Using Patent to Predict Book-Value-Per-Share and Investment -- Evidence in China A-Shares

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Received 17 February 2020; received in revised form 23 October 2020; accepted 29 October 2020

Abstract

Patent, a legal representation of innovation achievement, is strongly meaningful for almost every country's economy growth and technology development. China, the world No.2 stock market, is the world largest patent application country. In this research, we observed 2,197 China listed companies (A-shares) in Shanghai Main Board, Shenzhen Main Board, GE Board, and SME Board from 2016 to 2018 to discuss the prediction ability of patent to A-shares' performance. The relationship among 570 valid patent indicators and the book-value-per-share (BPS) were examined. We constructed patent leading indicators and patent prediction equations for predicting BPS via Granger Causality test and the time series regression model. The investment strategies based on the patent prediction equations were thoroughly discussed. We found that the stock portfolios selected by the higher predictive BPS in Shanghai Main Board and Shenzhen Main Board had better performance than the market trend, the stock portfolios selected by the higher predictive BPS growth rate in GE Board and SME Board worked well even though these two stock boards were seriously impacted to decline by the China-US trade conflict. The underlying concept behind this research is that though the overall economic environment fluctuated, the patent based prediction algorithm proposed was proved to be useful to discover good stock portfolios.

Keywords: Investment Performance, Patent Leading Indicator, Patent Prediction Equation, Granger Causality test, time series regression Model, China A-share

1. Introduction

Global economic growth seems to lose momentum in 2019. Productivity growth hits a low record, trade wars continue, and economic uncertainty remains high. Despite sluggish market sentiment, however, innovation is in full swing around the world. Either developed economies or developing economies, innovation activities, which can be measured by R&D and patents, are booming, and innovation spending has been increasing.

Innovation is an essential driver of economic progress that benefits consumers, businesses and the economy as a whole. Most economists agree that technological innovation is a key driver of economic growth and human well-being. The innovation can lead to higher productivity. Broughel and Thierer (2019) proposed that the innovation increases productivity and brings citizens new and better goods and services that improve their overall standard of living. It means the same input generates a greater output. As productivity rises, more goods and services are produced – in other words, the economy grows.

Patent is the outcome of innovation. China has been the world largest patent application country for many years. In 2018, there are 4.32 millions new China patent applications[1]. By the end of 2018, there are more than 22 million patent publications[2] in China patent database, which is also the world largest patent database.

For another, when GDP surpassed Japan, China has become the world No. 2 economy since 2010. The market value and transaction volume of China stock market, which comprising more than 3,400 listed companies of RMB common stocks called A-shares, is both ranked as the world No. 2. The China stock market is the most important stock market in Asia.

The stock market usually reflects the economic conditions of an economy. If an economy is growing then output will be increasing and most firms should be experiencing increased profitability. This higher profit makes the company shares more attractive because they can give bigger dividends to shareholders. A long period of economic growth will tend to benefit shares. If the economy is forecast to enter into a recession, then stock markets will generally fall. This is because

[1] China patent applications comprise: the invention applications, the utility model applications, and the design applications.

[2] China patent publications comprise: the invention publication which under examination, the invention grant which passed the substantial examination, the utility models which passed the initial examination, and the designs which passed the initial examination.

a recession means lower profits, fewer dividends and even the prospect of firms going bankrupt, which would be bad news for shareholders (Pettinger, 2018).

For such enormous amount of patents and huge stock market, it is believed that China patents also drive China stock market. But the specific relationship therebetween is less discussed.

Chen, Wei, and Che (2018) tried to use patent indicators to predict the stock price of China A-shares in Shanghai Main Board. Based on the data from 2011 to 2017, they found the stock portfolios selected by the predictive stock price growth rate have better performance than the market trend. However, the exact patent leading equation for giving the predictive stock price is not statistically test nor revealed.

The China A-shares comprise companies listed in four stock boards: Shanghai Main Board, Shenzhen Main Board, GE Board, and SME Board[3]. Most A-shares in Shanghai Main Board and Shenzhen Main Board are state-owned companies and big size companies. Most A-shares in GE Board and SME Board are small and medium companies. It is therefore that the stock price fluctuation in Shanghai Main Board and Shenzhen Main Board is much smaller, slower and more steady when compared with that of GE Board and SME Board. In addition, the volume of Shanghai Main Board is bigger than the other stock boards, what Chen, et al. (2018) proposed may not be applied to other stock boards.

On March 22, 2018, the US government launched a trade war against China through the tariff system. US President Trump officially signed a trade memorandum for imposing tariffs on 60 billion US dollars of imports from China and restrict Chinese companies' investment, merges and acquisitions in the US. On April 4, 2018, the US government released a list of goods subject to tariffs, which imposing a 25% tariff on approximately 50 billions USD in imports from China. On April 5, 2018, US President Trump requested to impose additional tariffs on 100 billions USD in imports from China. On July 6, 2018, the first batch of 34 billions USD of imports began to impose a 25% tariff. The China-US trade conflict not only seriously affects China's exports to the US, but also impacts on the Chinese stock market. From the beginning to the end of 2018, the CSI 300 Index[4] fell by 25.3% and the Shanghai Composite Index[5] fell by 24.6%. Oppositely, the number of China patent publications in 2018 grows to have a annual growth rate of 29.5%. Stocks were down, patents were up. It seems to be contrary to general knowledge.

However, based on patent informatics, the processed patent indicators may not show corresponding trend to the number of patent publications. Therefore, the first objective of this research is to verify that some China patent indicators is still capable of predicting China A-share's financial performance before and during China-US trade conflict. The verification is executed not only to Shanghai Main Board but also to Shenzhen Main Board, GE Board, SME Board and the whole A-shares. The second objective of this research is to build the patent prediction equations for quantitatively predicting the A-share's financial performance. The third objective of this research is to find out the optimal investment strategy based on the proposed patent prediction equations and show the effectiveness of the criteria.

Furthermore, we know that the quantitative investment algorithm is a hot issue of prediction. Lots of financial factors and behavior factors involved therein have been studied. However, patent and its derived patent indicators as the principal factors are rarely discussed. In this research, we focus on patent only and discover patent indicator's implicit effect on investment.

2. Literature Reviews

R&D capability and market structure are important factors for driving a company's growth and maintaining competitive advantages. Branch (1974) found that in the early US market from 1950 to 1965, an increase in the number of company's patents usually resulted in predictive growth in sales and profits. Griliches (1981) found a significant relationship between the market value of the firm and its intangible capital, proxied by past R&D expenditures and the number of patents, based on a time-series cross-section analysis of data for large US firms. Cockburn and Griliches (1988) discussed the effectiveness of patents as a mechanism for protecting the returns from innovation turn out to be of some use. They found evidence of an interaction between industry level measures of the effectiveness of patents and the market's valuation of a firm's past R&D and patenting performance, as well as its current R&D moves. Hall, Jaffe, and Trajtenberg (2005) found patent citations significantly affect market value, with an extra citation per patent boosting market value by 3%.

Branch and Chichirau (2010) found patent count and patent citations are all positively

[3] Chian has two stock exchanges, one in Shanghai and the other in Shenzhen. Shanghai Main Board is listed in Shanghai exchange; Shenzhen Main Board, GE Board, and SME Board are listed in Shenzhen exchange.

[4] CSI 300 Index, code 000300, composed of 300 large-scale, liquidity and most representative high-quality stocks selected in the whole A-shares, represents the top stocks in China.

[5] Shanghai Composite Index, code 000001, composed of all Shanghai A shares, represents the market trend of the Shanghai Main Board stocks.

associated with growth and negatively associated with profitability. Investors who can effectively evaluate the quality of the R&D performed, may be able profitably to exploit the risk premium applied to the stock of R&D-intensive companies. Crossan and Apaydin (2010) conducted a research findings in all peer-reviewed literature on innovation in the Social Science Citation Index Database (SSCI) from 1981 to 2008 and found that the company's disclosure of its innovation results is significantly positively related to its earnings such as gross profit margin.

Pandit, Wasley, and Zach (2011) examined whether both R&D expenditures and patent count and citations and their interaction associate with the level and variability of future earnings and operating cash flows. The examination contributed to determine whether the relationship between firm-level innovation and operating performance is conditional on the success of a firm’s R&D efforts. Fabrizi, Lippert, Norback and Persson (2011) proposed if venture capitalists (VCs) are sufficiently better at judging an idea's value and if it is sufficiently more costly to patent low than high value ideas, VCs acquire valuable ideas, develop them beyond the level incumbents would have chosen, and use patents to signal their companies' high value to acquirers prior to exiting.

Hirshleifer, Hsu and Li (2013) found innovative efficiency (IE), patents or citations scaled by R&D expenditures, is a strong positive predictor of future returns after controlling for firm characteristics and risk. The IE-return relation is associated with the loading on a mispricing factor, and the high Sharp ratio of Efficient Minus Inefficient (EMI) portfolio suggest that mispricing plays an important role.

