues constant innovation. As a result, the rapid growth of liberalization, globalization, and technologization has increasingly intensified the competition between enterprises. Furthermore, in the face of uncertainties within information technology (IT) development and the ever-changing external environment, innovation becomes the key to the survival of an enterprise.

Patents are an important metric to measure a company's innovative achievements and are an important part of intellectual properties. However, exclusive rights also entitle inventors to the ownership of the creative, intellectual activities they have engaged in and prevent others from making, selling, using, or importing patented inventions without the permission of the owner (Al-Jinini et al. 2019). As such, patents can protect a company's research and development (R&D) results and function as a competitive edge for enterprises. In the electronics industry, technology is advancing rapidly. As a result, electronics companies must invest heavily in developing new technologies and products so that they can seize the market and maintain their competitiveness. In addition, disclosure of a technological change in patent instructions can reveal details of an emerging, disruptive technology (Campbell 1983; Suominen et al. 2017). Disruptive technologies are an important intangible asset that plays an important role in enterprise sustainability. When a company owns a core patented technology, the company can attain a large market share. In this way, a patented technology becomes a major contributor to enterprise revenue. For example, Philips from the Netherlands owns the DVD specifications patent, and each year receives a large sum of royalties from Taiwanese optical disk-drive manufacturers. To this end, any enterprise should attach great importance to its patent performance in view of developing its technological innovation capability.

A patent is measured by two criteria. The first is quantity, which is the number of patents, and the second is quality, which refers to the times patents are cited. A direct effect of a patent is to enable the measurement of an enterprise's innovation results, and an indirect effect is the increase in an enterprise's bargaining power and competitiveness as well as enterprise value. Therefore, patents have always been a focus of enterprises. Enterprises such as Hon Hai Precision Industry and Taiwan Semiconductor Manufacturing Company (TSMC) attach significant importance to technological R&D and patent management to reduce costs, achieve differential strategic effects, and increase the number of patents. Further, patents can form an endowment shield to safeguard enterprise capability development, which exemplifies the importance of patents.

R&D expenditure is one of the most significantly influential factors for patents. The number of patents increases along with R&D expenditure. For example, Pakes and Griliches (1980), Lin and Lee (1996), and Montalvo (1997) found in empirical studies that R&D expenditure has a positive effect on the production of patents. However, some scholars argue that R&D input results in a disproportionate output, and therefore, they used R&D intensity to represent enterprise R&D and innovation strategy (Al-Fazari and Teng 2020). Fisher and Temin (1979), Acs and Audretsch (1988), Brouwer and Kleinknecht (1999) and Hall and Bagchi-Sen (2002) found that R&D intensity has a positive effect on the production of patents (Lee et al. 2017).

By paying royalties or technical maintenance costs for technological imports, enterprises can reduce the cost and time for R&D and prevent intellectual property infringement in obtaining new industrial technological patents. Yang and Chen (2001) found that technological imports have a significantly positive effect on patent applications. In addition, large organizations have complex structures, rich resources, and good risk tolerance (Johns 1993). Large organizations can afford to employ senior technicians, which is beneficial for technological R&D. Therefore, enterprise scale has an effect on technology innovation (Damanpour 1996; Al-Fazari and Teng 2020). However, Robinson and Stern (1998) argue that with effective and smooth information circulation within organizations, large organizations have better inventive capabilities. Lieberman (1987) found that patents increased with enterprise scale and market scale (Kim et al. 2018).

An industry represents a group of unique production or profit organizations. Different industries face different environments and survival conditions, and adopt different strategies. Accordingly, knowledge strategies are applied in different ways (Hansen et al. 1999; Anggadwita et al. 2019). The electronics industry has various characteristics. The effects of industry characteristics on patents should not be underestimated. In empirical studies relating to patents, Shih et al. (2020b) found that there were significant differences between the semiconductor industry and the computer peripherals and components industry, and also between the semiconductor industry and traditional and other industries. In the era of the knowledge-based economy, the role that humans play has evolved from labor only to the combination of information, technology, and mental labor. The exploitation of knowledge improves productivity and maintains sustainable economic growth. Wolfe (1994) argues that humans are one of the key factors that influence organizational innovation. Employee contribution or production is often reflected in enterprise revenue. Dzinkowski (2000) used employee productivity as an index for measuring enterprise human capital. Employee productivity can represent employee contributions to an enterprise (Caviggioli et al. 2020). Ayoub et al. (2017) argues that technological innovation can shorten the valid period of knowledge. Organizations must make human capital investments with a strategic view to improve enterprise productivity and gain a competitive edge. Doi (1996) found that enterprises with a larger number of employees were more motivated to use patents as a completive edge. The number of employees affects both the quantity and quality of patents. In addition, patent inventors are important assets of enterprises. This further reflects the importance of manpower (Siegel 2018). Mariani (2004) found that the number of patent inventors has a positive effect on the production of patents (Petruzzelli and Murgia 2020). Human capital is the source of enterprise growth, innovation, and strategic innovation. Methods for how to build, use, and measure human capital are of great concern to the industry and academic community (Manakhova et al. 2020).

The number of patents and the frequency of patent citations are two patent metrics. Some of the previous studies on patents discuss the correlation between patent metrics and enterprise value (Griliches 1981; Bosworth and Rogers 2001; Shih et al. 2020b; Grimaldi et al. 2018; Allison 2019); the influential factors contributing to the number of national patents (Inkmann et al. 2000; Sun 2003; Almeida et al. 2021); analyzed technological positions of European multinational enterprises in developing foreign activities through patents (Cantwell and Janne 1999); and measured the R&D capabilities and technologically innovative development of American states based on patents data (Acs et al. 2002; Grimaldi and Cricelli 2020). In view of the above, the relevant literature mostly uses causal models to discuss the direct impact of explanatory variables on corporate patents, but ignores the complexity of the data among explanatory variables and the problem of data allocation, which may cause potential problems of estimation bias. Therefore, this study first reduces the complexity among variables through principal component analysis and identifies the most important multiple characteristic variables, then uses the quantile regression model to explore the important characteristic variables of the patents of the shadow display enterprise under the quantiles of different components. The research results are helpful in increasing the completeness of industry economic and technological management theories. This paper comprises four parts: Part I, Introduction; Part II, Research Methods, including samples and data sources, operational definitions of variables, and the empirical model; Part III, Empirical Results Analysis; and Part IV, Conclusion and Suggestions.

