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Investigating China's Stock Market Efficiency and Forecasting China's Stock Price Volatility

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Investigating China's Stock Market Efficiency and Forecasting China's Stock Price Volatility

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Contents

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Abstract

This thesis aims to investigate the efficiency of China's stock market, detect the macroeconomic and financial drivers of China's stock price volatility, and assess the power of the most significant drivers for predicting China's stock price volatility. The data used in this thesis starts from 2005 since this is when the non-tradable reform was implemented, significantly influencing on the efficiency of China's stock market. The stock price volatility has been obtained using the GARCH-MIDAS model and a comprehensive set of drivers is considered to try to exploit more information. Using a variety of unit root tests, this study shows that China's stock market is weak-form efficient. In addition, this thesis also finds that the US stock market and the development and openness of China's stock market has a significant effect on China's stock price volatility using several novel significance tests and the time-varying VAR model. However, this information is shown to have no additional ability in predicting China's stock volatility after controlling for the past information contained in the stock prices using the penalized regression models and Support Vector Regression model. This thesis contributes to the current literature in several aspects. First, a panel unit root test allowing for the smooth structural breaks and accounting for the cross-sectional dependence, which has not been applied in the current literature, is used to examine the weak-form efficiency of China's stock market; Second, it considers a comprehensive set of potential drives, especially the drivers related to the development and openness of China's stock market which the current literature has not put an emphasis on. Moreover, a number of new significance tests based on the penalized regression models are used for the first time to detect the impact of these drivers on the stock price volatility; Third, it uses machine learning techniques and penalized regression models to assess the power of the macroeconomic and financial variables in predicting China's stock price volatility, which can provide more robust evidence than those provided by the current literature.

Chapter 1

Introduction

1.1 Introduction

1.1.1 Motivations and Objectives

The Chinese stock market has been in process of development for the last thirty years, in first ten years the evidence suggested it was inefficient, characterized by enormous speculation investment, accounting fraud, government interference, regulation lack, etc (Donegan, 2017). Thus, it had even been compared with a casino by Jinglian Wu, a renowned Chinese Economist, at the end of 90s. However, China's stock market has experienced a substantial level of development over the previous decades, especially after China joined the WTO in 2001. In the last fifteen years, a series of reforms and initiatives associated with the openness, legalization, privatization, trading and innovations of the markets as well as the allowing of derivative products and practices such as short selling have been implemented in China, which have boosted the development of China's stock market and moved it closer to the developed level as with the US stock market. Meanwhile, China's economy has become the second largest in the world, with China's stock market also playing an increasingly important role and attracting high levels of both domestic and foreign investment. Therefore, based on the Efficient Market Hypothesis (Fama, 1970), there is a need to ask whether the Chinese stock market has moved from a state of inefficiency to the level of weak-form efficiency. The reason for only considering a investigation of the weak-form efficiency of China's stock market is due to the consideration of the development stage of China's stock market, in which there are still many obstacles to reach efficiency , which are preventing the markets becoming semi-strong form efficiency.

According to the literature, there existed a number of studies examining the weak-form efficiency of China's stock market (Qian et al., 2008; Kang et al., 2010; Hasanov et al., 2007; Li et al., 2012; Tian, 2007; Wang et al., 2015). However, these studies have not reached to a consensus on whether or not China's stock market is efficient, which is mainly due to different data periods and models used in these studies. Specifically, Firstly, the degree of the efficiency of China's stock market varies with the different stages of China's economic development. It has become more efficient as a series of reforms such as the non-tradable shares reform in 2005 have been carried out. Therefore, the different time spans used in these studies might lead to variable results; Secondly, frequent manipulation by the government and speculative investment behaviour by investors have resulted in more complicated behaviour of the stock indices, which might cause different models to produce different results.

There are indeed a number of methods which can be applied to examine the weak-form efficiency. However, this thesis restricted itself to only use unit root tests to investigate the weak-form efficiency of China's stock market considering the following reasons: firstly, unit root tests are used to test random walk hypothesis, which, thus, can be used for test for the weak-form efficiency. Secondly, unit root tests have been developed substantially and applied widely in the literature, there are a number of advanced unit root tests that can be applied to the more complex form of data and they theoretically have more power in examining the weak-form efficiency of markets than the other methods. In addition, the data covering the last fifteen years is used to limit the potential impact of the data periods on the evaluation. Therefore, firstly, this thesis used the most recent fifteen years data and the widely used unit root tests to answer the question: is China's stock market weak-form efficient?

Despite massive development in China's stock market, China's stock market is largely exposed to both potential external and internal risks. Externally, China's economy is experiencing a structural transition from being an industrial driven economy to a tech-driven economy, during which the former no longer provides new growth opportunities, whilst the later has just started. Furthermore, as the first two largest economies in the world, China-US relations have been deteriorating, characterized by China-US trade, which began in March 2018.

Internally, China's financial markets are exposed to a number of issues. First, the constitution of the investors is inequitable with individual investors accounting for more than 80% of the volume of market trading (Pan and Mishra, 2018). Although individual investors can promote the market liquidity, they are prone to speculative trading and herd behaviour, which exacerbates market volatility. On the contrary, in the developed financial markets, the institutional investors account for 70%–80% of the total investment in the stock markets, which makes a key contribution in stabilizing the stock market. Second, the financial derivatives market in China is undeveloped with the facts that there are only two equity index futures, the China Securites Index (CSI) 300 index futures established on April 16, 2010 and Shanghai Stock Exchange 50 (SSE 50) index future launched on April 16, 2015, and one equity option, Shanghai Stock Exchange (SSE) 50 exchange-traded fund (ETF) option established on April 16, 2015 (Gong et al., 2016; Ren et al., 2019). Third, the cost of violating rules is low, which leads to frequent insider trading, market manipulation, illegal disclosures and other violations of law (Pan and Mishra, 2018).

From both the external and internal perspectives, China's stock market is experiencing many uncertainties, though there is also massive investment opportunities. Thus, it is of great importance for the risk managers and investors to find the drivers of risks in China's stock market. There exists extensive literature in modeling asset volatilities that are crucial in risk measures such as Value-at-Risk (VaR) or Expected Shortfall. One of the most successful volatility models is the ARCH model introduced by (Engle, 1982). Stochastic volatility (SV) models, another class of volatility models in the literature, are also applied wildly to model the time-varying volatility in option pricing, portfolio allocation and risk management. The realized volatility, another relatively new form of volatility modeling by Andersen et al. (2001) and Barndorff-Nielsen and Shephard (2002), has enjoyed an increasing popularity in modeling asset volatilities using high-frequency intra-day asset returns.

However, these volatility models only capture the information contained in the stock returns but ignore some other potential information contained in macroeconomic and financial variables. The examination of the role played by macroeconomic and financial variable in driving the stock volatility can be dated back to the the seminal work by Schwert (1989) where the author posed a question: what drives the variation in the US stock return volatility? Although the author only provided weak evidence supporting the usefulness of these macroeconomic and financial variables in driving the US stock return volatility, this study suggested that the US stock volatility is negatively related with the business cycle. More encouraging evidence has been provided by subsequent research, showing the usefulness of the information contained in macroeconomic and financial variables, e.g., Paye (2012), Engle and Rangel (2008), Engle et al. (2013), Christiansen et al. (2012) and Mittnik et al. (2015).