Caner, Bruyaka, and Prescott (2016) demonstrated the value of a temporal lens in explaining why diversity in a firm's patent and alliance portfolios send flow signals that establish expectations among market observers and have performance implications. Yu and Hong (2016) investigated whether the patents can complement R&D expenditure in explaining stock returns. They found that the number of patents have more significant explanatory power than R&D expenditure; incorporating the number of patents in explaining stock returns could add value.

Mama (2018) used a large international sample to see if a firm’s innovative efficiency (IE) is positively related to future returns or not. It is found that the relationship is robustly U-shaped. Long-short investment strategies based on highest and lowest IE are inefficient.

Regarding to the quantitative measure of stock performance by patents, Deng, Lev, and Narin (1999) and Thomas (2001) proposed that the main objective of technology analyses is to understand how investing in technological innovation can have commercial benefits. They demonstrated that quantitative patent indicators may be used in modeling company return-on-equity ratio by multi-regression analysis for US stock market. They concluded that the quality of a company's technology is reflected in its patent portfolio. A company with a large percentage of influential patents is much more likely to be technologically successful than a company with weaker patents, and is also more likely to be more successful in capital markets.

China, as the largest patent application country in the world, the effects of China patents are discussed fewer than those of US patents. Dang and Motohashi (2015) found patent count is correlated with R&D input and financial output, which suggests that patent statistics are meaningful indicators. He, Tong, Zhang, and He (2016) found it is difficulties in integrating Chinese patent data with firm data. They construct a China patent database of all listed firms and their subsidiaries in China from 1990 to 2010. They also found that foreign firms experience substantial delay in publishing patent applications and requesting for substantive examination compared to Chinese firms. Such delay accounts for 40–60% of the longer duration from application date to decision date for foreign firms.

Regarding the world No. 2 market value of all China , Chen et al. (2018) used data from 2011 to 2017 to discuss the leading effects of patents to the stock price over A-shares in Shanghai Main Board[6] in China. , roughly proposed a quantitative model for predicting stock price by hundreds of patent indicators which processed by patent data from 2011 to 2017.

However, there are two stock exchanges in China, one in Shenzhen, the other in Shanghai. A-shares are listed in four stock boards including Shanghai Main Board which belonging to Shanghai stock exchange; Shenzhen Main Board[7], GE Board[8], and SME Board[9], all of these three stock boards belonging to Shenzhen Main Board. The work of Chen et al. (2018) on Shanghai Main Board started a good try, and there are still lots of issues left to study.

In this research, we looked at all the four stock boards in China, followed the idea of Chen et al. (2018), studied the patent’s leading effect to the other financial indicator such as the book-value-per-share (BPS) which suitable for investment than the stock price, and constructed the patent prediction equations for predicting BPS. At last, we proposed preferable investment strategies

[6] Stock codes start with 600, 601, and 602.

[7] Stock codes start with 000, and 001.

[8] “GE” means “Growing Enterprise”. Stock codes start with 300.

[9] “SME” means “Small & Medium Enterprise”. Stock codes start with 002.

based on said patent prediction equations, discussed the stock performance. The methodology we proposed was therefore proved useful even under the impact of the China-US trade conflict.

3. Methodology

3.1 Panel Data Modeling Period

2016Q4~2018Q3, total of 8 quarters before and during the China-US trade conflict are used.

3.2 Patent Indicator

Though China is the largest patent application country in the world, most China A-shares have filed foreign patents less than 5% of China patents. Therefore, we only focused on patent indicators processed by China patents because the amount of foreign patents, such as US patents, PCT patents, European patents, etc., is too small to be ignored when compared with China patents.

For boosting industry innovation, China government had carried out a fee subsidy policy for new patent applications. Many companies apply a large amount of patents to get subsidies, and abandon unimportant patents when the annual fees are due. Such invalid patents are usually recognized as the “garbage patents”. Hence, only valid patent indicators processed by valid patents are discussed in this research. The valid patents comprises: (1) annual fee maintained patents of invention grants, utility model grants and design grants; and (2) invention publications under examination. The valid patent indicators are identified as PAij, i=1 to 10 years data collection interval (for avoiding confusion, 10 is represented by X hereinafter); j=1 to 41, 45 to 60. There are 57 valid patent indicators for each data collection interval, and total of 570 patent indicators for overall 10 data collection intervals. The definitions of PAij are shown in Appendix 1. The processing of PAij is based on patent raw data by the last day of each quarter. .

The patent raw data for processing PAij are published by the State Intellectual Property Office of China, including data on invention publications, invention grants, utility model grants, design grants, and legal status thereof.

According to the Kolmogorov-Smirnov test, the original data distribution of PAij is seriously skewed, so all PAij applied in the analysis have been cox-box transformed to reduce the skewness.

3.3 Financial Indicator

In contrary to Chen et al. (2018) using the stock price as the observing and predictive financial indicator, in this research we use a more rational indicator: the book-value-per-share (BPS).

BPS is the ratio of the book value to total number of shares. It is used mainly by stock investors to evaluate a company's stock price for investment. When a stock is undervalued, it will have a higher BPS in relation to its current stock price in the market. When a stock is overvalued, it will have a lower BPS in relation to its current stock price. In this research, BPS in each quarterly settlement is selected. Data of BPS are retrieved from information revealed by the stock exchanges, annual reports, semi-annual reports and quarterly reports.

3.4 Population and Sample

The population is China A-shares in Shanghai Main Board, Shenzhen Main Board, GE Board, and SME Board. Chinese companies listed in Hong Kong and overseas are excluded. As of now, the number of whole China A-shares is more than 3,400 and is still increasing.

An effective sample must meet two conditions:

(1) During the eight quarters from 2016Q4 to 2018Q3, the A-share remained listed; and
(2) In each of eight quarters from 2016Q4 to 2018Q3, the A-share had a new patent publication for last one year, but no restriction for patent species.

For those A-shares whose subsidiaries’ revenue merged with the parent company in the annual report, we assume that patents of subsidiaries have corresponding contributions to the parent company, so patents of such subsidiaries are also merged with the parent company for processing patent indicators.

Table 1 shows A-shares and effective samples statistics by the end of 2018Q3. Total of 2,197 effective samples are extracted with the overall sampling rate 63.4%. Shanghai Main Board has the most 1,389 A-shares, the most 776 effective samples and the highest proportion 35.3% of all effective samples. SME Board has the highest sampling rate for effective samples, reaching 74.8%. The sampling rates for effective samples of Shanghai Main Board and Shenzhen Main Board are both lower than the overall sampling rate, the innovation initiative of A-shares does not corresponds to the company size.

Table 1: China A-share Statistics in 2018Q3

	Shanghai Main Board	Shenzhen Main Board	GE Board	SME Board	Total
A-shares	1,389	465	710	903	3,467
Effective Samples (Proportion)	776 (35.3%)	258 (11.7%)	488 (22.2%)	675 (30.7%)	2,197
Sampling Rate for Effective Samples	55.9%	55.5%	68.7%	74.8%	63.4%

Table 2 shows ANOVA of five fundamental patent indicators between and within four stock boards in 2018Q3. PA101, PA102, PA103, PA104, and PA145 are the counts of valid invention publications, valid utility model grants, valid design grants, and all valid patents for last one year respectively.

All p values in Table 2 reach 0.01 significance, it shows the variation of five patent indicators exist between four stock boards. Therefore the following analysis is executed respectively to each stock board and integrated in discussion.

Table 2: ANOVA of Patent Counts of Four Stock Boards in China A-share

Patent Indicator		Square Sum	df	Mean Square	F	p
PA101	Between Stock Boards	30.093	3	10.031	4.775	0.003**
	Within Stock Boards	4606.897	2193	2.101		
	Total	4636.990	2196			
PA102	Between Stock Boards	50.436	3	16.812	7.020	0.001***
	Within Stock Boards	5252.324	2193	2.395		
	Total	5302.760	2196			
PA103	Between Stock Boards	24.285	3	8.095	4.792	0.002**
	Within Stock Boards	3704.750	2193	1.689		
	Total	3729.035	2196			
PA104	Between Stock Boards	26.913	3	8.971	5.177	0.001**
	Within Stock Boards	3800.499	2193	1.733		
	Total	3827.412	2196			
PA145	Between Stock Boards	37.906	3	12.635	6.814	0.001***
	Within Stock Boards	4066.368	2193	1.854		
	Total	4104.274	2196			

p*<0.05, p**<0.01, p***<0.001

3.5 Patent Leading Indicator (PLI)

The Patent Leading Indicator (hereinafter, PLI) is the specific patent indicator which is useful in predicting BPS for a predetermined leading period.

The Granger Causality test, which applied for finding PLI, is a statistical hypothesis test for determining whether one time series variable (in this research: patent indicator) is useful in forecasting another (in this research: BPS). It is not for determining a true cause-and-effect relationship but for finding a probabilistic account of causality. It uses empirical data sets to find leading/lagging patterns of correlation.

In this research, each of valid patent indicators is sequentially applied as one time series variable, and BPS is applied as the other. The PLI is obtained when any of the patent indicators satisfies the Granger Causality test (F-test, p*<0.05) under the Lag condition.