2. Materials and Methods

2.1. Samples and Data Sources

Observations were obtained in the study. After deducting 23 observations (companies that were delisted) and 501 observations with incomplete financial data, a total of 986 observations were used. Information about the number of patents, frequency of patent citations, and the number of patent inventors of sample companies from 2000 to 2005 was obtained from the online patent database of the United States Patent and Trademark Office (USPTO). Financial data was obtained from TEJ and included R&D expenditure, gross revenue, total assets, number of employees, net profit after tax, royalties, and technology maintenance costs. From 2000 to 2005, many Taiwan listed electronics companies set up plants in mainland China, and subsequently applied for patents through their subsidiaries in mainland China. Therefore, we focused on parent companies listed in Taiwan during 2000 to 2005, excluding subsidiaries in mainland China.

Table 1 lists the distribution of samples in each year. Since 1993, Taiwan's electronics industry has invested heavily in semiconductors, kinescopes, and other key parts and products. The number of listed electronics companies increased year by year. After 2000, the number of listed electronics companies increased sharply but the number of delisted electronics companies also increased gradually, which was mainly attributable to the Taiwanese economic downturn. Improper investments or misappropriation of enterprise capital funds by substantial shareholders resulted in many bankruptcy cases.

Table 1. Research samples.

Year	Listed Company	Delisted Company	Incomplete Financial Information	Subtotal
2000	147	2	60	85
2001	193	1	95	97
2002	256	4	116	136
2003	286	1	107	178
2004	312	5	75	232
2005	316	10	48	258
total	1510	23	501	986

This study bases the characteristics of the electronics industry on the six categories classified by the "Industry & Technology Intelligence Services" (ITIS) of the Department of Industry Technology, Ministry of Economic Affairs. These characteristics are as follows: (1) semiconductor (wafer, mask, transistor, thyristor, diode, memory, integrated circuit manufacturing, design, testing, and packaging); (2) photoelectricity/IO (photoelectric materials and components, optical instruments and equipment, flat panel display, picture tube, battery); (3) network communications (network interface controller, hub, switch, modem, mobile phone, mobile phone parts, Internet service); (4) electronic parts (PCB, computer main board, barebone, computer chassis, adapter, power supply unit, capacitor); (5) computers and peripherals (desktop PC, laptop, mini-notebook, electronics, display, terminal manufacturing); (6) other electronics (household electrical appliances, software, consumer electronics, circuit, other electronics that cannot be classified into previous categories). Table 2 lists the distribution of the industry characteristics of the samples. The computer peripherals and parts category contains the largest number of samples (309), followed by photoelectricity/IO (205), and computers and peripherals (97).

Table 2. Distribution of industry characteristics of samples.

Industry Characteristics	2000	2001	2002	2003	2004	2005	Total
Semiconductor	13	14	18	24	29	36	134
Photoelectricity/IO	17	23	28	38	47	52	205
Network communications	12	12	14	14	22	24	98
Electronic parts	23	27	46	59	74	80	309
Computers and peripherals	11	11	13	16	22	24	97
Other electronics	9	10	17	27	38	42	143
Total	85	97	136	178	232	258	986

This study focuses mainly on patent variables and the perspectives of different industries in order to analyze their impacts on operating performance, and the current patent research takes a strategic perspective to discuss and analyze those impacts. As patents have the function of monopolizing the market, enterprises can thus improve their wealth and that of shareholders. Defending the effect of innovative research and development can also be a bargaining chip for negotiating a win–win strategy, so patent litigation is a powerful tool for companies (Park and Park 2004; Chang et al. 2015). In addition, companies continue to enhance their value through continuous innovation in industrial competition. However, although small-scale companies have superior innovative capabilities, they are too small in scale, immature in technology, and limited in capital, and innovation is easily affected by resources. Similar large companies compulsorily acquire their core patents (Bessen and Maskin 2009; Shih et al. 2020a).

Further to this, high-cost and long-term patent litigation creates unknown risks in the stock market. As such, for investors, there are many uncertain factors hidden in the patent litigation process. Patent diversity and scale have a significant impact on the company's corporate value, causing the company's operation progress to be delayed or its value to be reassessed. The results of the litigation will also reflect the stock price through media reports, sometimes overreacting or too late to react, giving investors the opportunity to obtain compensation for the difference in stock price (Koku et al. 2001; Bhagat and Romano 2002; Lee et al. 2013).

2.2. *Operational Definitions of Variables*

2.2.1. Explained Variable

1. Patent: Based on principal component analysis, the number of patents and frequency of patent citations of each company are defined as the first principal component named as a patent. This is example 1 of an equation:

$$\text{Patent} = 0.947 \times \text{number of patents} + 0.947 \times \text{frequency of patent citations} \tag{1}$$

2. Principal component analysis (PCA): A dimensionality-reduction method that is often used to reduce the dimensionality of large data sets by transforming a large set of variables into a smaller one that still contains most of the information in the large set.

2.2.2. Explanatory Variables

1. R&D: In this study, according to the practice in Yang and Chen (2001) based on principal component analysis, the R&D expenditure and R&D intensity of each company in the current period (RD_t) and the two consecutive time lag periods are defined as the first principal component, named RD.

   RD_t = 0.806 × R&D expenditure + 0.806 × R&D intensity.
   RD_{t-1} = 0.808 × R&D expenditure + 0.808 × R&D intensity.
   R&D in the second time lag period RD_{t-2} = 0.821 × R&D expenditure + 0.821 × R&D intensity

2. Technological import: In this study, according to the practice in Yang and Chen (2001), royalties and maintenance costs in the current period and the two consecutive time lag periods are defined as technological imports.

2.2.3. Control Variables

1. Total assets: total assets of each company in each year. This is a proxy variable of enterprise scale.
2. Number of employees: total number of employees of each company in each year. This is a proxy variable of enterprise scale.
3. Employee productivity: Employee productivity = Net profit after tax/number of employees in each year.
4. Number of patent inventors: number of patent inventors of each company in each year.