Inspired by the these studies, a number of studies have investigated whether the macroeconomic and financial factors drive China's stock volatility (Girardin and Joyeux, 2013 and Cai et al., 2017). However, the scholars haven't not reached a consensus, which is primarily duo to the facts that the literature is too limited to draw a conclusion and studies applied different predictors and different econometric approaches.

Nowadays, a series of China's economic and financial databases or the ones related to China's economy and finance have been well developed and applied, e.g, China Stock Market & Accounting Research (CSMAR) database, RESSET database and Global Economic Data, Indicators, Charts & Forecasts database (CEIC). As a result, it's no longer a big challenge as before to access the data about China's economy and finance in both quantity and quality aspects, though there is still a big gap compared with the US databases, particularly in the quantity aspect. As more data is becoming available, a number of new regression/variable selection techniques, e.g., Least Absolute Shrinkage and Selection Operator (LASSO) (Tibshirani, 1996), Least Angle Regression (LARS) (Efron et al., 2004) and Elastic-Net (Zou and Hastie, 2005), have been developed to exploit as much as possible of the information contained in these high-dimensional data without suffering the overfitting problem as seriously as the traditional estimators like ordinary least squares (OLS) does. However, the use of these techniques with economic data has been limited by the lack of statistical inference for a long time. Recently, a number of papers (Lockhart et al., 2014; Taylor et al., 2014) have empowered these techniques with the relevant significant tests, which, based on my knowledge, haven't been used in the economic and financial literature.

Therefore, motivated by the limited literature on analyzing the drivers of the China's stock return volatility, the available larger set of data and the new powerful techniques, this thesis next investigated the question: what drives the variation in China's stock return volatility? The results showed that the VIX index, measuring the degree of fear in the US stock markets, is the most significant driver of China's stock volatility. Given the importance of the relationship between China and the US for the economy and finance of both countries and even the whole world, this takes this thesis to another question: how does the VIX index drive China's stock volatility over time?

The results showed that the information contained in some macroeconomic and financial variables played an important role in driving China's stock volatility. This triggers the next interest of this thesis in investigating whether incorporating the information contained in macroeconomic and financial variables into the forecasting model can achieve some gains in predicting stock volatility. There existing a large number of literature assessing the predictive ability of macroeconomic variables on the other macroeconomic variables (Bai and Ng, 2008). According to the best of my knowledge, however, only a few studies have assessed the predictive power of macroeconomic and financial variables on the stock volatility (Ludvigson and Ng, 2007, Paye, 2012).

Furthermore, most of the forecasting models used in this limited literature are linear parametric ones. Although parametric models are simple to be implemented and explained, they make specific assumptions about the functional form of the data generation process and the distribution of error terms, which could mean that the economic significance of macroeconomic and financial variables cannot be captured. In contrast, non-parametric models provide much more flexibility in modeling the underlying data generation process. Instead of specifying a particular functional form and making a prior distributional assumption, the non-parametric model will search for the best fit over a large set of alternative functional forms. Thus, many nonlinear non-parametric models are developed and employed in economic and financial applications, among which the Support Vector Machine (SVM) models (Vapnik, 2013), generally called the machine learning techniques, including Support Vector Classification (SVC) model and Support Vector Regression (SVR) model, have enjoyed a wide popularity.

Compared with the linear regression models, the SVR model estimates the parameters using cross-validation methods without assuming any probability density function (PDF) over the data series, which can produce more accurate predictions than those obtained using the least squares approaches (Chen et al., 2010, Pérez-Cruz et al., 2003).Compared with the other machine learning techniques, it allows nonlinearities in the data which the linear machine learning techniques, like the LASSO, LARS and Elastic-Net , cannot deal with, and can obtain the optimal parameters so that to attenuate the overfitting problem which the other machine learning techniques such as the Artificial Neutral Network (ANN) model and the trees model are struggling with. In addition, the ability to deal with the large dataset is another outstanding advantage of the machine learning techniques.

As this thesis has shown the significance of some macroeconomic and financial variables in driving China's stock return volatility, motivated by the limited studies predicting China's stock return volatility, and the superiority of the machine leaning techniques in predicting, lastly, this thesis investigated the question: can the macroeconomic and financial variables provide useful information in predicting China's stock volatility?

1.1.2 Methodology and Results

Driven by the motivations above and research objectives, generally, this thesis firstly applied a variety of unit root tests into the Chinese stock market returns to examine the weak-form efficiency of the Chinese stock markets; then this thesis moves to investigate the drivers of the Chinese stock volatility and analyze the dynamic impact of these drivers on the Chinese stock volatility; lastly, this thesis examined the usefulness of the information contained in the macroeconomic and financial variables through a forecasting framework. We next introduce the methodology of this thesis specifically.

Following the introduction, Chapter 2 provides an overview of China's stock market, and recent development , then Chapter 3, 4 and 5 suggest answers to the research questions of this thesis. Finally, a conclusion and policy implications are enclosed in Chapter 6.

Chapter 2 gives an overview of China's stock market in terms of the market's development, openness, privatization and legalization. It showed that China's stock market has experienced enormous growth and improvements in its governance. A series of reforms and initiatives, especially after 2005, have been applied to China's stock market. In addition, a comprehensive legal system has been established and also has recently been updated along with the improvements to the system for new issues in China's stock market. All of these changes have driven China's stock market to join the group of the developed and mature markets headed by the US.

Chapter 3 aims to investigate the efficiency of China's stock market using a series of unit root tests. Since the conclusion on the non-stationarity can be contaminated by the presence of nonlinearlity of the data series, this chapter firstly applied a number of tests to specify the form of the nonlinearity. These pre-tests used in this study are able to produce a robust set of results regardless of whether the series is stationary or contains a unit root, which can further provide assurance on the reliability of the inference on the non-stationarity of the series. The results of these tests show that China's stock prices are characterized by smooth structural breaks. Then, a group of unit root tests including both univariate and panel unit root tests are applied to investigate the efficiency of China's stock markets.

Among these unit root tests, the panel unit root test with smooth structural breaks as measured by the Fourier function provided the most persuasive conclusions that China's stock market is weak-form efficient over the last fifteen years, which implies that the development and openness of China's stock market following recent developments has played an important role improving the market's efficiency.

Chapter 4 aims to find the determinants of the Chinese stock volatility from a large set of potential macroeconomic and financial variables using the penalized regression techniques and the corresponding significance tests. Specifically, the GARCH-MIDAS model is used as filter on the realized volatility to produce a less noisy monthly Chinese stock volatility. Based on the literature on both the developed stock markets and the Chinese stock markets, the potential determinants are classified into three categories: international variables, macroeconomic and financial variables and the variables representing the specific characteristics of the Chinese stock markets. Then the LASSO regression based on the LARS algorithm and Gradient decent algorithm is used to select the most important variables from these potential variables. Further, the Post-LASSO, Truncated Gaussian and CovTest significance tests are applied to find the variables that have statistically significant effects on the Chinese stock markets. The results showed that VIX is the most significant driver among these potential drivers of the Chinese stock volatility.