In this research, we test four kinds of Lags to see how long of the leading period the PLI could predict BPS. Lag=1 means the leading period is one quarter, Lag=2 means two quarters, Lag=3 means three quarters, and Lag=4 means four quarters.

3.6 Patent Prediction Equation

The patent prediction equation is an equation for generating the predictive BPS by PLIs. It is constructed via the time series regression model as follows:

$$y_t = y_{t-4} + \sum_{i=1}^{n} c_i x_{i,t-4} + e_t$$

Wherein, the subscript -4 means Lag=4; y_t is the predictive BPS which applied as the dependent variable; $x_{i,t-4}$ are PLIs which applied as the independent variable under Lag=4 and satisfying F-test while p*<0.05; e_t is the error term.

Though we may obtain PLIs and patent prediction equations under all Lags=1 to 4, but only the patent prediction equation with PLIs under Lag=4 will be empirically applied. It is because during previous communication with financial investment institutions, they considered the patent prediction equations under Lags=1 to 3 are inappropriate and suggested to use Lag=4. They commented the reasonable investment behavior is not short-term speculation. Once a stock is invested, at least one year for keeping and observation is need. Therefore, Lag=4 for the patent prediction Equation is applied in this research.

3.7 Research Step

The analysis for this research are executed as follows:

(1) Collecting all A-shares with their patent data and EPS data during panel data modeling periods;
(2) Processing valid patent indicators for each A-share;
(3) Extracting effective samples with their corresponding valid patent indicators and BPS;
(4) Mining PLIs for BPS via Granger Causality test;
(5) Obtaining patent prediction equations for predicting BPS via the time series regression model and PLIs;
(6) Discussing the performance of stock portfolios which selected by the predictive BPS and the predictive BPS growth rate, and propose the optimal investment strategies.

4. Result and Discussion

4.1 Patent Leading Indicator

Table 3 shows statistics of PLI analysis via the Granger Causality test. Not all 570 patent indicators reach statistical significance. However, some PLIs statistically exist in predicting BPS for the whole A-shares and each stock board.

Meanwhile, PLIs exist under each of Lags. That means, some present PLIs can predict future BPS in one quarter, some present PLIs can predict future BPS in two quarters, some present PLIs can predict future BPS in three quarters, some present PLIs can predict future BPS in four quarters.

The most PLIs are found under Lag=2. After that, as the Lag increases, the number of PLIs tends to decrease.

If we put the whole A-shares aside, Shenzhen Main Board has the most PLIs under Lags=1, 2 and 4. SME Board has the most PLIs under Lag=3. It is interesting that Shanghai Main Board has the most effective samples, but the number of PLIs does not show correspondence. Shenzhen Main Board has the least effective samples, but it has the most PLIs for most of Lags. However, the number of PLIs is irrelevant to the number of effective samples. It depends on whether the patent indicators show correspondence to future BPS or not. Though Shanghai Main Board has the most effective samples, its patent indicators do not show high correspondence to future BPS under the Lag condition, so it has less PLIs than the other stock boards.

Table 3: Number of PLIs for Each Stock Board

Board	Number of PLIs			
	Lag=1	Lag=2	Lag=3	Lag=4
Whole A-shares	178	264	132	94
Shanghai Main Board	19	64	33	34
Shenzhen Main Board	139	279	17	98
GE Board	24	115	50	30
SME Board	37	93	133	81

PLIs exist under different Lags. For different prediction purpose, we may choose PLIs under different Lags. In this study, we are more concerned about PLIs under Lag=4 because the patent prediction equation is constructed by PLIs under Lag=4. Details of PLIs under Lag=4 of the whole A-shares and all stock boards are shown in Table 4.

Table 4: PLIs under Lag=4 in Stock Boards

Board	PLI (Lag=4)
Whole A-shares	PA101, PA104, PA105, PA106, PA107, PA108, PA109, PA110, PA111, PA114, PA117, PA118, PA120, PA123, PA124, PA126, PA132, PA135, PA138, PA141, PA145, PA146, PA149, PA153, PA154, PA155, PA158, PA159, PA160, PA204, PA208, PA211, PA214, PA220, PA226, PA232, PA238, PA254, PA258, PA259, PA260, PA304, PA308, PA320, PA326, PA345, PA354, PA359, PA360, PA404, PA408, PA424, PA426, PA445, PA451, PA454, PA459, PA460, PA504, PA508, PA520, PA526, PA545, PA554, PA559, PA560, PA604, PA608, PA626, PA654, PA659, PA660, PA704, PA745, PA754, PA759, PA760, PA845, PA854, PA860, PA904, PA906, PA924, PA926, PA945, PA954, PA959, PA960, PAX04, PAX06, PAX26, PAX45, PAX54, PAX60
Shanghai Main Board	PA104, PA108, PA109, PA111, PA114, PA117, PA120, PA126, PA132, PA138, PA153, PA154, PA158, PA160, PA204, PA208, PA226, PA254, PA347, PA411, PA447, PA448, PA452, PA454, PA459, PA460, PA513, PA528, PA551, PA559, PA659, PA752, PA952, PAX52
Shenzhen Main Board	PA108, PA102, PA104, PA111, PA113, PA116, PA119, PA122, PA125, PA126, PA128, PA131, PA137, PA140, PA145, PA147, PA151, PA154, PA159, PA201, PA202, PA207,

Board	PLI (Lag=4)
	PA210, PA212, PA213, PA215, PA216, PA218, PA219, PA222, PA225, PA228, PA231, PA236, PA237, PA239, PA240, PA245, PA247, PA250, PA251, PA259, PA302, PA303, PA307, PA312, PA325, PA330, PA336, PA345, PA403, PA445, PA503, PA512, PA515, PA536, PA539, PA545, PA559, PA603, PA612, PA615, PA630, PA636, PA639, PA645, PA659, PA703, PA712, PA715, PA736, PA739, PA745, PA757, PA759, PA803, PA812, PA815, PA830, PA836, PA839, PA845, PA903, PA912, PA915, PA930, PA936, PA938, PA939, PA945, PAX03, PAX12, PAX15, PAX30, PAX36, PAX39, PAX45, PAX59,
GE Board	PA104, PA105, PA107, PA108, PA110, PA111, PA114, PA117, PA120, PA126, PA138, PA141, PA146, PA149, PA150, PA153, PA154, PA155, PA158, PA160, PA212, PA218, PA246, PA250, PA259, PA260, PA346, PA445, PA618, PA621
SME Board	PA104, PA108, PA109, PA110, PA111, PA114, PA120, PA126, PA132, PA138, PA145, PA154, PA158, PA160, PA204, PA205, PA208, PA211, PA214, PA217, PA220, PA223, PA226, PA238, PA241, PA245, PA249, PA253, PA254, PA258, PA259, PA304, PA308, PA320, PA324, PA326, PA345, PA358, PA360, PA405, PA414, PA417, PA438, PA441, PA453, PA454, PA501, PA505, PA506, PA508, PA524, PA526, PA529, PA553, PA604, PA606, PA608, PA624, PA626, PA653, PA706, PA724, PA745, PA753, PA806, PA824, PA829, PA845, PA853, PA901, PA906, PA918, PA924, PA929, PA950, PA953, PAX06, PAX24, PAX29, PAX50, PAX53

According to PLIs found in Table 4, Figure 1 shows the statistics of PLIs in each data collection interval over the whole A-shares and four stock boards. The one year data collection interval which having 96 PLIs (PA1j) is the most. The next is two years data collection interval of 62 PLIs (PA2j). After that, the number of PLIs drops to a very low level of 25 or so. Recent and new patents generate more PLIs than old patents do. It seems the short term innovation which representing by the new patents in China A-shares is highly related to BPS than the long term innovation which representing by the old patents.

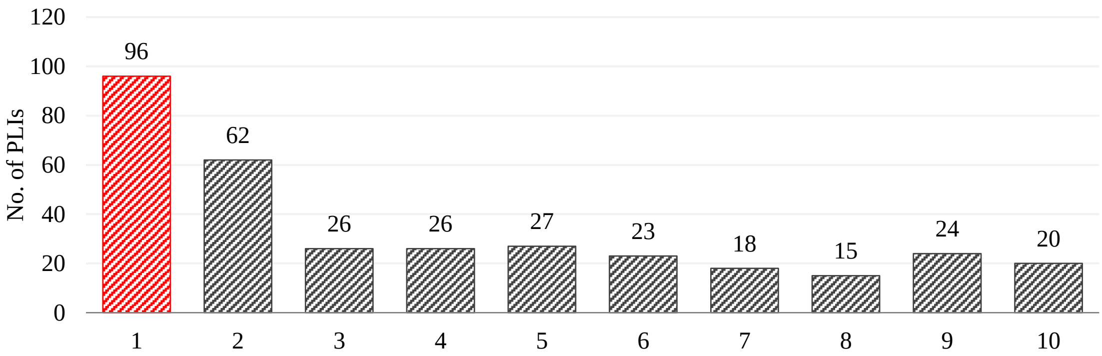

Figure 1: No. of PLIs in Each Data Collection Interval

There are 57 PLI species defined in this research. According to PLIs found in Table 4, Figure 2 shows the top species which having at least 10 PLIs. These top PLI species relate to BPS more than the other PLI species. The top one species is "All valid patent count (PAi45)" of 24 PLIs. The next is “Total forward patent citation count of valid patents (PAi59)” of 19 PLIs. The followings is “Total backward patent citation count of valid invention grants (PAi54)” “valid invention grants count (PAi04)”, “Total independent claim count of valid invention grants (PAi26)”, “Total backward non-patent citation count for valid invention grants (PAi60)”, “Total IPC count of valid invention grants (PAi08)”, “Average lifespan of valid invention grants (PAi53)”, and “Total independent claim count of valid invention publications (PAi24)”.