2.2.4. Disturbance Variable

Industry characteristic: As classified by ITIS, dummy variable semiconductor is set to 1; dummy variable photoelectricity/IO is set to 2, dummy variable network communications is set to 3; dummy variable electronic parts is set to 4; dummy variable computers and peripherals is set to 5; and dummy variable other electronics is set to 0.

2.3. Empirical Model

This study applies principal component analysis to define R&D expenditure and R&D intensity as R&D. R&D and technological imports are used as explanatory variables. The number of employees, total assets, employee productivity, and number of patent inventors are used as control variables. Industry characteristics are used as a disturbance variable. Since the previous ordinary least squares (OLS) method is based on the conditional average of the explained variable, the regression coefficient represents "on average, the marginal influence of each explanatory variable on the explained variable", and cannot fully describe the characteristics of the research data on the unconditional average. That is, the coefficient estimates only represent the concept of average and cannot explain the relationship between the dependent variable and the independent variable in different components (Huang et al. 2017). To make up for the limitation of the OLS method, this study adopts quantile regression to describe the characteristics of the research data in different conditional components. Especially for large enterprises and small- and medium-sized enterprises, whether in input or output, there are considerable differences in the number, which is suitable for analyzing the effect of strain number on the overall condition allocation. Finally, in the setting of the model, if the distribution of the error term is heterogeneous or abnormal, the component regression estimation method is more effective than the OLS estimate (Buchinsky 1998).

In the relevant empirical literature on innovation issues, most research focuses on the relationship between innovative activities and performance. With the expansion of the research scope, more related studies used quantile regression to further discuss the matter, with different quantile distributions (Coad and Rao 2008; Ebersberger and Herstad 2013; Wei et al. 2017; Cardamone 2021). This study uses the following empirical model to discuss the effects of preceding variables on patents. This is example 2 of an equation:

$$\hat{\beta_\theta} = argmin\left[\theta \sum\nolimits_{y_t \geq x'_t} \left|y_t - x'_t\beta\right| + (1-\theta) \sum\nolimits_{y_t \leq x'_t\beta} \left|y_t - x'_t\beta\right|\right] \tag{2}$$

where θ is quantile; y is the number of patents at the tth observed value; x'_t is a 16×1 vector, representing the tth observed value of each variable (R&D, technological import, number of employees, total assets, employee productivity, number of patent inventors, interaction between industry characteristic and R&D in each period, and interaction between industry characteristics and technological imports in each period); and β is a 16×1 vector, and a coefficient of regression for each explanatory variable.

3. Empirical Result Analysis

3.1. Basic Statistical Analysis

This study employs principal component analysis to define the number of patents and frequency of patent citations of each company in each year as the first principal component, which is used as a proxy variable of a patent (Tsai 2007). Table 3 lists the quantile distribution analysis of the dependent variable. The patent standard deviation of all samples is 254.1 (maximum: 3226.29 of TSMC in 2001; minimum: 0). A total of 552 observations are involved. The coefficient of skewness is 9.93 and the kurtosis coefficient is 106.39. As listed in Table 3, the samples show significant differences between patents. About 50% of the observations have zero patents. When the quantile is greater than 75%, the patent gap increases, which further highlights the right-skewed distribution of the samples. When the quantile is 0.99, the patents are owned by several specific enterprises, such as Hon Hai Precision Industry, TSMC, and United Microelectronics.

Table 3. Basic statistical analysis of dependent variable.

Quantile	Patent (pcs)	Quantile	Patent (pcs)
0.00	0	0.50	0
0.10	0	0.75	6.52
0.05	0	0.90	41.01
0.10	0	0.95	98.79
0.25	0	0.99	1126.79

Note: Standard deviation of all samples is 254.10 (maximum: 3226.29; minimum: 0), skewness is 9.93, and Kurtosis coefficient is 106.39.

The results of basic statistical analysis of independent variables are shown in Table 4 (Tsai 2007). Overall, among all variables, the standard deviation value is very large, which is attributable to the great variance of R&D in the current period, technological imports in the current period, total assets, number of employees, employee productivity, and number of patent inventors among the samples.

Table 4. Basic statistical analysis of independent variables.

Variable	Maximum	Minimum	Mean	Standard Deviation
R&D	10,797,015.65	0	460,835.49	1,119,879.05
Technology import (NTD Thousand)	2,445,478	0	41,467.43	191,437.81
Total assets (NTD Thousand)	507,539,815	476,335	23,487,077.00	53,199,911.12
Number of employees (person)	29,070	10	1434.17	2496.80
Employee productivity (NTD Thousand)	25,856.16	−64,013.47	270.59	4172.05
Number of patent inventors (person)	853	0	15.18	64.53
Industry characteristic	5	0	2.60	1.61

3.2. Analysis of Correlation

Table 5 lists the results of correlation analysis among all variables (Tsai 2007). At the 5% significance level, patents show an insignificantly positive correlation with technological imports, an insignificantly negative correlation with the industry characteristic, and a significantly positive correlation with all other variables.

Variable and independent variable correlation analysis: as listed in Table 5, at the 5% significance level, R&D in the current period shows a significant negative correlation with the industry characteristic and a significant positive correlation with all other variables. At the 5% significance level, technological imports in the current period show a significant positive correlation with the total assets, number of employees, and number of patent inventors, and show as significant negative correlation with the industry characteristic. At the 5% significance level, the total assets show an insignificant negative correlation with the industry characteristic, and a significant positive correlation with all other variables. At the 5% significance level, the number of employees shows a significant positive correlation with employee productivity and the number of patent inventors, and an insignificant negative correlation with the industry characteristic. The employee productivity shows an insignificant negative correlation with the industry characteristic, and a significant positive correlation with all other variables. At the 5% significance level, the number of patent inventors shows a significant negative correlation with the industry characteristic, and a significant positive correlation with all other variables.

Table 5. Variable correlation analysis.