Given the importance of the relationship between China and the US for the economy and finance of both countries and even the whole world, this thesis continues to analyze the relationship between these markets by applying TV-VAR model, which allows for both heteroskedasticity of the shocks and time variation in the simultaneous relationships between the variables in the model. Firstly, I investigated if the innovations of the VIX index have changed over time, secondly I analyzed how shocks to the VIX index affect the Chinese stock price volatility over time through the impulse response function and thirdly compared the influence of the US stock market on the Chinese stock market covering three China-US presidency periods. One interesting finding is that the US stock markets have the strongest effect on the Chinese stock price volatility during the Jinping Xi and Donald Trump presidency, which is in line with the China-US trade war happening during this period.

Chapter 5 aims to investigate whether the forecasting accuracy of the Chinese stock price volatility can be improved by incorporating the information included in the macroeconomic and financial variables into a forecasting model where the lags of the stock volatility have also been included. Firstly, the GARCH-MIDAS model was applied to obtain the stock volatility. Meanwhile, 49 macroeconomic and financial variables are considered in order to gain as much predictive information related to stock volatility as possible.

Then both the in-sample analysis and the one-step-ahead out-of-sample forecasting framework were implemented to assess the predictive power of the macroeconomic and financial variables. Considering the overfitting problem caused by a relatively larger number of macroeconomic and financial variables, some recent techniques were applied to extract information from the whole set of predictors or shrink the number of relevant predictors. This chapter firstly applied the diffusion index methodology and the shrinkage methods including LARS and LARS Elastic-Net. However, all these models are linear parametric models. Since non-parametric models can provide much more flexibility in modeling the underlying data generation process, this chapter applied the SVR model to address the research question.

Finally, this chapter found that the information contained in the macroeconomic and financial variables cannot provide help in improving the forecasting of China's stock price volatility after the information contained in the past stock price is controlled for. This evidence is similar to the US market, using different approaches to that used here. This implies that China's stock market is efficient since the past information contained in the stock prices already contains the macroeconomic and financial information.

1.1.3 Contributions

There are a number of contributions of this study to the current literature. First, this thesis provides comprehensive evidence on the recent levels of efficiency in the Chinese stock markets, overall producing mixed evidence on its efficiency, but suggesting China's stock market is a weak-form efficient stock market over the last fifteen years based on a variety of unit root tests, particularly the more recent panel unit root test (Lee et al., 2016a) allowing smooth structural breaks (Enders and Lee, 2012b) and accounting for cross-sectional dependence (Pesaran et al., 2013), which hasn't been applied in the current literature (Qian et al., 2008; Kang et al., 2010; Hasanov et al., 2007; Li et al., 2012; Tian, 2007; Wang et al., 2015) , and is able to model the significant impact of the reforms and initiatives implemented in China's stock market.

Second, although there are many studies investigating the relationship between the information contained in past stock price in respect of current stock price volatility, only a limited number of papers investigated the macroeconomic and financial drivers of China's stock price volatilities (Girardin and Joyeux, 2013 and Cai et al., 2017), and furthermore, these studies only use the linear parametric models which cannot capture the nonlinearities in the data and would suffer from the overfitting problem when dealing with a large set of data and didn't systematically account for the drivers associated with the unique characteristics of China's stock market over the last fifteen years. This thesis contributed the current limited studies by using a large data including the variables capturing the development, openness and privatization of China's stock market and a number of novel significant tests (Lockhart et al., 2014) based on the penalized regression models to investigate the macroeconomic and financial drivers of China's stock price volatility. Moreover, this thesis also analyzed the relationship between China's stock price volatility and the political cycle using a time-varying parameter VAR model (Primiceri, 2005) covering the recent fifteen years, which contributed to the literature studying the volatility spillovers between China's and US stock markets using the GARCH related models (Wang and Wang, 2010; Zhou et al., 2012; Hua and Sanhaji, 2015).

Third, the current literature mostly use econometric models and past stock price information to predict the stock volatility or other economic and financial variables (Schwert, 1989; Paye, 2012; Chen et al., 2016a). This thesis contributed to the literature by applying the machine learning techniques, like the Support Vector Regression model which can attenuate the overfitting problem and allow for the nonlinearities in the data, to investigate whether the macroeconomic and financial variables are useful for predicting China's stock price volatility.

Chapter 2

Overview of China's stock market

2.1 Overview of China's stock market

This chapter makes an overview of China's stock market through several dimensions including its development, openness, trading, privatization and legalization, showing the progress China's stock market has already made in the last thirty years. This overview aims to provide the background for this thesis, from which it is easy to be seen that it is reasonable to ask whether China's stock market has already weak-form efficient and what risk factors would influence China's stock volatility.

There are two stock exchanges in mainland of China, namely, the Shanghai Stock Exchange (SHSE) and Shenzhen Stock Exchange (SZSE) which were set up on December 19th, 1990 and July 3rd, 1991 respectively. The SHSE only includes the main board which lists the larger and more mature stocks. Apart from the main board, the SZSE additionally includes the Small and Medium Enterprise Board and the ChiNex Board. The latter, also known as the Growth Enterprise Board, serves the smaller and high-technology stocks.

There are a number of distinctive features in China's stock market. First, China's stock market has dual-share system. Both the main boards of the Shanghai and Shenzhen Stock Exchanges include A-share list stocks which are traded among Chinese citizens and B-share list stocks which are traded among non-Chinese citizens and overseas Chinese. In addition, many firms are cross-listed in both the mainland and Hong Kong Stock Exchanges. Second, China's stock market is a pure order-driven market rather than a quote-driven market, while the US and several other stock markets adopt the hybrid stock market system. Third, China's stock market is a centralized market, whereas the US stock market is uncentralized with a number of stock exchanges, other off-exchange trading and dark pools. China's stock market has no dark pools so as to all orders are visible. In addition, there is a daily price change limit of 10% in

China's stock market,which aims to reduce the excess stock return volatility.

2.1.1 Development

These two stock markets have been expanding rapidly over the past years. By December 31st, 2018, there are a total of 1906 A-share listed stocks, of which 1443 are traded in the SHSE and 463 traded in the SZSE. There are a total of 99 B-share listed stocks, of which 51 were traded in the SHSE and 48 traded in SZSE. The A-share market capitalization has increased to about 32296.5 billion RMB with about 26869 billion RMB for A-share Shanghai stock market capitalization and 5427.5 billion RMB for A-share Shenzhen stock market capitalization.

China's stock market has experienced several distinctive phrases over the past thirty years. The first stage of development of China's stock market, from 1991 to 1997, witnessed the opening and construction of the Shanghai and Shenzhen stock exchanges. During this period, the number of companies listed on the Shanghai and Shenzhen stock exchanges increased from eight to more than five hundred. Many companies moved from the OTC platform to the electronic trading platforms established in Shanghai and Shenzhen stock exchanges. During the second stage from 1998 to 2001, the famous casino theory was proposed by Chinese financial economist Jinglian Wu. The theory described China's stock market as a casino, suggesting that China's stock market was extensively manipulated and the stock price didn't reflect the fundamental values.