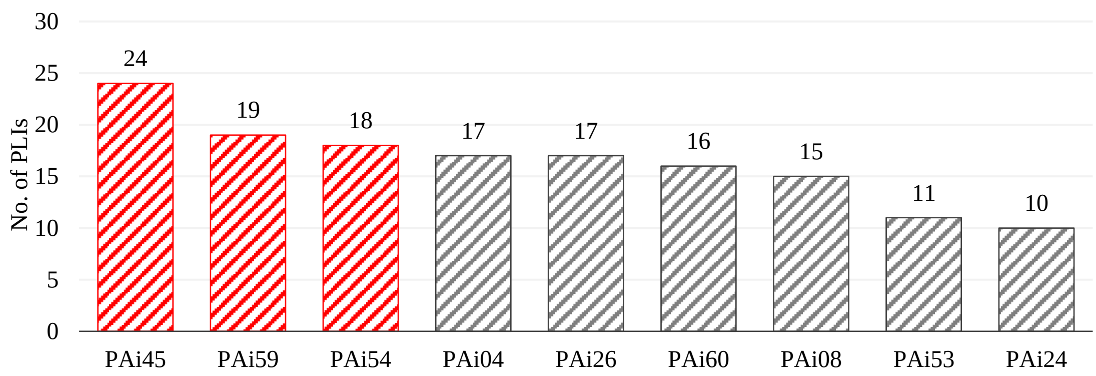

Figure 2: Top PLI Species

4.2. Patent Prediction Equation

PLIs are found, we therefore construct the patent prediction equation via the time series regression to combine PLIs for quantitatively modelling and predicting BPS.

Since Lag=4, the patent prediction equation is constructed by four prediction periods, namely:

Period I: 2016Q4 predicting 2017Q4,
Period II: 2017Q1 predicting 2018Q1,
Period III: 2017Q2 predicting 2018Q2,
Period IV: 2017Q3 predicting 2018Q3.

Since 2018Q2 and 2018Q3 are during the China-US trade conflict, we may say periods I and II are not affected by the China-US trade conflict, but periods III and IV are affected.

The composition of all patent prediction equations for the whole A-shares and four stock boards are shown in Table 5, wherein the subscript -4 represents Lag=4. Details of statistical tests for each patent prediction are shown in Appendixes 2 to 6.

Regarding the number of PLIs included in the patent prediction equations in Table 5, the whole A-shares has 21 PLIs which less than 94 in Table 3, Shanghai Main Board has 6 PLIs which less than 34 in Table 3, Shenzhen Main Board has 24 PLIs which less than 98 in Table 3, GE Board has 7 PLIs which less than 30 in Table 3, SME Board has 24 PLIs which less than 81 in Table 3. The number of PLIs included in all patent prediction equations is much less than those found by Granger Causality test. It is because in the constructed patent prediction equation, all PLIs are linearly combined and each combined PLI must satisfy significance p*<0.05. Lots of PLIs are removed by losing their significance when they combined with the other PLIs during the time series regression analysis.

Table 5: Patent Prediction Equations

Whole A-shares	Patent Prediction Equation	$BPS = 0.2432 + 0.8677*BPS_{-4} + 0.0115*PA106_{-4} - 0.0077*PA118_{-4} + 0.0068*PA132_{-4} + 0.0245*PA354_{-4} + 0.0181*PA359_{-4} - 0.0605*PA404_{-4} - 0.0219*PA459_{-4} + 0.0248*PA460_{-4} - 0.0289*PA560_{-4} + 0.0590*PA604_{-4} + 0.0266*PA608_{-4} - 0.0383*PA654_{-4} + 0.0367*PA659_{-4} - 0.0294*PA759_{-4} + 0.0594*PA760_{-4} - 0.3205*PA904_{-4} - 0.1698*PA906_{-4} + 0.3528*PAX04_{-4} + 0.1555*PAX06_{-4} - 0.0357*PAX26_{-4} - 0.04817*PAX60_{-4}$
	Adjusted R^2	0.7634
	p (F-statistic)	0.0001***
Shanghai Main Board	Patent Prediction Equation	$BPS = 0.1650 + 0.9264*BPS_{-4} + 0.0093*PA132_{-4} - 0.0113*PA254_{-4} + 0.0700*PA347_{-4} - 0.0047*PA452_{-4} + 0.0099*PA460_{-4} - 0.0157*PA551_{-4}$
	Adjusted R^2	0.8409
	p (F-statistic)	0.0001***
Shenzhen Main Board	Patent Prediction Equation	$BPS = 0.1736 + 0.9177*BPS_{-4} + 0.2156*PA102_{-4} + 27.1867*PA113_{-4} - 27.1797*PA116_{-4} - 27.3625*PA137_{-4} + 27.3349*PA140_{-4} - 0.0206*PA159_{-4} + 0.1975*PA201_{-4} + 0.0881*PA207_{-4} - 0.1290*PA210_{-4} - 0.0333*PA213_{-4} + 0.1024*PA215_{-4} - 0.0781*PA225_{-4} - 0.1640*PA236_{-4} + 0.1067*PA251_{-4} - 0.0228*PA336_{-4} + 0.1498*PA345_{-4} - 0.1685*PA445_{-4} - 0.0477*PA515_{-4} - 0.3222*PA615_{-4} + 2.0330*PA739_{-4} + 0.0314*PA759_{-4} + 0.0086*PA803_{-4} + 0.3080*PA815_{-4} - 1.9215*PA939_{-4}$
	Adjusted R^2	0.8787
	p (F-statistic)	0.0001***

GE Board	Patent Prediction Equation	$BPS = 0.3496 + 0.7394*BPS_{-4} - 0.0336*PA218_{-4} - 0.2034*PA246_{-4} + 0.0458*PA250_{-4} + 0.0258*PA259_{-4} + 0.1640*PA346_{-4} - 0.0348*PA445_{-4} + 0.0426*PA618_{-4}$
	Adjusted R^2	0.5793
	p (F-statistic)	0.0001***
SME Board	Patent Prediction Equation	$BPS = 0.2948 + 0.8419*BPS_{-4} - 0.0541*PA104_{-4} + 0.0073*PA114_{-4} + 0.0126*PA132_{-4} + 0.3939*PA204_{-4} - 0.0406*PA211_{-4} - 0.0176*PA217_{-4} - 0.2216*PA220_{-4} + 0.2745*PA223_{-4} - 0.0828*PA226_{-4} - 0.3191*PA258_{-4} + 0.3574*PA358_{-4} + 0.0194*PA360_{-4} - 0.1140*PA438_{-4} + 0.1074*PA441_{-4} - 0.1274*PA501_{-4} + 0.0802*PA508_{-4} + 0.0489*PA524_{-4} + 0.3348*PA529_{-4} - 0.1008*PA553_{-4} + 0.2189*PA604_{-4} + 0.1040*PA606_{-4} - 0.2152*PA626_{-4} + 0.1052*PA901_{-4} - 0.1402*PA906_{-4}$
	Adjusted R^2	0.7465
	p (F-statistic)	0.0001***

p*<0.05, p**<0.01, p***<0.001

We also found that in the patent prediction equations, not all PLIs are of positive coefficients, while some PLIs are of negative coefficients. For example, in the patent prediction equation of SME Board, PA220 (Total claim count of valid invention grants for last 2 year) has a negative coefficient -0.2216. It means the total claim count of valid invention grants in SME Board is already much more than it expected to be. The higher PA220 will reduce more the predictive BPS.

In Table 5, the patent prediction equation of Shenzhen Main Board has the highest adjusted $R^2=0.8787$, while the patent prediction equation of GE Board has the lowest adjusted $R^2=0.5793$. The explanatory capability is not good though all patent prediction equations reach $p^{***}<0.001$ significance. It is why we do not apply principal component analysis (PCA) or factor analysis (FA) to reduce the collinearity of PLIs before constructing the patent prediction equations. Though the numbers and collinearity of variables could be reduced by PCA and FA, the explanatory capability of variables is also reduced. If PLIs with lower explanatory capability are applied in constructing the patent prediction equation, the resulted explanatory capability might be too low to explain nothing.