	Patent	R&D	Technology Import	Total Assets	Number of Employees	Employee Productivity	Number of Patent Inventors	Industry Characteristic
Patent								
R&D	0.520 ** (0.000)							
Technology import	0.026 (0.410)	0.289 ** (0.000)						
Total assets	0.519 ** (0.000)	0.821 ** (0.000)	0.330 ** (0.000)					
Number of employees	0.340 ** (0.000)	0.647 ** (0.000)	0.241 ** (0.000)	0.839 ** (0.000)				
Employee productivity	0.119 ** (0.000)	0.125 ** (0.000)	0.022 (0.489)	0.159 ** (0.000)	0.093 ** (0.003)			
Number of patent inventors	0.682 ** (0.000)	0.826 ** (0.000)	0.172 ** (0.000)	0.783 ** (0.000)	0.583 ** (0.000)	0.104 ** (0.001)		
Industry characteristic	−0.039 (0.221)	−0.091 ** (0.004)	−0.075 * (0.019)	−0.053 (0.095)	−0.020 (0.525)	0.024 (0.449)	−0.102 ** (0.001)	

Note: 1. ** (*) represents that, at the significance level of 1% (5%), correlation is significant. 2. This study uses Pearson Product-moment Correlation Analysis. Figures in brackets are two tailed *p*-values.

3.3. *Quantile Regression Analysis*

General regression analysis relates to the mean conditional distribution. However, such analysis results may be negatively affected by extreme sample values or if residuals do not follow a normal distribution. To this end, this study employs quantile regression that does not require any hypothesis on the distribution. With conditional distribution of the same samples under different quantiles, this study discusses the changes in the coefficient of regression estimates. This study uses patents as the explained variable and R&D in the current period (RD_t), R&D in the first time lag period (RD_{t-1}), R&D in the second time lag period (RD_{t-2}), technological imports in the current period (TI_t), technological imports in the first time lag period (TI_{t-1}), and technological imports in the second time lag period (TI_{t-2}) as the explanatory variables. The total assets, number of employees, employee productivity, and number of patent inventors are used as the control variables and the industry characteristic as a disturbance variable. This study discusses the significance and stability of the coefficient of regression estimates with different quantiles: 0.05, 0.1, 0.25, 0.5, 0.75, 0.9, and 0.95.

3.3.1. Analysis of Influencing Factors on Patents of Listed Electronics Companies

Table 6 lists the coefficient of quantile regression estimates and verification results. When the quantile is 0.95, the model has the best explanatory ability, which is up to 79.74%. With other quantiles, the explanatory ability of the model ranges from 16% to 70%, which indicates that the model has better explanatory ability when the quantile value is greater (Tsai 2007). When the quantile is less than 0.25, the coefficient estimate of RD_t is a negative value. At the 5% significance level, only when the quantile is 0.1, RD_t has a significantly negative effect on patents. When the quantile is greater than 0.25, the RD_t is a positive value. With different quantiles, the coefficient sign is different and RD_t has different effects on patents. These results are inconsistent with the conclusion of Pakes and Griliches (1980), which was obtained using a log-linear model, which may be attributable to the effects of samples with zero patents when the quantile is less than 0.25.

Table 6. Coefficient of quantile regression estimate and verification.

Variable \ Quantity	0.05	0.1	0.25	0.5	0.75	0.9	0.95
RD_t	-2.69×10^{-7} * (1.76×10^{-7})	-3.66×10^{-7} ** (1.51×10^{-8})	7.99×10^{-7} ** (1.52×10^{-8})	5.97×10^{-6} ** (7.67×10^{-8})	1.19×10^{-5} ** (5.27×10^{-7})	1.16×10^{-5} ** (1.17×10^{-6})	2.57×10^{-5} ** (2.65×10^{-6})
RD_{t-1}	−1.7759 (0.7285)	−0.1196 (0.1300)	0.3733 ** (0.1164)	1.7559 ** (0.5267)	21.6297 ** (2.1761)	40.4569 ** (4.8190)	98.9267 ** (6.5939)
RD_{t-2}	1.63×10^{-6} ** (2.25×10^{-7})	5.27×10^{-7} ** (2.09×10^{-8})	-3.92×10^{-6} ** (1.35×10^{-8})	-1.86×10^{-5} ** (6.72×10^{-8})	-5.30×10^{-5} ** (4.59×10^{-7})	-7.11×10^{-5} ** (9.42×10^{-7})	-2.33×10^{-5} ** (1.05×10^{-6})
TI_t	7.82×10^{-6} ** (7.04×10^{-7})	7.55×10^{-6} ** $(1.23E \times 10^{-7})$	1.24×10^{-5} ** (6.86×10^{-8})	-2.82×10^{-5} ** (4.29×10^{-7})	-3.77×10^{-5} ** (1.47×10^{-6})	-2.39×10^{-5} ** (4.10×10^{-6})	3.63×10^{-5} ** (4.13×10^{-6})
TI_{t-1}	-7.24×10^{-6} ** (8.23×10^{-7})	-8.44×10^{-6} ** (1.18×10^{-7})	-2.86×10^{-5} ** (1.09×10^{-7})	-1.45×10^{-6} * (6.08×10^{-7})	-4.16×10^{-5} ** (2.70×10^{-6})	-7.47×10^{-5} ** (4.87×10^{-6})	1.62×10^{-5} ** (4.06×10^{-6})
TI_{t-2}	-7.04×10^{-6} ** (7.80×10^{-7})	-1.18×10^{-5} ** (1.28×10^{-7})	-4.50×10^{-6} ** (1.16×10^{-7})	-3.62×10^{-6} ** (5.18×10^{-7})	-1.68×10^{-5} ** (2.67×10^{-6})	-8.54×10^{-5} ** (4.95×10^{-6})	−0.0003 ** (4.32×10^{-6})
TA	9.67×10^{-9} ** (5.88×10^{-9})	2.86×10^{-9} ** (5.47×10^{-10})	1.10×10^{-9} ** (3.20×10^{-10})	4.88×10^{-9} ** (1.48×10^{-9})	1.38×10^{-7} ** (7.95×10^{-9})	4.58×10^{-7} ** (1.48×10^{-8})	3.62×10^{-8} * (2.14×10^{-8})
E	−0.0008 ** (0.0001)	−0.0002 ** (9.68×10^{-6})	−0.0001 ** (4.76×10^{-6})	-6.48×10^{-5} ** (2.11×10^{-5})	−0.0002 ** (9.94×10^{-5})	-0.0019 ** (0.0003)	−0.0006 ** (0.0004)
EP	-9.10×10^{-7} (4.20×10^{-5})	4.51×10^{-7} (2.12×10^{-6})	6.07×10^{-7} (1.18×10^{-6})	-2.08×10^{-6} (6.75×10^{-6})	-3.73×10^{-5} (3.86×10^{-5})	1.64×10^{-5} (1.34×10^{-4})	3.92×10^{-5} (0.0003)
PI	0.5372 ** (0.0030)	0.5757 ** (0.0003)	0.8588 ** (0.0002)	1.6886 ** (0.0009)	3.8610 ** (0.0057)	7.1203 ** (0.0180)	7.7642 ** (0.0357)
$IC \times RD_t$	1.40×10^{-7} (7.00×10^{-8})	1.32×10^{-7} ** (5.86×10^{-9})	4.96×10^{-7} ** (4.91×10^{-9})	1.07×10^{-6} ** (2.47×10^{-8})	1.55×10^{-6} ** (1.43×10^{-7})	8.83×10^{-6} ** (4.29×10^{-7})	1.14×10^{-5} (7.82×10^{-7})
$IC \times RD_{t-1}$	−1.8222 (1.6723)	−0.1345 (0.1781)	0.1383 (0.1513)	1.7593 ** (0.6242)	−0.5476 (2.9710)	5.2517 (7.3048)	−49.8663 (14.9548)
$IC \times RD_{t-2}$	0.2869 (0.4306)	−0.0123 (0.0431)	−0.0909 ** (0.0336)	−0.3703 ** (0.1427)	0.2961 (0.7320)	−2.4905 (1.7045)	4.5854 (3.4740)
$IC \times TI$	-1.80×10^{-6} ** (2.15×10^{-7})	-1.74×10^{-6} ** (3.26×10^{-8})	-3.30×10^{-6} ** (2.13×10^{-8})	4.72×10^{-6} ** (1.19×10^{-7})	2.17×10^{-6} ** (4.10×10^{-7})	6.01×10^{-8} (1.14×10^{-6})	-2.11×10^{-5} (1.41×10^{-6})
$IC \times TI_{t-1}$	1.64×10^{-6} ** (4.34×10^{-7})	1.76×10^{-6} ** (5.97×10^{-8})	6.74×10^{-6} ** (6.13×10^{-8})	2.75×10^{-7} ** (2.36×10^{-7})	1.78×10^{-5} ** (1.26×10^{-6})	2.72×10^{-5} ** (2.82×10^{-6})	-4.55×10^{-6} (1.89×10^{-6})
$IC \times TI_{t-2}$	1.57×10^{-6} ** (5.80×10^{-7})	3.20×10^{-6} ** (1.01×10^{-7})	1.05×10^{-7} ** (8.84×10^{-8})	8.51×10^{-6} ** (3.55×10^{-7})	1.90×10^{-5} ** (1.78×10^{-6})	5.67×10^{-5} ** (3.96×10^{-6})	0.0001 ** (3.37×10^{-6})
Intercept	−0.0163 (0.1493)	0.0036 (0.0135)	0.0320 ** (0.0097)	0.0940 * (0.0430)	0.5330 * (0.2443)	4.1844 ** (0.6254)	3.8615 ** (1.0501)
Pseudo R^2	0.1649	0.1765	0.2220	0.3188	0.5068	0.7073	0.7974