When it came to the third stage from 2001 to 2005, China's stock market experienced a series significant changes aiming to protect the minority shareholders, improve the accounting transparency and audit quality, privatize the state-owned enterprises and open the market to the foreign investors. These changes moved the stock market in the direction of increased openness, privatization and legalization. Built on the third stage, China's stock market continued to experience wider and deeper reforms in terms of its openness, privatization and legalization in the fourth stage from 2005 until to now. Under these developments during this stage, China's stock market has been gradually closed to the developed market such as the US stock market and has grown to the second largest stock market in the world.

In this thesis, we only consider SHSE because the majority of A-share companies are listed in SHSE. In addition, we have only used the data after 2005 considering that China's stock market is undeveloped and uninformative in the last three stages. Figure 2.1shows the plots of the market capitalization of SHSE A shares and the number of A-share companies listed in the SHSE. It is obvious to see a rapid increase in both the market capitalization and number of listed companies although there are some jumps during some periods, especially during the financial crisis in 2008 and the Chinese financial turbulence in 2015.

2.1.2 Openness

At the initial stage of the development of the Chinese stock markets, the listed companies were only allowed to issue "A" shares, which were denominated in RMB and could only be invested by domestic investors. To attract foreign investors especially the foreign institutions, listed companies were as well allowed to issue "B" shares in 1992, which were traded in US dollars on the Shanghai stock exchange and Hong Kong dollars on the Shenzhen stock exchange. However, B shares were shown to be unattractive to foreign investors although they were traded at a huge price discount relative to "A" shares, which was attributed to the inefficiency of the Chinese stock markets at the earlier stage and also this pushed the Chinese government into opening the stock markets. In order to develop the B-share stock market, the domestic investors were also allowed to trade B-shares on the SHSE and the SZSE in February 2001. Furthermore, mainland companies were also allowed to be listed in foreign stock markets, particularly the Hong Kong and New York Stock Exchanges.

China has further implemented series of initiatives related to market openness after it joined the WTO in late 2001 to meet its membership requirements. By the end of 2006, China had fulfilled all the commitments in terms of stock market openness (Kwon, 2009). Specifically, these commitments include: First, allowing foreign companies to purchase state-owned and legal person shares in November 2002; Second, launching the Qualified Foreign Institutional Investor (QFII) programme in December 2002; Third, authorizing the Qualified Domestic Institutional Investor (QDII) programme to invest in overseas capital markets in May 2006.

Figure 2.2 (a) and (b) show the plots of the approved investment fund and the number of qualified institutions in the QFII scheme since 2005. It can be seen that both the approved investment fund and the number of qualified institutions have experienced a rapid growth. Particularly, they increase more after Apr. 2012, which is due to the fact that the Chinese government approved another 50000 million US dollars investment fund for the QFII scheme.

Apart from these commitments, a series of initiatives have been further implemented to accelerate the openness of stock markets since the end of 2011. The RMB Qualified Foreign Institutional Investor (QFII) programme was launched in December 2011. The qualified foreign institutions are allowed to invest mainland China's security markets though the RMB-denominated funds established in Hong Kong (including other approved countries/areas later). Figure 2.2 (c) and (d) show that both the approved investment fund and the number of qualified institutions in the RQFII program have experienced a rapid growth since it was launched.

In addition, China launched the first round of reforms to the exchange rate in July 2005. China began to target the value of the RMB to a "reference basket" of currencies, and the RMB exchange rate can fluctuate by up to 0.3% (later 0.5%) on a daily basis against this basket. In June 2010, China resumed the reforms on the RMB exchange rate because the first round of reforms were interrupted by the global financial crisis in 2008. In August 2015, the People's

Bank of China (PBC) decided to float the RMB exchange rate. However, this action caused market panic and RMB quickly devalued. Consequently, this experiment was halted and a new central parity rate mechanism was used.

Based on Figure 2.3, it can be seen that the RMB exchange rate with the US dollar had declined after the first round of reforms, suggesting that the value of the RMB has appreciated. Then the exchange rate kept at the same level from 2008 to 2010, during which the reforms on the RMB exchange rate were halted. After that, the RMB continued to appreciate until about 2015. Since August 2015, the RMB exchange rate with the US dollars began to depreciate and then fluctuated later with regard to the China-US trade war.

In addition, as the first mutual access channel between the Chinese and Hong Kong equity markets, the Shanghai-Hong Kong Stock Connect (SHSC) was launched in 2014. This scheme allows the Hong Kong and international investors to purchase shares listed in SHSE, meanwhile it also allows the eligible Chinese investors to purchase eligible shares listed in Hong Kong stock markets. Similarly, the Shenzhen-Hong Kong Stock Connect (SHSC) was launched in December 2016, which further provide investors with a channel to purchase shares on both sides.

2.1.3 Trading

For the SHSE and SZSE, there are about 243 trading days in a year. In each trading day, the morning trading session is 9:30 to 11:30 am and the afternoon trading session is 1 to 3 pm.

The Chinese government has imposed stamp duty on the trading of shares in both the SHSE and SZSE, which can effectively be used to control the stability of China's stock market by affecting investors' trading activities. The stamp duty was first imposed on the SZSE, then it was also imposed on the SHSE, starting from the 23rd October 1991. Based on Table 2.1, it can be seen that the rate of stamp duty was increased from 0.3% to 0.5% in May 1997 , which aimed to control the fluctuations and the speculative tradings in the initial stages of China's stock market development. Then the stamp duty was reduced in the following years. On 30 May 2007, the stamp duty increased to 0.3% to limit the frequent market tradings. On 24 April 2008, the stamp duty was cut again to 0.1%. On 19 September 2008, the stamp duty started to be levied upon the selling side only and kept at 0.1% level until to now.

Another important initiative was that margin trading and short selling was introduced on a trial basis to China's stock market in 2008. A group of 11 top brokerage firms were authorized to start the experiment on margin trading and short selling. In March 2010, a limited number of stocks were allowed to be bought on margin or sold short. It started with less than 100 stocks and then increased to nearly 700 over the next few years. However, the government halted short selling activity for all stocks because of the Chinese financial crash in 2015. Then, in March 2016, a number of brokerages were allowed again to participate in short selling activity. In May 2017, a set of rules were revised, which aimed to strengthen and stabilize China's stock market. Among them, the key one is to regulate sales by major shareholders of listed firms.

Table 2.1: Stamp Duty

Date	Rate (%)	Selling or Buying
1991-10-23	0.3	Both
1997-05-10	0.5	Both
1998-06-12	0.4	Both
1999-06-01	0.3	Both
2001-11-16	0.2	Both
2005-01-24	0.1	Both
2007-05-30	0.3	Both
2008-04-24	0.1	Both
2008-09-18	0.1	Selling

Data is collected from the database RESSET.