The adjusted R^2 of all patent prediction equations ranges from 0.5793 to 0.8787, they are not inappropriate to be applied for precisely predicting BPS for any specific stock. However, we will try to use the predictive BPS to construct specific stock portfolios and see whether these stock portfolios have better investment performance or not.

4.3. stock portfolio Performance

Based on the predictive BPS, we apply two investment strategies:

(I) The stock in the stock portfolio is selected by the higher predictive BPS;

(II) The stock in the stock portfolio is selected by the higher predictive BPS growth rate.

Since Lag=4 is applied in patent prediction equations, that is, four quarters, so annual stock price return rates of all stock portfolios are compared. Four prediction periods are applied for constructing patent prediction equations, the investment performance is also observed over these four prediction periods.

Period I: 2016Q4 to 2017Q4;
Period II: 2017Q1 to 2018Q1;
Period III: 2017Q2 to 2018Q2;
Period IV: 2017Q3 to 2018Q3.

In order to objectively discuss the performance of stock portfolios, we also compare with the performance of the whole A-shares which representing the whole market trend, and the performance of each of four stock boards which representing the market trends of the stock boards. In addition, the performance of all A-share effective samples and effective samples of each stock board is compared.

The comparison is shown in Table 6, wherein, EA stands for all A-share effective samples; ESH stands for all effective samples of Shanghai Main Board; ESZ stands for all effective samples of Shenzhen Main Board; EGE stands for all effective samples GE Board; ESME stands for all effective samples of SME Board. Because of the decline in the overall economic environment, the annual stock price return rates of the whole A-shares and all stock boards from period I to Period IV are all negative. Especially due to the impact of the China-US trade conflict, the decline in periods III and IV is more serious. Meanwhile, GE Board and SME Board which comprising lots of small and medium companies declined more extremely than Shanghai Main Board and Shenzhen Main Board which comprising lots of big companies and state-owned companies.

However, except GE Board, the performance of the effective samples in each stock board is better than that of the whole stock board. EA is better than the whole A-shares; ESH is better than the whole Shanghai Main Board; ESZ is better than the whole Shenzhen Main Board; ESME is better than the whole SME Board. Since an effective sample should have a new patent for last one year, Table 6 shows the A-shares with patent outcome for the last one year generally have better stock performance than those A-shares without patent outcome for the last one year, no matter under the impact of China-US trade conflict or not.

Table 6: Performance Comparison of Effective Samples and A-shares

stock portfolio	Actual Stock Price Return Rate				
	Period I	Period II	Period III	Period IV	Average
Whole A-shares	-19.42%	-22.77%	-27.85%	-36.86%	-26.73%
EA	**-18.12%**	**-21.51%**	**-26.94%**	**-35.79%**	**-25.59%**
Whole Shanghai Main Board	-14.35%	-20.70%	-26.10%	-33.86%	-23.75%
ESH	**-11.70%**	**-17.84%**	**-23.12%**	**-31.09%**	**-20.94%**
Whole Shenzhen Main Board	-14.69%	-20.03%	-26.92%	-35.24%	-24.22%
ESZ	**-10.87%**	**-16.61%**	**-23.78%**	**-33.04%**	**-21.07%**
Whole GE Board	-31.37%	-26.24%	-30.01%	-40.98%	-32.15%
EGE	**-30.97%**	-27.52%	-32.19%	-41.34%	-33.01%
Whole SME Board	-21.04%	-24.79%	-29.36%	-39.08%	-28.57%
ESME	**-18.98%**	**-23.25%**	**-28.72%**	**-38.23%**	**-27.29%**

4.3.1 Investment strategy (I)

For investment strategy (I), the stocks in stock portfolios are selected by the higher predictive BPS. The patent prediction equations are applied to generate the predictive BPS in the first quarter of each period. Top 100, Top 200, and Top 300 stocks selected by the higher predictive BPS are set as the stock portfolios of said period. The averages of actual annual stock price return rates of the stock portfolios are then examined. The performance comparison is shown in Table 7.

Table 7: Performance Comparison of Investment strategy (I)

stock portfolio	Actual Stock Price Return Rate				
	Period I	Period II	Period III	Period IV	Average
EA	-18.12%	-21.51%	-26.94%	-35.79%	-25.59%
A100	**-17.18%**	**-19.65%**	**-19.28%**	**-28.42%**	**-21.13%**
A200	**-16.30%**	**-20.96%**	**-22.35%**	**-30.33%**	**-22.49%**
A300	**-17.43%**	**-22.75%**	**-24.48%**	**-32.65%**	**-24.33%**
ESH	-11.70%	-17.84%	-23.12%	-31.09%	-20.94%
SH100	**-7.43%**	**-14.39%**	**-21.12%**	**-26.11%**	**-17.26%**
SH200	**-7.41%**	**-15.00%**	**-19.51%**	**-26.38%**	**-17.07%**
SH300	**-9.14%**	**-15.54%**	**-20.24%**	**-27.16%**	**-18.02%**
ESZ	-10.87%	-16.61%	-23.78%	-33.04%	-21.07%
SZ100	**-3.04%**	**-10.46%**	**-18.99%**	**-26.72%**	**-14.80%**
SZ200	**-8.12%**	**-15.26%**	**-22.58%**	**-31.25%**	**-19.30%**
EGE	-30.97%	-27.52%	-32.19%	-41.34%	-33.01%
GE100	-42.26%	-40.28%	-38.21%	-48.18%	-42.23%
GE200	-39.78%	-36.45%	-36.22%	-45.63%	-39.52%
GE300	-35.07%	-31.34%	-34.72%	-43.28%	-36.10%
ESME	-18.98%	-23.25%	-28.72%	-38.23%	-27.29%
SME100	-23.59%	-27.31%	-30.14%	-41.87%	-30.73%
SME200	-19.85%	-23.38%	-28.80%	-38.77%	-27.70%
SME300	-19.98%	-24.61%	**-27.72%**	**-37.33%**	-27.41%

(1) A100~A300 stand for stock portfolios of top 100~300 stocks selected by the higher predictive BPS from all A-share effective samples; SH100~SH300 stand for top 100~300 stocks selected by the higher predictive BPS from Shanghai Main Board; SZ100, SZ200 stand for top 100, 200 stocks selected by the higher predictive BPS from Shenzhen Main Board; GE100~GE300 stand for top 100~300 stocks selected by the higher predictive BPS from GE Board; SME100~SME300 stand for top 100~300 stocks selected by the higher predictive BPS from SME Board.

(2) Shenzhen Main Board has 258 effective samples, so only Top 100 and 200 stocks are selected.

Regarding the whole A-shares, among four periods, A100 has the best performance in three periods (periods II, III and IV), A200 has the best performance in one period (period I). Compared with EA, each of A100, A200 and A300 is better, wherein A100 is preferable for the average of four periods and 4.46% better than the EA.

Regarding Shanghai Main Board, among four periods, SH100 has the best performance in two periods (periods II and IV), SH200 has the best performance in two periods (periods I and III). Compared with ESH, each of SH100, SH200 and SH300 is better, wherein SH200 is preferable for the average of four periods and 3.87% better than ESH.

Regarding Shenzhen Main Board, among four periods, SZ100 has the best performance in all periods. Compared with ESZ, each of SZ100 and SZ200 is better, wherein SZ100 is preferable for the average of four periods and 6.27% better than ESZ.

Regarding GE Board, among four periods, GE300 has the best performance in all periods. Compared with EGE, none of GE100, GE200 and GE300 is better, wherein GE300 is preferable for the average of four periods and still 3.09% less than EGE.

Regarding to SME Board, among four periods, SME200 has the best performance in two periods (periods I and II), SME 300 has the best performance in two periods (periods III and IV). Compared with ESME, none of SME100, SME200 and SME300 is better, wherein SME300 is preferable for the average of four periods and 0.12% less than ESME.

Obviously, the investment strategy (I) works well on the whole A-shares, Shanghai Main Board and Shenzhen Main Board not only in periods I and II, but also in period III and IV which under the impact of China-US trade conflict. The stock portfolios selected have better performance than whole the effective samples. A100~A300 are better than EA, SH100~SH300 are better than ESH, SZ100 and SZ200 are better than ESZ. However, the investment strategy (I) seems to fail on GE Board and SME Board.

With the higher predictive BPS as a stock selection criteria, Figure 3 shows the stock performance average over four periods of the effective samples and the preferable stock portfolios of each stock board. For clear comparison, the performance of A-shares is shifted to the zero line, the positive value means performance better than the market trend, the negative value means performance worse the whole A-shares average.

In Figure 3, both EGE and ESME are negative, it means GE Board and SME Board have seriously negative performance. Put these two stock boards aside, the other preferable stock portfolios have better performance than the market trend, wherein, SZ100 is outstanding.

The result shows that the investment strategy (I) is kind of a good strategy for Shanghai Main Board and Shenzhen Main Board. But it does not work on GE Board and SME Board.