Note: 1. ** (*) represents that at the significance level of 1% (5%), correlation is significant. 2. Figures in brackets are standard errors which are calculated using bootstrapping method. 3. Pseudo $R^2 = 1 -$ (Weighted residual of estimated quantile/Sum of weighted residual of original quantile). 4. Model: $\hat{\beta_\theta} = argmin\left[\theta \sum_{y_t \geq x'_t} |y_t - x'_t\beta| + (1-\theta) \sum_{y_t \leq x'_t\beta} |y_t - x'_t\beta|\right]$ where θ is quantile; y is the number of patents at the tth observed value; x'_t is a 27×1 vector, representing the tth observed value of each explanatory variable; and β is a 27×1 vector, and a coefficient of regression for each explanatory variable.

The coefficient estimate of R&D in the first time lag period is a negative value. When the quantile is greater than 0.25, the coefficient estimate of RD_{t-1} is a positive value. RD_{t-1} has a positive effect on patents. With different quantiles, the coefficient sign is different and RD_{t-1} has different effects on patents. These results are inconsistent with the conclusion of Montalvo (1997), which was obtained using a generalized method of moments and conditional maximum likelihood estimation, which may be attributable to the effects of samples with zero patents when the quantile is less than 0.25.

The coefficient estimate of RD_{t-2} is a positive value when the quantile is less than 0.25. That is, RD_{t-2} has a positive effect on patents. When the quantile is greater than 0.25, the coefficient estimate of RD_{t-2} is a negative value. RD_{t-2} has a negative effect on patents. The sign is different and RD_{t-2} has different effects on patents with different quantiles. These results are inconsistent with the conclusion of Lin and Lee (1996), which was obtained by a negative binomial model, which may be attributable to decreasing returns to scale. That is, the patent output increase proportion is smaller than the input increase proportion.

When the quantile is 0.05, 0.1, 0.25, and 0.95, the coefficient estimates of TI_t are positive values. That is, TI_t has a positive effect on patents. When the quantile is 0.5, 0.75, and 0.9, the coefficient estimates of TI_t are negative values; TI_t has a negative effect on patents. With different quantiles, TI_t has different effects on patents, which may be because most samples with a quantile ranging from 0.5 to 0.9 are photoelectric companies. These companies, such as RITEK and Cenpro Technology, choose technological imports to prevent infringement and do not prioritize technological innovation during the sample period.

When the quantile is 0.95, the TI_{t-1} has a positive effect on patents. When the quantile is less than 0.95, the coefficient estimate of TI_{t-1} is a negative value. That is, TI_{t-1} has a negative effect on patents. With different quantiles, TI_{t-1} has different effects on patents, which may be due to imported technologies or enterprises with more patents choosing to improve and innovate to increase future patents. TI_{t-2} has negative values with different quantiles. The technological imports in the second time lag period have a positive effect on patents.

This study finds that, with technological imports with different quantiles, the signs of coefficient estimates of technological imports in different periods are different, which weakens the reliability of the model. This finding is inconsistent with the conclusion of Yang and Chen (2001), which was obtained by the generalized method of moments. In terms of technology in the current period or the first time lag period, for other technologies, enterprises with more patents tend to improve and innovate to maintain their competitiveness. This also indicates that technological imports have a time lag effect on enterprises' innovative activities.