2.1.4 Privatization

At the initial stage, the SHSE and the SZSE both established a split share structure under which approximately two-thirds of domestically listed A-shares were not tradable. However, holders of these non-tradable shares were entitled to exactly the same voting and cash flow rights as holders of tradable shares. These non-tradable shares were held by the state and legal persons and the tradable shares were held by domestic and foreign individual investors as well as domestic institutional investors. However, Chinese government recognized that the predominance of non-tradable shares obstructed the development of the Chinese stock markets and was attributed to large part of inefficiency of the stock markets. In order to promote the development of the stock markets, the Chinese stock markets launched a non-tradable share reform in April 2005 which aimed to convert all non-tradable shares into tradable shares. By the end of 2007, 1254 firms, representing over 97% of the Chinese A-share market capitalization at the time, had completed the reform.

2.1.5 Legalization

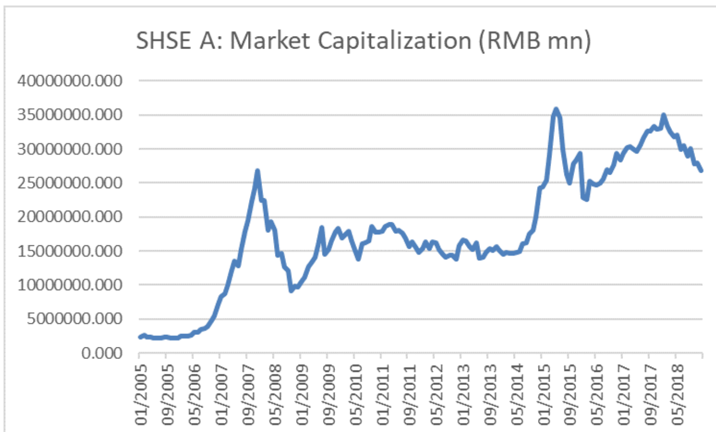
The Company Law and Securities Law forged the fundamentals of the legalization of China's stock market. They were developed during the first two stages of China's stock market from 1992 to 2001 and modified in the later years along with the appearance of new issues. Specifically, the Standing Committee of the National People's Congress (NPC) passed the Company Law in December 1993, providing a concrete legal standards for the company formation and operation. The Securities Law was passed in December 1998 and took effect on the 1st of July, 1999. The Securities Law provided a comprehensive legal system for various requirements regarding the stock markets such as when there are the public offerings, listings, trading, information disclosure, anti-fraud measures amongst other reforms. The establishment of the Securities Law marked that a basic law system was formed.

Apart from the enactment of the laws, another significant achievement was that, by the July 1999, a unified and centralized regulatory system was established by putting all the local regulators under the control of the China Securities Regulatory Commission (CSRC). Before the CSRS became the central regulator, the regulatory system was fragmented. For example, The State Planning Commission was responsible for the formulation and distribution of quotas for share issues; the People's Bank of China (PBOC) had the mandate to license and supervise investment funds and securities institutions; the Ministry of Finance was responsible for the regulation of the accounting sectors. In addition, the regulatory system was locally controlled. Shanghai and Shenzhen set up their own regulators in 1993 and the other governments in other provinces also follows this action later. These regulators were only under the control of each local government and the CSRC had no jurisdiction over them and even had trouble accessing the information of the stock exchanges.

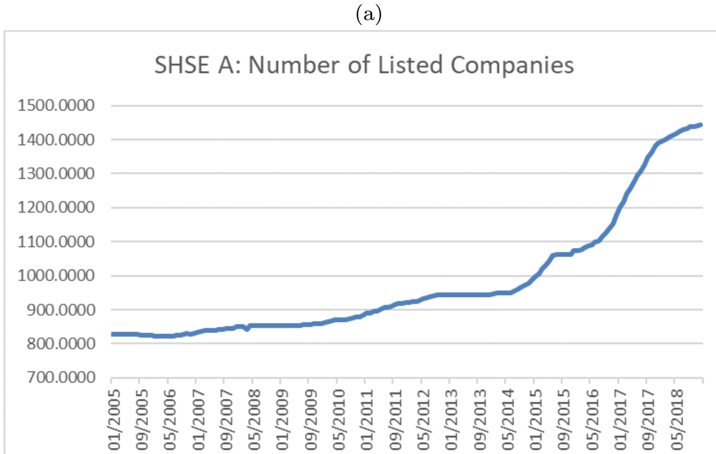
Although a basic legal framework was built before China's stock market came into the third stage. However, during the second stage, a series of serious problems appeared such as financial distress, stock price manipulation, accounting fraud and misappropriation. In the end of 90s, a large number of listed companies experienced enormous loss. To warn the market, against this the Shanghai and Shenzhen Stock Exchanges labeled the companies with continuous two years losses as Special Treatment (ST) companies in 1998 and the companies with consecutive three years losses as Particular Transfer (PT) companies. The number of the ST companies increased from 26 in 1998 to 66 by 2000 and there were only 4 PT companies in 1991 but this increased to 20 by 2001. This serious situation called for an urgent need to improve the performance and governance of companies. Accordingly, the CSRC launched a document in August 2001 stating that the companies should keep at least one-third of the directors independent by the mid 2003. Further, a corporate governance code for listed companies was issued in January 2002. It was involved in many serious problems such as the dominance of the controlling shareholders and the dependence of the listed companies on the controlling shareholders.

In 1998, the companies labeled as ST began to soar, suggesting that the stock prices were manipulated heavily. In addition, the average price earning (PE) ratio increased to 70 by the end of 2000, which indicated that the stock prices deviated form the fundamental values excessively. According to (Donegan, 2017), accounting fraud was another serious problem during this period and a series of accounting scandals were revealed. For example, in August 2001, Caijing, a respected magazine, reported that the profits of a blue-chip and high-growth company, Yinguangxia, were completely fabricated. In addition, the misappropriation problem was also in urgent need of address during this period. The controlling shareholders dominated the governance of the listed companies and abused their positions by benefiting authority at the expense of public investors. all these problems lead to the modification of Company Law and Securities Law in 2005. By 2006, a comprehensive legal system was established and China's stock market became more regulated and trustworthy.

To conclude, following the analysis of the Chinese stock markets, I will use formal econometric models to examine the weak-form efficiency of China's stock market, and to see if the results are in line with the suggestions from the progress shown above. After that, this thesis will investigate risk factors of China's stock volatility. Among them, a special focus will be paid on the risk factors associated with the characteristics of China's stock market in relation to the aspects discussed above to analyze how these factors influence China's stock volatility. Lastly, using these factors and some other macroeconomic and financial factors, this thesis will investigate their ability in predicting China's stock volatility.