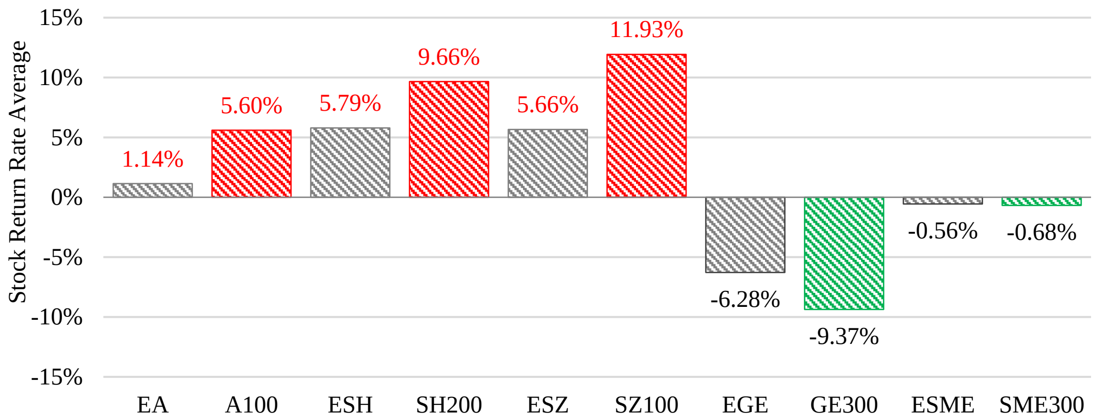

Figure 3: Performance Comparison of Investment strategy (I)

4.3.2 Investment strategy (II)

For investment strategy (II), the stocks in stock portfolios are selected by higher predictive BPS growth rates. The patent prediction equations are applied to generate predictive BPS in the first quarter of each period. When operating with real BPS in the first quarter of each period, the predictive BPS growth rate is correspondingly resulted. Top 100, 200, and 300 stocks selected by the higher predictive BPS growth rate are set as the stock portfolios of said period. The averages of actual annual stock price return rates are then examined. The comparison is shown in Table 8.

Regarding the whole A-shares, among four periods, A200R has the best performance in three periods (periods II, III and IV), A300R has the best performance in two periods (periods I and IV). Compared with EA, each of A200R and A300R is slightly better, wherein A200R is preferable for the average of four periods and 0.49% better than EA.

Regarding Shanghai Main Board, among four periods, SH100R has the best performance in two periods (periods I and III), SH300R has the best performance in thee periods (periods I, II and IV). Compared with ESH, none of SH100R, SH200R and SH300R is better, wherein SH300R is preferable for the average of four periods but still 1.06% less than ESH.

Regarding Shenzhen Main Board, among four periods, SZ100R has the best performance in all periods. Compared with ESZ, only SZ100R is better for the average of four periods and 2.64% better than ESZ.

Regarding GE Board, among four periods, GE100R has the best performance in two periods (periods III and IV), GE200 has the best performance in one period (period I), GE300 has the best performance in one period (Period II). Compared with EGE, each of GE100R, GE200R, GE300R is better, wherein GE100R is preferable for the average of four periods and 5.73% better than EGE.

Regarding to SME Board, among four periods, SME100R has the best performance in one period (Period IV), SME200R has the best performance in two periods (periods I and III), SME300R has the best performance in one period (Period II). Compared with ESME, each of SME100R, SME200R and SME300R is better, wherein SME200R is preferable for the average of four periods and 3.06% better than ESME.

Table 8: Performance Comparison of Investment strategy (II)

stock portfolio	Actual Stock Price Return Rate				
	Period I	Period II	Period III	Period IV	Average
EA	-18.12%	-21.51%	-26.94%	-35.79%	-25.59%
A100R	-18.56%	-22.44%	-26.04%	-38.66%	-26.43%
A200R	-18.22%	**-20.59%**	**-24.69%**	-36.91%	**-25.10%**
A300R	**-17.86%**	-22.27%	**-25.24%**	-36.91%	**-25.57%**
ESH	-11.70%	-17.84%	-23.12%	-31.09%	-20.94%
SH100R	**-11.60%**	-19.69%	-23.33%	-35.07%	-22.42%
SH200R	-11.85%	-21.00%	-25.26%	-34.90%	-23.25%
SH300R	**-11.60%**	-19.21%	-24.18%	-33.02%	-22.00%
ESZ	-10.87%	-16.61%	-23.78%	-33.04%	-21.07%
SZ100R	**-3.88%**	**-11.13%**	-24.23%	-34.49%	**-18.43%**
SZ200R	**-10.20%**	**-16.36%**	-25.36%	-34.69%	-21.65%
EGE	-30.97%	-27.52%	-32.19%	-41.34%	-33.01%
GE100R	**-24.22%**	**-22.57%**	**-27.49%**	**-34.81%**	**-27.28%**
GE200R	**-24.04%**	**-21.26%**	**-28.75%**	**-38.18%**	**-28.06%**
GE300R	**-26.14%**	**-22.20%**	**-28.78%**	**-38.39%**	**-28.88%**
ESME	-18.98%	-23.25%	-28.72%	-38.23%	-27.29%
SME100R	**-14.79%**	-24.12%	**-27.40%**	**-36.64%**	**-25.74%**
SME200R	**-12.20%**	**-20.43%**	**-26.99%**	**-37.29%**	**-24.23%**
SME300R	**-14.85%**	**-19.79%**	**-27.08%**	**-37.87%**	**-24.90%**

A100R~A300R stand for stock portfolios of top 100~300 stocks selected by the higher predictive BPS growth rate from all A-share effective samples; SH100R~SH300R stand for top 100~300 stocks selected by the higher predictive BPS growth rate from Shanghai Main Board; SZ100R, SZ200R stand for top 100, 200 stocks selected by the higher predictive BPS growth rate from Shenzhen Main Board; GE100R~GE300R stand for top 100~300 stocks selected by the higher predictive BPS growth rate from GE Board; SME100R~SME300R stand for top 100~300 stocks selected by the higher predictive BPS growth rate from SME Board.

On the contrary to the investment strategy(I), the investment strategy (II) works well on the GE Board and SME Board not only in periods I and II, but also in period III and IV which under the impact of China-US trade conflict. But the investment strategy (II) does not seem to work well on Shanghai Main Board and Shenzhen Main Board.

With the higher predictive BPS growth rate and the higher predictive BPS as the stock selection criteria, Figure 4 shows the stock performance average over four periods of ten preferable stock portfolios selected from four stock boards and the whole A-shares. For clear comparison, the performance of the whole A-shares is shifted to the zero line. Hence, the positive value means performance better than the market trend, while the negative value means performance worse than the market trend.

In Figure 4, there are 7 preferable stock portfolios have better performance than the market trend, only three preferable stock portfolios selected from GE Board and SME Board have worse performance than the market trend. The investment strategy (I) are likely better than the investment strategy (II) because A100, SH200 and SZ100 are respectively better than A100R, SH300R and SZ100R. However, we are more concerned about GE Board and SME Board which being impacted seriously by China-US trade conflict. In these two stock boards, GE100R and SME200R are better than GE300 and SME300 respectively. Furthermore, SME200R is 2.50% better than the market trend and GR100R is just 0.55% less than the market trend. It means the investment strategy (II) might help more in constructing valuable stock portfolios from GE Board and SME Board.

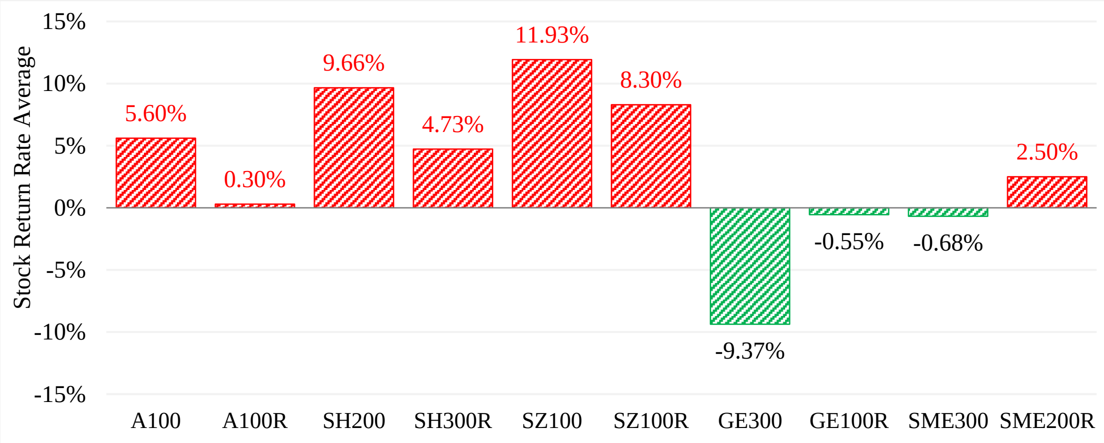

Figure 4: Performance Comparison of Investment Strategies I & II

5. Conclusion and Recommendation

Based on patent indicators and BPS data of China A-shares from 2016Q4 to 2018Q3, this research proposed specific algorithms to find PLI and patent prediction equations for BPS. And investment strategies for the whole A-shares and four stock boards including Shanghai Main Board, Shenzhen Main Board, GE Board, and SME Board were discussed. The following conclusions were obtained:

(1) Via Granger Causality test, PLIs were found to predict BPS for the whole A-shares and each of four stock boards under all predetermined Lags. The number of PLIs was usually the most under Lag=2, i.e. two quarters. As the Lag increased, the number of PLIs tended to decrease.