With different quantiles, total assets have a positive effect on patents in different quantiles, which is consistent with the conclusion of Lieberman (1987), which was obtained using a negative binomial model, indicating that large-scale enterprises are driven more by innovation, and therefore, gain an edge in innovation.

With different quantiles, coefficient estimates of the number of employees are negative values. The number of employees has a negative effect on patents, which is inconsistent with the conclusion of Doi (1996), obtained using a log-linear model, which may be attributable to decreasing returns to scale. That is, when the number of employees increases at a certain proportion, the patent output increase proportion is smaller than the input increase proportion.

When the quantile is 0.05, 0.5, and 0.75, employee productivity has negative values. When the quantile is 0.1, 0.25, 0.9, and 0.95, coefficient estimates of employee productivity have positive values. With different quantiles, the signs of coefficient estimates of employee productivity are different, suggesting that employee productivity has different effects on patents.

With different quantiles, coefficient estimates of the number of patent inventors are positive values. At the 5% significance level, correlation is significant. That is, the number of patent inventors has a positive effect on patents, which is consistent with the conclusion of Mariani (2004), which was obtained using a negative binomial model, indicating that enterprises with more patent inventors have more resources to enable technological breakthroughs.

3.3.2. Analysis of Influencing Factors on Patents within the Same Electronics Industry Characteristic

The coefficient estimates of interactions between industry characteristics and RD_t have positive values. That is, interaction between industry characteristics and RD_t has a positive effect on patents.

When the quantile is 0.5, the coefficient estimate of the interaction between industry characteristics and RD_{t-1} is a positive value. That is, interaction between the industry characteristic and RD_{t-1} has a positive effect on patents. In addition, there is interaction between industry characteristics and RD_{t-2} when the quantile is 0.25 and 0.5, respectively. With different quantiles, the interactions between industry characteristics and RD_{t-1} and between industry characteristic and RD_{t-2} do not show a significant effect. This indicates that, for most samples, RD_{t-1} and RD_{t-2} have no effect on patents due to different industry characteristics; only RD_t has an effect on patents due to different industry characteristics.

The coefficient estimates of interaction between industry characteristics and TI_t are negative values. Interaction between industry characteristics and TI_t has a negative influence on patents. When the quantile is 0.5, 0.75, and 0.9, the coefficient estimates of interactions between industry characteristics and TI_t are positive values. The interactive effect of industry characteristics and TI_t has a positive influence on patents.

When the quantile is less than 0.95, the coefficient estimate of interaction between industry characteristics and TI_{t-1} is a positive value. That is, the interaction between industry characteristics and TI_{t-1} has a positive influence on patents. When the quantile is 0.95, the coefficient estimate of interaction between industry characteristics and TI_{t-1} is a negative value. The interaction between industry characteristics and TI_{t-1} has a negative influence on patents.

With different quantiles, the coefficient estimates of interactions between industry characteristics and TI_{t-2} are positive values. The interaction between industry characteristics and TI_{t-2} has a positive influence on patents.

With different quantiles, the interaction between industry characteristics and technological imports in each period shows a significant effect, indicating that technological imports in each period have different effects on patents due to different industry characteristics. When the quantile is 0.95, interaction between industry characteristics and technological imports in each period shows a less significant effect, which may be because enterprises with a large number of patents have minor differences in technological imports in each period due to different industry characteristics.

As listed in Table 6, with different quantiles, the coefficient estimates of total assets and the number of patent inventors have positive values, whereas TI_{t-2} and the number of employees have negative values. Therefore, the five variables show high stability and influence the model, though variables include both positive and negative values. In addition, with different quantiles, the five variables have a significant influence, and therefore are major influential factors for patents. With the disturbance variable of the industry characteristic, only interaction between the industry characteristic and TI_{t-2} has a positive coefficient estimate with different quantiles and shows significant influence. Therefore, TI_{t-2} has different effects on patent outputs due to different industry characteristics.

In addition, when the quantile ranges from 0.75 to 0.95, the sign of coefficient estimates of variables is consistent, which indicates that the number of samples with zero patents has a certain influence on the stability of the model.

4. Conclusions and Suggestions

4.1. Conclusions

This study aimed to discuss the correlation between R&D, technology, and patents in Taiwanese listed electronics companies. This study focused on Taiwan's listed electronics companies from 2000 to 2005 and applied principal component analysis to define the number of patents and frequency of patent citations to represent patents, and defining R&D expenditure and R&D intensity to represent R&D. R&D and technological imports were used as two explanatory variables. The number of employees, total assets, employee productivity, and number of patent inventors were used as control variables. Industry characteristics were used as a disturbance variable. This study discussed the significance and stability of coefficient estimates of explanatory variables with different quantiles. The research concluded that, when the quantile is 0.95, there are separate interactions between industry characteristics and R&D in the current period. R&D in two consecutive time lag periods, technological imports in the current period, and technological imports in two consecutive time lag periods generally show no significant correlation. This indicates that enterprises with a large number of patents have minor differences in these variables with different industry characteristics. In terms of the overall distribution of samples, about 50% of samples have zero patents. For these enterprises, the significance and stability of coefficient estimates of explanatory variables are low. In addition, patents are principally owned by several specific enterprises, such as Hon Hai Precision Industry, TSMC, and

United Microelectronics. A significant gap in the number of patents approved in the U.S. and the frequency of patent citations is also observed. Therefore, it can be interpreted that enterprises with a large number of patents prioritize both technological innovation and resource input and allocation. The latter also has an influence on patents. To this end, some Taiwanese electronics companies always have the Matthew Effect patented.