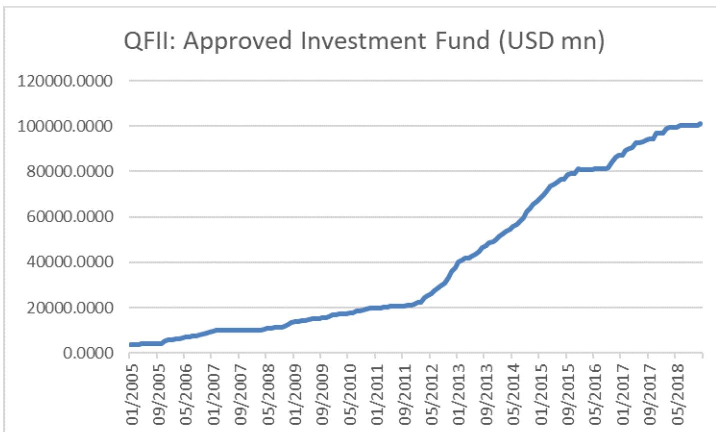


(a)



(b)

Figure 2.1: SHSE A
Source: Data is collected from the database CEIC (Global Economic Data, Indicators, Charts Forecasts)



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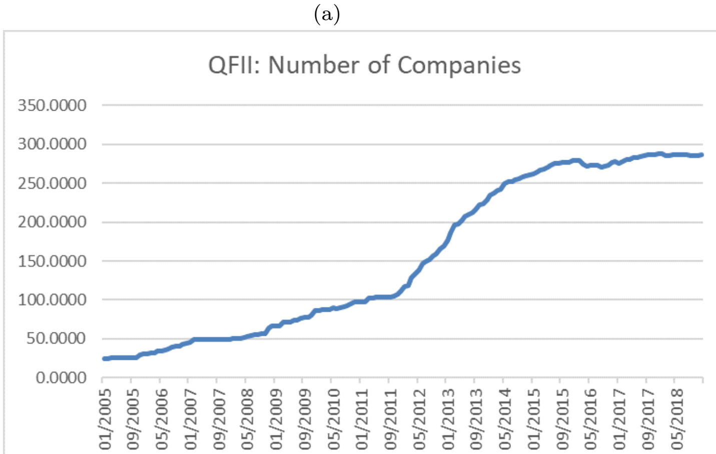
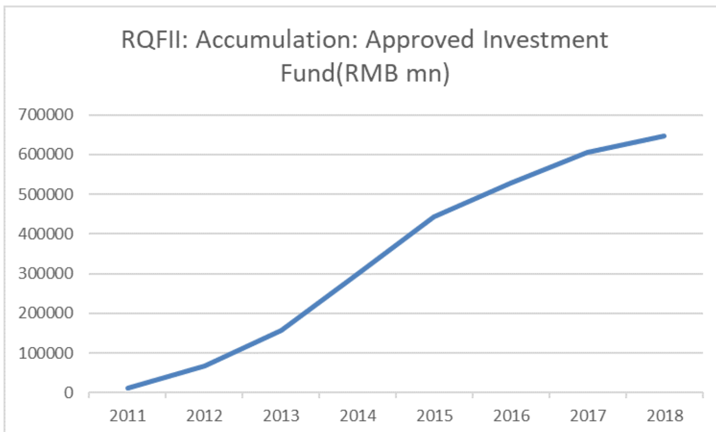


(b)

Figure 2.2: QFII and RQFII



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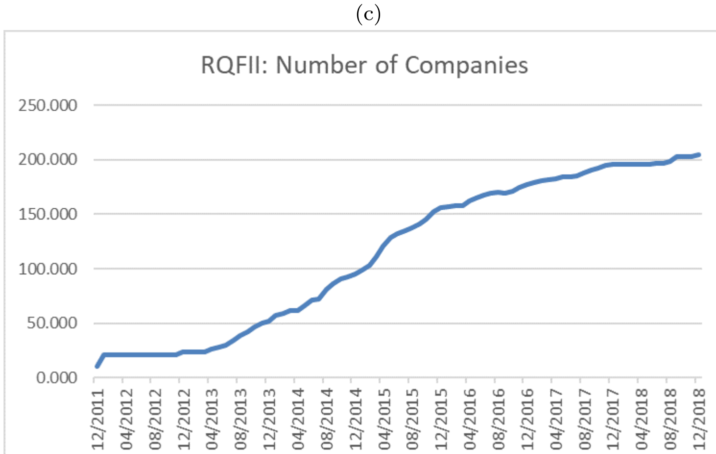

(d)

Figure 2.2: QFII and RQFII
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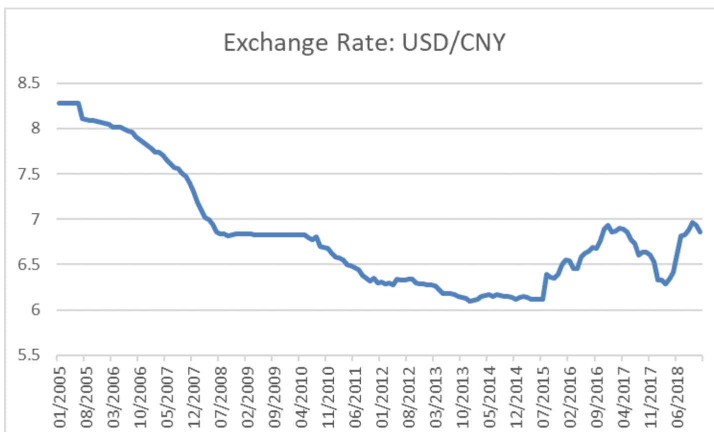


Figure 2.3: USD/CNY
Source: Data is collected from the database CEIC (Global Economic Data, Indicators, Charts Forecasts)

Chapter 3

Investigating the Weak-Form Efficiency of China's Stock Markets Using Unit Root Tests

This declaration concerns the article entitled:			
Investigating the Weak-Form Efficiency of China's Stock Markets Using Unit Root Tests			
Publication status (tick one) **Draft manuscript** ✔ **Submitted** ☐ **In review** ☐ **Accepted** ☐ **Published** ☐			
Publication details (reference)			
Copyright status (tick the appropriate statement) I hold the copyright for this material ✔ Copyright is retained by the publisher, but I have been given permission to replicate the material here ☐			
Candidate's contribution to the paper (provide details, and also indicate as a percentage)	The candidate contributed to / considerably contributed to / predominantly executed the… Formulation of ideas:100% Design of methodology: 100% Experimental work: 100% Presentation of data in journal format: 100%		
Statement from Candidate	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature.		
Signed	Yuexian Tang	**Date**	30/08/2020

3.1 Introduction

The Efficient Market Hypothesis (EMH) was first formalized by Fama (1970), which has become one of the most important theories in finance in the past decades. Broadly, a capital market is efficient if the security price can fully reflect all relevant information instantly. Specifically, there are three variants of the EMH, namely, the weak-form EMH claiming the security prices fully reflect all the past publicly available information, the semi-strong EMH which claims that the security prices fully reflect all publicly available information and react to the new information immediately and the strong EMH where the security prices additionally fully reflect even the hidden internal information immediately. Therefore, the security prices in an efficient market are able to provide an accurate signal for resource allocation which is the primary role of the capital market. It is very helpful for allowing investors to make investment or production decisions.

Because of the importance of the market efficiency, a voluminous literature has been developed to examine the EMH for different capital markets since it was proposed. As one of the most important investment channels and indicators of the economy, the efficiency of the stock markets has been examined by many researchers using a variety of techniques. Among these techniques, unit root tests has enjoyed a great popularity in testing the weak-form EMH in stock markets. This is because unit root tests can be used to test the random walk hypothesis stating that stock prices evolve according to a random walk and thus cannot be predicted. This is consistent with the weak-form EMH.