(2) Based on PLI species analysis, "All valid patent count (PAi45)", “Total forward patent citation count of valid patents (PAi59)”, and “Total backward patent citation count of valid invention grants (PAi54)” showed more. These patent indicators showed more relevance to A-share’s BPS than the others did.

(3) Based on PLI’s data collection interval analysis, the short term innovation which representing by the new patents showed more relevance to A-share’s BP than the long term innovation which representing by the old patents did.

(4) Via the time series regression model, the patent prediction equations, which consisting of plural PLIs, for quantitatively predicting BPS were obtained for the whole A-shares and four stock boards. The adjusted R^2 ranged from 0.5793 (GE Board) to 0.8787 (Shenzhen Main Board). Though all patent prediction equations reached $p^{***}<0.001$ significance, the explanatory capability represented by the adjusted R^2 was not good enough. The patent prediction equations were not inappropriate for precisely predicting BPS for any specific stock.

(5) The investment strategies based on the predictive BPS were proved to be useful no matter before or during China-US trade conflict. The higher predictive BPS for selecting potential stocks worked well on the whole A-shares, Shanghai Main Board and Shenzhen Main Board. The higher predictive BPS growth rate for selecting potential stocks worked well on GE Board and SME Board.

(6) Although the overall economic environment fluctuated to decline and the China-US trade conflict impacted, the patent indicator based BPS prediction algorithm proposed in this research was proved to be useful to discover good stock portfolios. It showed that patent indicators would be good factors for observing company’s financial performance even under the impact of China-US trade conflict. This proposed prediction algorithm could also be incorporated with other quantitative financial approaches for improving the investment performance .

References

Branch, B. (1974). Research and development activity and profitability: A distributed lag analysis. *Journal of Political Economy*, *82*(5), 999−1011.

Branch, B., & Chichirau, C. (2010). Mispricing vs risk premia in R&D-intensive firms. *International Review of Financial Analysis*, *19*(5), 358-367.

Broughel, J., & Thierer, A. (2019). *Technological Innovation and Economic Growth: A Brief Report on the Evidence*. Mercatus Research, Mercatus Center at George Mason University.

Caner, T., Bruyaka, O., & Prescott, J. E. (2016). Flow signals: Evidence from patent and alliance portfolios in the US biopharmaceutical industry. *Journal of Management Studies*, *55*(2), 232-264.

Chen, T.-M., Wei, C.-C., & Che, H.-C. (2018). Contribution of Patent Indicators to China Stock Performance. *Proceedings of 7th International Congress on Advanced Applied Informatics (ICAAI 2018)*, 793-798.

Cockburn, I., & Griliches, Z. (1988). Industry effects and appropriability measures in the stock M. *The American Economic Review*, *78*(2), 419.

Crossan, M. M., & Apaydin, M. (2010). A multidimensional framework of organizational innovation: A systematic review of the literature. *Journal of Management Studies*, *47*(6), 1154-1191.

Dang, J., & Motohashi, K. (2015). Patent statistics: A good indicator for innovation in China? Patent subsidy program impacts on patent quality. China Economic Review, *35*, September, 137-155. DOI:10.1016/J.CHIECO.2015.03.012

Deng, D., Lev, B., & Narin, F. (1999). Science and technology as predictors of stock performance. *Financial Analysts Journal*, *55*(3), 20-32.

Fabrizi, S., Lippert, S., Norback P., & Persson, L. (2011). Venture Capital, Patenting, and Usefulness of Innovations. *SSRN working paper*.

Griliches, Z. (1981). Market value, R&D, and patents. *Economics Letters*, *7*(2), 183-187.

Hall B.H., Jaffe, A., & Trajtenberg, M. (2005). Market value and patent citations. *RAND Journal of Economics*, *36*(1), 16-38.

Harhoff, D., Narin, F., Scherer, F, & Vopel, K. (1999). Citation frequency and the value of patented inventions. *The Review of Economics and Statistics*, *81*(3), 511-515.

He, Z. L., Tong, T. W., Zhang, Y., & He, W. (2016). Constructing a Chinese patent database of listed firms in China: Descriptions, lessons, and insights. *Journal of Economics & Management Strategy*, *27*(3), 579-606. DOI: 10.1111/jems.12186

Hirshleifer, D., Hsu, P., & Li, D. (2013). Innovative efficiency and stock returns. *Journal of Financial Economics*, *107*(3), 632-654.

Mama, H.B. (2018). Innovative efficiency and stock returns:Should we care about nonlinearity?, *Finance Research Letters*, *24*, 81-89.

Pandit, S., Wasley, C. E., & Zach, T. (2011). The effect of research and development (R&D) inputs and outputs on the relation between the uncertainty of future operating performance and R&D expenditures. *Journal of Accounting, Auditing &Finance*, *26*(1), 121-144.

Pattinger, T. (2018, Dec. 9). Relationship between stock market and economy. https://www.economicshelp.org/blog/541/economics/relationship-between-stock-market-and-economy/

Thomas, P. (2001). A relationship between technology indicators and stock market performance. *Scientometrics*, *55*(1), 319-333.

Yu, G.J., & Hong, K.H. (2016). Patents and R&D expenditure in explaining stock price movements. *Finance Research Letters*, *19*, 197-203.

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Appendix 1: Valid Patent Indicator

Valid Patent Indicators PAij (i = 1~10) & Definitions	
PAi01	Count of valid invention publications for last i year(s)
PAi02	Count of valid utility model grants for last i year(s)
PAi03	Count of valid design grants for last i year(s)
PAi04	Count of valid invention grants for last i year(s)
PAi05	Average of the patent examination duration of valid invention publications for last i year(s)
PAi06	Total International Patent Classification (IPC) count of valid invention publications for last i year(s)
PAi07	Total IPC count of valid utility model grants for last i year(s)
PAi08	Total IPC count of valid invention grants for last i year(s)
PAi09	Average IPC count of valid invention publications for last i year(s)
PAi10	Average IPC count of valid utility model grants for last i year(s)
PAi11	Average IPC count of valid invention grants for last i year(s)
PAi12	Total specification words of valid invention publications for last i year(s)
PAi13	Total specification words of valid utility model grants for last i year(s)
PAi14	Total specification words of valid invention grants for last i year(s)
PAi15	Average specification words of valid invention publications for last i year(s)
PAi16	Average specification words of valid utility model grants for last i year(s)
PAi17	Average specification words of valid invention grants for last i year(s)
PAi18	Total claim count of valid invention publications for last i year(s)
PAi19	Total claim count of valid utility model grants for last i year(s)
PAi20	Total claim count of valid invention grants for last i year(s)
PAi21	Average claim count of valid invention publications for last i year(s)
PAi22	Average claim count of valid utility model grants for last i year(s)
PAi23	Average claim count of valid invention grants for last i year(s)
PAi24	Total independent claim count of valid invention publications for last i year(s)
PAi25	Total independent claim count of valid utility model grants for last i year(s)
PAi26	Total independent claim count of valid invention grants for last i year(s)
PAi27	Average independent claim count of valid invention publications for last i year(s)
PAi28	Average independent claim count of valid utility model grants for last i year(s)
PAi29	Average independent claim count of valid invention grants for last i year(s)
PAi30	Total drawing count of valid invention publications for last i year(s)
PAi31	Total drawing count of valid utility model grants for last i year(s)
PAi32	Total drawing count of valid invention grants for last i year(s)
PAi33	Average drawing count of valid invention publications for last i year(s)
PAi34	Average drawing count of valid utility model grants for last i year(s)
PAi35	Average drawing count of valid invention grants for last i year(s)
PAi36	Total abstract words of valid invention publications for last i year(s)
PAi37	Total abstract words of valid utility model grants for last i year(s)
PAi38	Total abstract words of valid invention grants for last i year(s)
PAi39	Average abstract words of valid invention publications for last i year(s)
PAi40	Average abstract words of valid utility model grants for last i year(s)
PAi41	Average abstract words of valid invention grants for last i year(s)
PAi45	All valid patent count for last i year(s)
PAi46	Proportion of valid invention publications in all invention publications for last i year(s)
PAi47	Proportion of valid utility model grants in all utility model grants for last i year(s)
PAi48	Proportion of valid design grants in all design grants for last i year(s)
PAi49	Proportion of valid patents in all invention grants for last i year(s)
PAi50	Average lifespan of valid invention publications for last i year(s)
PAi51	Average lifespan of valid utility model grants for last i year(s)
PAi52	Average lifespan of valid design grants for last i year(s)
PAi53	Average lifespan of valid invention grants for last i year(s)
PAi54	Total backward patent citation count of valid invention grants for last i year(s)
PAi55	Proportion of inventions publication patents in all valid patents for last i year(s)
PAi56	Proportion of utility model grants in all valid patents for last i year(s)
PAi57	Proportion of design grants in all valid patents for last i year(s)
PAi58	Proportion of inventions grants in all valid patents for last i year(s)
PAi59	Total forward patent citation count of valid patents for last i year(s)
PAi60	Total backward non-patent citation count for valid invention grants for last i year(s)