Taiwanese listed electronics companies must have certain innovative plans and patent strategies for R&D or technological import to maintain their technological advantages. They should gradually increase the number of patents and frequency of patent citations so that their technologies can act as their competitive edge. Further, they should maintain their benefits and gain market exclusivity through patent protection. Taiwanese listed electronics companies should expand their enterprise scale, increase their economic benefits, and reduce internal costs to achieve economies of scale, boost investor confidence, and increase their industry competitiveness. In the era of a knowledge-based economy, people are important assets of companies. The development of patent inventors is greatly helpful in improving technological innovation capabilities. This can change the current situation in that patents are owned by several specific companies. In view of serious plagiarism in the electronics industry and high turnover rate, the development of talent helps achieve inheritance of technologies. Enterprises must focus on both the quality and quantity of patents and keep abreast of industry and market trends, and accordingly, devise and optimize patent policies and strategies. Business operations can increase enterprise values under the guidance of patent policies and strategies. This study uses quantile regression to describe the characteristics of the research data in different conditional components. Especially for enterprises of various sizes (such as large enterprises and small- and medium-sized enterprises), in terms of inputs and outputs, the difference in the causal relationship between the variables is suitable for detailed analysis of the impact on the overall output's conditional distribution.

4.2. Research Limitations

(1) This study focused on Taiwan's listed electronics companies and therefore, the conclusion does not apply to the whole electronics industry.

(2) Over recent years, many Taiwan listed electronics companies set up plants in mainland China, and subsequently applied for patents through their subsidiaries in mainland China. This study focused on parent companies listed in Taiwan during 2000 to 2005, excluding subsidiaries in mainland China.

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References

Acs, Zoltan J., and David B. Audretsch. 1988. Innovation in Large and Small Firms: An Empirical Analysis. *American Economic Review* 78: 678–90.

Acs, Zoltan J., Luc Anselin, and Attila Varga. 2002. Patents and Innovation Counts as Measures of Regional Production of New Knowledge. *Research Policy* 31: 1069–85. [CrossRef]

Al-Fazari, Hamdan, and Jimmy Teng. 2020. A Model of Duopolistic Patent Contest with Private Provisions of Industry Collective Goods. *Journal for Global Business Advancement* 13: 70–87. [CrossRef]

Al-Jinini, Dina Khalid, Samer Eid Dahiyat, and Nick Bontis. 2019. Intellectual Capital, Entrepreneurial Orientation, and Technical Innovation in Small and Medium-sized Enterprises. *Knowledge and Process Management* 26: 69–85. [CrossRef]

Allison, John R. 2019. Patent value. In *Research Handbook on the Economics of Intellectual Property Law*. Cheltenham: Edward Elgar Publishing, pp. 47–75.

Almeida, Heitor, Po-Hsuan Hsu, Dongmei Li, and Kevin Tseng. 2021. More Cash, Less Innovation: The Effect of the American Jobs Creation Act on Patent Value. *Journal of Financial and Quantitative Analysis* 56: 1–28. [CrossRef]

Anggadwita, Grisna, Sisca Eka Fitria, and Rega Eggitya Suyono. 2019. Strategy Development for Creating Competitive Advantages in Small and Medium Industries (Smis). *Jurnal Aplikasi Manajemen* 17: 688–96.

Ayoub, Heba Fawzi, Ayman Bahjat Abdallah, and Taghreed S. Suifan. 2017. The Effect of Supply Chain Integration on Technical Innovation in Jordan: The Mediating Role of Knowledge Management. *Benchmarking: An International Journal* 24: 594–616. [CrossRef]

Bessen, James, and Eric Maskin. 2009. Sequential Innovation, Patents, and Imitation. *RAND Journal of Economics* 40: 611–35. [CrossRef]

Bhagat, Sanjai, and Roberta Romano. 2002. Event Studies and the Law: Part I: Technique and Corporate Litigation. *American Law and Economics Review* 4: 141–68. [CrossRef]

Bosworth, Derek, and Mark Rogers. 2001. Market Value, R&D and Intellectual Property: An Empirical Analysis of Large Australian Firms. *The Economic Record* 77: 323–37.

Brouwer, Erik, and Alfred Kleinknecht. 1999. Innovative Output, and A Firm's Propensity to Patent: An Exploration of CIS Micro Data. *Research Policy* 28: 615–24. [CrossRef]

Buchinsky, Moshe. 1998. Recent Advances in Quantile Regression Models: A Practical Guideline for Empirical Research. *Journal of Human Resources* 33: 88–126. [CrossRef]

Campbell, Richard S. 1983. Patent Trends as a Technological Forecasting Tool. *World Patent Information* 5: 137–43. [CrossRef]

Cantwell, John, and Odile Janne. 1999. Technological Globalization and Innovative Centers: The Role of Corporate Technological Leadership and Locational Hierarchy. *Research Policy* 28: 119–44. [CrossRef]

Cardamone, P. 2021. A Quantile Regression Analysis of the Role of R&D Spillovers at Firm Level. *Technology Analysis & Strategic Management* 33: 109–22.

Caviggioli, Federico, Alessandra Colombelli, Antonio De Marco, and Emilio Paolucci. 2020. How Venture Capitalists Evaluate Young Innovative Company Patent Portfolios: Empirical Evidence from Europe. *International Journal of Entrepreneurial Behavior and Research* 26: 695–721. [CrossRef]

Chang, Matthew C., Yi-Hsien Wang, Jui-Cheng Hung, and Chen Sun. 2015. R&D, Patent Arrangements, and Financial Performances: Evidence from Taiwan. Periodica Polytechnica. *Social and Management Sciences* 23: 25–40.

Coad, Alex, and Rekha Rao. 2008. Innovation and Firm Growth in High-tech Sectors: A Quantile Regression Approach. *Research Policy* 37: 633–48. [CrossRef]

Damanpour, Fariborz. 1996. Organizational Complexity and Innovation: Developing and Testing Multiple Contingency Models. *Management Science* 42: 693–716. [CrossRef]

Doi, Noriyuki. 1996. Performance of Japanese Firms in Patented Inventions; An Analysis of Patents Granted in the U.S. *Review of Industrial Organization* 11: 49–68. [CrossRef]

Dzinkowski, Ramona. 2000. The Measurement and Management of Intellectual Capital: An Introduction. *Management Accounting* 78: 32–36.

Ebersberger, Bernd, and Sverre J. Herstad. 2013. The Relationship between International Innovation Collaboration, Intramural R&D and SMEs' Innovation Performance: A Quantile Regression Approach. *Applied Economics Letters* 20: 626–30.