Generally, the unit root tests can be classified into two types. One is the univariate unit root tests, which are mainly distinguished by the alternative hypothesis in the tests. For example, compared with the traditional tests such as Dickey-Fuller (DF) or Augmented Dickey-Fuller (ADF) unit root test Dickey and Fuller (1979) and Phillips-Perron (PP) unit root test Phillips and Perron (1988), a number of unit root tests are designed to test a unit root null against a stationary process around a trend function allowing sharp structural breaks which are accounted by the dummy variables (Zivot and Andrews, 2002 (ZA hereafter), Lumsdaine and Papell, 1997 (LP hereafter), Lee et al., 2004 and Lee and Strazicich, 2003 (LM hereafter)) or the smooth structural breaks tests which are accounted for by a nonlinear process such as Logistic Smooth Transition Autoregressive (LSTAR) model, Exponential Smooth Transition Autoregressive (ESTAR) model or Fourier function (Kapetanios et al., 2003 (KSS hereafter), Becker et al., 2006, Enders and Lee, 2012b). Considering the lack of power of the univariate unit root tests, the panel unit root tests have been developed to make the inference about the existence of the unit root more precise by combining the information in both the time series and cross-sectional dimensions such as the traditional panel unit root test (Im et al., 2003 (IPS hereafter)) and the panel unit root tests allowing structural breaks (Im et al., 2005, Im et al., 2010, Lluís Carrion-i Silvestre et al., 2005). Using the univariate or panel unit root tests, a number of empirical studies have been developed to investigate the efficiency of the developed or developing stock markets.

In summary, the studies using the traditional univariate approach suggest that the stock markets in both the developed economies (Choudhry, 1994, Worthington and Higgs, 2004, Syriopoulos, 2007) and developing economies (Choudhry, 1997, Batuo Enowbi et al., 2009,Arouri and Rault, 2012) are weak-form efficient. However, when taking into account the structural breaks including both the sharp structural breaks and the smooth structural breaks, there is some evidence indicating some stock markets are inefficient in both the developed countries (Wang et al., 2015) and especially the developing countries (Chaudhuri and Wu, 2003b, Hasanov et al., 2007,Wang et al., 2015).For the literature using the panel unit root tests, studies using the traditional panel unit root tests indicate that the both the developed and developing stock markets examined in these studies are weak-form efficient (Chaudhuri and Wu, 2003a, Ahmed, 2010, Zhang et al., 2012), which is consistent with the findings of the studies using the traditional unit root tests. However, the studies using the panel unit root or the stationarity tests allowing for the structural breaks detect much more inefficient stock markets in both the developed countries (Narayan and Smyth*, 2005, Narayan, 2008, Lu et al., 2010) and developing countries (Kim and Shamsuddin, 2008, Ahmad et al., 2010) than those examined by studies using the univariate unit root test allowing for structural breaks. It should be emphasized that the evidence indicating that developing countries are inefficient is more than that for the developed countries, which is consistent with the fact that the degree of efficiency of the developed stock markets should be stronger than that of the developing stock markets due to their greater liquidity.

In addition, based on the literature, the efficiency of the developing stock markets are getting more and more focus, which is mainly due to the developing economies is playing an increasingly important role in the world's economy. For example, China's economy, as the biggest developing economy, is playing an important role in the development of China itself and the world. The importance has become more notable since China become the world's second largest economy in 2010. Accompanying such a remarkable development in the economy, China's stock market has also experienced a rapid growth. In spite of this, there hasn't been much research done on the efficiency of China's stock markets. What's more, existing studies cannot provide a clear conclusion on whether China's stock market is efficient as noted by (Qian et al., 2008; Kang et al., 2010; Hasanov et al., 2007; Li et al., 2012; Tian, 2007; Wang et al., 2015). The reasons for the mixed conclusions can be summarized as follows: Firstly, the degree of the efficiency of China's stock market varies with the different stages of China's economies development. It has become more efficient as a series of reforms such as the non-tradable shares reform in 2005 have been carried out. Therefore, the different time spans used in these studies might lead to variable results; Secondly, frequent manipulation by the government and enormous speculated investment by investors have resulted in many nonlinearities in stock indices, which might cause different unit root tests to produce different results. Therefore, motivated by the mixed results on the efficiency of China's stock market, this study applied a variety of unit root tests and the recent data in the last fifteen years to investigate the research question: has China's stock market become weak form efficient since 2005?

The contributions made by this study can be listed as follows: First, the panel unit root tests (Lee et al., 2016a) allowing for a number smooth structrural breaks and accounting for the cross-sectional dependence is the first used for investigating the efficiency of the stock markets. Second, this thesis applied the test (Perron and Yabu, 2009) to specify the form of the deterministic component of data prior to testing for the non-stationarity of the series, which is able to improve the power of the unit root tests such that more reliable inference can be achieved. Third, this study suggested that the fourier function (Enders and Lee, 2012b; Perron et al., 2017) is the best one to model the nonlinearity in China's stock indices and the panel unit root test developed by Lee et al. (2016a) is the best one for investigating the efficiency of China's stock market.

The plan of this chapter is as follows: section 2 presents the relevant literature including the theoretical literature about the unit root tests and empirical literature on developed and developing stock markets and particularly China's stock market. Section 3 provides an overview of China's stock market. Section 4 describes the data used in this study. Section 5 introduces the methodology used for this study and presents details of the tests used in this study. Section 6 presents the results obtained from these tests and section 7 discusses the results. Section 8 is the conclusion.

3.2 Literature review

3.2.1 Theoretical Literature

Testing for the presence of a unit root in time series data has become an increasingly important topic. The linear univariate unit root tests such as ADF and PP tests are the most commonly used to examine whether the observed series contains a unit root.

However, most time series are characterised by one or more structural breaks. What is more, the behaviour of a stationary process with a linear trend allowing for one or more structural breaks to occur in the level or the slope can appear superficially similar to the unit root process. As Perron (1989) pointed out, a time series could be examined whether it contains a unit root using the standard unit root tests, if the structural breaks occurring in that series are not taken into account. Therefore, Perron (1989) developed a modified Dickey-Fuller test which used a dummy variable to account for a known break in the intercept or the slope of the deterministic trend function. However, the assumption that the break is known is not practical. In order to address this problem, a series of subsequent unit root tests allowing an unknown break were developed. For example, Zivot and Andrews (2002) developed a widely used unit root test which determines a break point by selecting the break point where the test t-statistic is minimized. In addition, Perron (1997) and Vogelsang and Perron (1998) suggested that the break can be determined by testing the significance of the dummy variable used to model the structural break in the test regression.