Appendix 2: Statistical Test of Patent Prediction Equation for the Whole A-shares

Dependent variable	BPS			
Independent variable	**Coefficient**	**Std. Error**	**t-Statistic**	**p**
C	0.2432	0.0128	19.0583	0.0001***
BPS$_{-4}$	0.8677	0.0053	164.7504	0.0001***
PA106$_{-4}$	0.0115	0.0035	3.2560	0.0011**
PA118$_{-4}$	-0.0077	0.0030	-2.5977	0.0094**
PA132$_{-4}$	0.0068	0.0021	3.2728	0.0011**
PA354$_{-4}$	0.0245	0.0071	3.4360	0.0006***
PA359$_{-4}$	0.0181	0.0051	3.5351	0.0004***
PA404$_{-4}$	-0.0605	0.0162	-3.7397	0.0002***
PA459$_{-4}$	-0.0219	0.0068	-3.2437	0.0012**
PA460$_{-4}$	0.0248	0.0068	3.6528	0.0003***
PA560$_{-4}$	-0.0289	0.0093	-3.1067	0.0019**
PA604$_{-4}$	0.0590	0.0283	2.0846	0.0371*
PA608$_{-4}$	0.0266	0.0067	3.9527	0.0001***
PA654$_{-4}$	-0.0383	0.0095	-4.0250	0.0001***
PA659$_{-4}$	0.0367	0.0104	3.5403	0.0004***
PA759$_{-4}$	-0.0294	0.0095	-3.1043	0.0019**
PA760$_{-4}$	0.0594	0.0142	4.1995	0.0001***
PA904$_{-4}$	-0.3205	0.0865	-3.7062	0.0002***
PA906$_{-4}$	-0.1698	0.0670	-2.5349	0.0113*
PAX04$_{-4}$	0.3528	0.0823	4.2865	0.0001***
PAX06$_{-4}$	0.1555	0.0670	2.3201	0.0204*
PAX26$_{-4}$	-0.0357	0.0105	-3.4084	0.0007***
PAX60$_{-4}$	-0.0482	0.0113	-4.2778	0.0001***

p*<0.05, p**<0.01, p***<0.001

Appendix 3: Statistical Test of Patent Prediction Equation For Shanghai Main Board

Dependent variable	BPS			
Independent variable	**Coefficient**	**Std. Error**	**t-Statistic**	**p**
C	0.1650	0.0177	9.3208	0.0001***
BPS$_{-4}$	0.9264	0.0074	125.2009	0.0001***
PA132$_{-4}$	0.0093	0.0028	3.3178	0.0009***
PA254$_{-4}$	-0.0113	0.0038	-2.9522	0.0032**
PA347$_{-4}$	0.0700	0.0230	3.0401	0.0024**
PA452$_{-4}$	-0.0047	0.0020	-2.3058	0.0212*
PA460$_{-4}$	0.0099	0.0025	3.9659	0.0001***
PA551$_{-4}$	-0.0157	0.0053	-2.9866	0.0028**

p*<0.05, p**<0.01, p***<0.001

Appendix 4: Statistical Test of Patent Prediction Equation For Shenzhen Main Board

Dependent variable	BPS			
Independent variable	**Coefficient**	**Std. Error**	**t-Statistic**	**p**
C	0.1736	0.0548	3.1695	0.0016**
BPS-4	0.9177	0.0119	77.2947	0.0001***
PA102-4	0.2156	0.0984	2.1909	0.0287*
PA113-4	27.1867	13.8148	1.9679	0.0493*
PA116-4	-27.1797	13.8245	-1.9661	0.0496*
PA137-4	-27.3625	13.8871	-1.9703	0.0491*
PA140-4	27.3349	13.8914	1.9678	0.0494*
PA159-4	-0.0206	0.0079	-2.6104	0.0092**
PA201-4	0.1975	0.0393	5.0309	0.0001***
PA207-4	0.0881	0.0276	3.1953	0.0014**
PA210-4	-0.1290	0.0496	-2.5994	0.0095**
PA213-4	-0.0333	0.0138	-2.4175	0.0158*
PA215-4	0.1024	0.0205	5.0044	0.0001***
PA225-4	-0.0781	0.0288	-2.7115	0.0068**
PA236-4	-0.1640	0.0333	-4.9215	0.0001***
PA251-4	0.1067	0.0364	2.9292	0.0035**
PA336-4	-0.0228	0.0108	-2.1079	0.0353*
PA345-4	0.1498	0.0561	2.6701	0.0077**
PA445-4	-0.1685	0.0534	-3.1570	0.0016**
PA515-4	-0.0477	0.0230	-2.0756	0.0382*
PA615-4	-0.3222	0.1365	-2.3597	0.0185*

Dependent variable	**BPS**			
Independent variable	**Coefficient**	**Std. Error**	**t-Statistic**	**p**
PA739-4	2.0330	0.4234	4.8016	0.0001***
PA759-4	0.0314	0.0075	4.1729	0.0001***
PA803-4	0.0086	0.0040	2.1735	0.0300*
PA815-4	0.3080	0.1307	2.3574	0.0186*
PA939-4	-1.9215	0.4196	-4.5793	0.0001***

p*<0.05, p**<0.01, p***<0.001

Appendix 5: Statistical Test of Patent Prediction Equation For GE Board

Dependent variable	**BPS**			
Independent variable	**Coefficient**	**Std. Error**	**t-Statistic**	**p**
C	0.3496	0.0563	6.2048	0.0001***
BPS$_{-4}$	0.7394	0.0144	51.4143	0.0001***
PA218$_{-4}$	-0.0336	0.0114	-2.9381	0.0033**
PA246$_{-4}$	-0.2034	0.0856	-2.3763	0.0176*
PA250$_{-4}$	0.0458	0.0147	3.1221	0.0018**
PA259$_{-4}$	0.0258	0.0074	3.4712	0.0005***
PA346$_{-4}$	0.1640	0.0790	2.0759	0.0380*
PA445$_{-4}$	-0.0348	0.0115	-3.0240	0.0025**
PA618$_{-4}$	0.0426	0.0129	3.3004	0.0011**

p*<0.05, p**<0.01, p***<0.001

Appendix 6: Statistical Test of Patent Prediction Equation For SME Board

Dependent variable	**BPS**			
Independent variable	**Coefficient**	**Std. Error**	**t-Statistic**	**p**
C	0.2948	0.0263	11.2102	0.0001***
BPS$_{-4}$	0.8419	0.0099	85.2113	0.0001***
PA104$_{-4}$	-0.0541	0.0157	-3.4488	0.0006***
PA114$_{-4}$	0.0073	0.0027	2.7247	0.0065**
PA132$_{-4}$	0.0126	0.0050	2.5379	0.0112*
PA204$_{-4}$	0.3939	0.0711	5.5371	0.0001***
PA211$_{-4}$	-0.0406	0.0188	-2.1633	0.0306*
PA217$_{-4}$	-0.0176	0.0082	-2.1398	0.0325*
PA220$_{-4}$	-0.2216	0.0566	-3.9186	0.0001***
PA223$_{-4}$	0.2745	0.0677	4.0514	0.0001***
PA226$_{-4}$	-0.0828	0.0304	-2.7245	0.0065**
PA258$_{-4}$	-0.3191	0.0979	-3.2608	0.0011**
PA358$_{-4}$	0.3574	0.1062	3.3655	0.0008***
PA360$_{-4}$	0.0194	0.0044	4.3739	0.0001***
PA438$_{-4}$	-0.1140	0.0228	-4.9955	0.0001***
PA441$_{-4}$	0.1074	0.0236	4.5450	0.0001***
PA501$_{-4}$	-0.1274	0.0407	-3.1334	0.0017**
PA508$_{-4}$	0.0802	0.0173	4.6442	0.0001***
PA524$_{-4}$	0.0489	0.0205	2.3819	0.0173*
PA529$_{-4}$	0.3348	0.1044	3.2077	0.0014**
PA553$_{-4}$	-0.1008	0.0205	-4.9127	0.0001***
PA604$_{-4}$	0.2189	0.0839	2.6100	0.0091**
PA606$_{-4}$	0.1040	0.0312	3.3274	0.0009***
PA626$_{-4}$	-0.2152	0.0731	-2.9436	0.0033**
PA901$_{-4}$	0.1052	0.0401	2.6250	0.0087**
PA906$_{-4}$	-0.1402	0.0335	-4.1915	0.0001***

p*<0.05, p**<0.01, p***<0.001