Fisher, Franklin M., and Peter Temin. 1979. The Schumpeterian Hypothesis: Reply? *Journal of Political Economy* 87: 386–89. [CrossRef]

Griliches, Zvi. 1981. Market value, R&D, and Patents. *Economics Letters* 7: 183–87.

Grimaldi, Michele, and Livio Cricelli. 2020. Indexes of Patent Value: A Systematic Literature Review and Classification. *Knowledge Management Research & Practice* 18: 214–33.

Grimaldi, Michele, Livio Cricelli, and Francesco Rogo. 2018. Valuating and Analyzing the Patent Portfolio: The Patent Portfolio Value Index. *European Journal of Innovation Management* 21: 174–205. [CrossRef]

Hall, Linda A., and Sharmistha Bagchi-Sen. 2002. A Study of R&D Intensity, Inovation and Business Performance in the Canadian Biotechnology Industry. *Technovation* 22: 231–44.

Hansen, Morten T., Nitin Nohria, and Thomas Tierney. 1999. What's Your Strategy for Managing Knowledge? *Harvard Business Review* 77: 106–16.

Huang, Cliff J., Tsu-Tan Fu, Hung-Pin Lai, and Yung-Lieh Yang. 2017. Semiparametric Smooth Coefficient Quantile Estimation of the Production Profile. *Empirical Economics* 52: 373–92. [CrossRef]

Inkmann, Joachim, Winfried Pohlmeier, and Luca Antonio Ricci. 2000. *Where to Patent? Theory and Arrangements for Global Economic Integration*. New York: St. Martin's Press.

Johns, G. 1993. Constraints on the Adoption of Psychology-based Personnel Practices: Lessons from Organizational Inneovation. *Personnel Psychology* 46: 569–92. [CrossRef]

Kim, Minseo, Ji-eung Kim, Yeong-wha Sawng, and Kwang-sun Lim. 2018. Impacts of Innovation Type SME's R&D Capability on Patent and New Product Development. *Asia Pacific Journal of Innovation and Entrepreneurship* 12: 45–61.

Koku, Paul Sergius, Anique A. Qureshi, and Aigbe Akhigbe. 2001. The Effects of News on Initial Corporate Lawsuits. *Journal of Business Research* 53: 49–55. [CrossRef]

Lee, Jun-De, Yi-Hsien Wang, Ching-Wen Lin, and Hsin-Ham Lin. 2013. Information Value of Patent Litigation and Industry Competition in Taiwan. *Technological and Economic Development of Economy* 19: 593–605. [CrossRef]

Lee, Leong-hwan, Do-sung Na, and Jin-Taek Jung. 2017. A Study on the Effect of Patent Indicator on the Company Innovation Index. *Research Journal of Pharmacy and Technology* 10: 2522–26. [CrossRef]

Lieberman, Marvin B. 1987. Patents Learning by Doing, and Market Structure in the Chemical Processing Industries. *International Journal of Industrial Organization* 5: 257–76. [CrossRef]

Lin, H. L., and H. F. Lee. 1996. Econometric Models Based on Nonnegative Integer Data: Application of the relationship of Taiwan Patents and R&D Expenditure. *Academia Economic Papers* 24: 273–301.

Manakhova, I., E. Levchenko, V. Bekher, and A. Bystrov. 2020. Quality of Human Resources and Personnel Security Risk Management in Digital Economy. *Quality-Access to Success* 21: 74–79.

Mariani, M. 2004. What Determines Technological Hits?: Geography versus Firm Competencies. *Research Policy* 33: 1565–82. [CrossRef]

Montalvo, Jose G. 1997. GMM Estimating of Count-Panel-Data Models with Fixed Effects and Predetermined Instruments. *Journal of Business and Economic Statistics* 18: 82–89.

OECD. 1996. *The Knowledge Based Economy*. Paris: OECD.

Park, Yongtae, and Gwangman Park. 2004. A New Method for Technology Valuation in Monetary Value: Procedure and Application. *Technovation* 24: 387–94. [CrossRef]

Pakes, A., and Z. Griliches. 1980. Patents and R&D at the Firm Level: A First Report. *Economics Letters* 5: 377–81.

Petruzzelli, Antonio Messeni, and Gianluca Murgia. 2020. University–Industry Collaborations and International Knowledge Spillovers: A Joint-Patent Investigation. *The Journal of Technology Transfer* 45: 958–83. [CrossRef]

Robinson, Alan, and Sam Stern. 1998. *Corporate Creativity*. San Francisco: Berrett-Koehler Publishers.

Shih, Kuang-Hsun, Fu-Ju Yang, Jhih-Ta Shih, and Yi-Hsien Wang. 2020a. Patent Litigation, Competitive Dynamics, and Stock Market Volatility. *Mathematics* 8: 795. [CrossRef]

Shih, Kuang-Hsun, Chung-Ming Tsai, and Yi-Hsien Wang. 2020b. The Association between Corporate Patent and Corporate Value. *Journal of Accounting, Finance & Management Strategy* 15: 53–74.

Siegel, Donald S. 2018. Academic Entrepreneurship: Lessons Learned for Technology Transfer Personnel and University Administrators. *University Technology Transfer and Academic Entrepreneurship* 1: 1–21.

Sun, Yifei. 2003. Determinants of Foreign Patents in China. *World Patent Information* 25: 27–37. [CrossRef]

Suominen, Arho, Hannes Toivanen, and Marko Seppänen. 2017. Firms' Knowledge Profiles: Mapping Patent Data with Unsupervised Learning. *Technological Forecasting and Social Change* 115: 131–42. [CrossRef]

Tsai, Chung-Min. 2007. *A Study of the Relationship from R&D, Technology Import and Patent Performance: Evidences form Taiwan Listed Electronic Companies*. Taipei: Aletheia University.

Wei, Fenfen, Nanping Feng, and Kevin H. Zhang. 2017. Innovation Capability and Innovation Talents: Evidence from China Based on a Quantile Regression Approach. *Sustainability* 9: 1218. [CrossRef]

Wolfe, Richard A. 1994. Organizational Innovation: Review, Critique and Suggested Research Directions. *Journal of Management Studies* 31: 405–30. [CrossRef]

Yang, Chih-Hai, and Jong-Rong Chen. 2001. R&D, Technology Import and Patent-GMM on Count Panel Data. *Taiwan Economic Review* 29: 69–87.