Although the above unit root tests allow for the structural break to be determined endogenously, considering only one structural break in the test will lead to a loss of power if the true data generating process (DGP) contains two or more structural breaks. In order to equip the test with more power, Lumsdaine and Papell (1997) developed a unit root test allowing for two endogenous structural breaks, which is an extension of the minimum ZA unit root test. However, Nunes et al. (1997) and Lee et al. (2004) pointed out one important issue in the above or similar endogenous unit root tests is that these tests assume no structural breaks under the null. This assumption will lead to two undesirable results when the DGP contains a unit root with a break(s). First, it will cause a significant size distortion which can cause the unit root null to be rejected too often. Second, the rejection of the unit root null does not necessarily imply that the series is stationary because the possibility exists that the series contains a unit root and a structural break cannot be ruled out. By allowing endogenous structural breaks to occur in the intercept and/or the slop of the trend function under both the null and the alternative hypotheses, Lee et al. (2004) and Lee and Strazicich (2003) developed a minimum LM unit root test with one structural break and a minimum LM unit root test with two structural breaks, which not only exhibits no size distortion in the presence of the breaks under the null hypothesis, but also a rejection of the null is able to unambiguously imply that the series is a trend stationary process. However, it should be noted that all the above unit root tests assume the structural breaks occur instantaneously. However, this assumption is not necessarily the most appropriate for many time series, considering that the effect of the structural breaks on the level and/or the slope of the trend function can be gradual. A number of researchers such as Leybourne et al. (1998) and Kapetanios et al. (2003) developed the unit root tests to test a unit root null against a stationary process around a nonlinear deterministic component which can change gradually and smoothly. However, this type of nonlinear unit root tests are also criticized due to the assumption that there is only a single gradual break with a known break date. This is actually inconsistent with the fact that the number of the structural breaks are more likely to be unknown. To address this problem, Enders and Lee (2012a) and Enders and Lee (2012b) proposed a unit-root test which uses the low frequency components of a Fourier expansion to approximate a number of smooth structural breaks in a series. They also pointed out that the tests assume neither the date nor the number of the structural breaks a priori and just need to estimate a smaller number of the parameters using a Fourier approximation. Hence, the tests have a good power and size properties. In addition, it should be noted that although the tests are developed for the smooth breaks which can be modeled by, for example, ESTAR or LSTAR process, the authors also showed that the tests also perform reasonably well in the presence of sharp breaks.

The univariate unit root tests discussed above are commonly criticised due to the lack of power when testing in the presence of a unit root in a series. In this case, the panel unit root tests have been developed to gain an increased power by combining the information in the time series dimensions with that in the cross-sectional dimensions. To date, a great deal of panel unit root tests have been developed. For example, a number of researchers such as Choi (2001), Im et al. (2003), Levin et al. (2002) and Maddala and Wu (1999) developed a battery of tests which can test the presence of a unit root in heterogeneous panels. However, the assumption in these tests that the individual time series are cross-sectionally independent is too restrictive. To break this limitation, the tests allowing cross-sectional dependence between the individual time series were developed by a number of researchers such as Chang (2002), Choi (2006), Phillips and Sul (2003),Bai and Ng (2004), Breitung and Das (2005), Choi and Chue (2007), Moon and Perron (2004) and Smith et al. (2004). However, as pointed out before, it is very important to consider the structural breaks in the unit root tests. Therefore, a few panel unit root tests considering structural breaks have been developed. For example, based on the Lagrangian multiplier (LM) principle, Im et al. (2005) proposed a panel unit root test allowing for the structural breaksto occur in the level of the linear trend of the series. Apart from this test, Im et al. (2010) also developed a panel unit root test allowing for the presence of two endogenous structural breaks in both the level and the slope of the linear trend. The key feature of the test is that the test statistic is invariant to nuisance parameters indicating the size and location of breaks, such that the problem of size distortion can be addressed. In addition, this test can also be easily modified to correct for the cross-sectional dependence between the individual time series in the panel by using the cross-sectionally ADF (CADF) procedure of Pesaran (2007) to the test statistic. Based on the Im et al. (2010),Im et al. (2014) proposed a two-step procedure in another panel unit root test which is able to achieve better power and size distortion properties. Apart from the panel unit root tests allowing for structural breaks, there are also a few panel stationarity tests allowing for the presence of the structural breaks in the literature. Lluís Carrion-i Silvestre et al. (2005) proposed a panel stationarity test which allows for the presence of multiple structural breaks (more than two) in the level and/or slope of the linear trend. This model is flexible enough to allow the number of breaks and their positions to differ across individuals.

However, as pointed out before, the structural break could have a gradual effect on a time series rather than an instantaneouse impact caused by the sharp structural breaks. Therefore, a number of panel unit root tests allowing a smooth structural break are developed to capture such gradual effect (Ucar and Omay, 2009, Wu and Lee, 2009, Cerrato et al., 2011). Considering it could be unpractical to take only one smooth structural break into account, therefore, recently a few researchers developed the panel unit tests where a Fourier function is used as an approximation to a nonlinear process characterized by a number of smooth structural breaks (Lee et al., 2016a).

3.2.2 Empirical Literature

Considering that the efficiency of the stock markets might depend on the level of the development of the stock markets, this study reviews the literature in the developed and developing stock markets, respectively. In addition, because this study focuses on investigating the efficiency of China's stock market, the literature about China is introduced separately. It should be pointed out that this study tries to mention as many other studies as possible where the unit root tests have been applied to test stock prices regardless of whether the purposes of these studies are to test the efficiency of the stock markets or not. This is because the results of the unit root tests for the behaviour of the stock prices can suggest whether the stock markets are weak-form efficient or not. In addition, we divided the literature into two types, one is the literature using the univariate unit root tests, the other is the literature using the panel unit root tests. In each type, the studies will be presented in the sequence of the number of structural breaks included in the tests.

3.2.2.1 Univariate unit root tests

1. Traditional unit root test

Since the seminal study developed by Nelson and Plosser (1982), who found many macroeconomic time series of the United States including the common stock price contained a unit root, many subsequent empirical studies have been developed to examine whether the time series are stationary or not using a variety of unit toot tests. This study starts with a review of the literature using the traditional unit root tests such as the ADF, PP and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests.

- Developed stock markets

Based on the literature, most of the studies using the traditional unit root tests suggested that the developed stock markets are weak-form efficient. For example, using monthly stock price indices for the United Kingdom, Canada, France, Japan, Italy and Germany from 1953 to 1989, Choudhry (1994) found that both the results of the ADF and KPSS tests indicated all of these stock indices contained a unit root. Hence, they concluded that the presence of a unit root shows that the post-World War Two stock prices in these countries cannot be predicted. Groenewold (1997) examined weak-form efficiency of the stock markets in Australia and New Zealand using the ADF test and PP test. The data employed in this study was daily stock indices collected from Statex Actuaries' Index and NZSE-40 Index respectively from 1975 to 1992. Based on the results of the tests, they concluded that the stock markets in both countries are weak-form efficient. Worthington and Higgs (2004) employed the ADF test, PP test and KPSS tests to examine the efficiency of 16 developed stock markets (Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland and the United Kingdom) over the period from December 1987 to May 2003. The results of the tests showed that most of the European stock markets were weak-form efficient. Syriopoulos (2007) collected daily stock price indices from the United States, Britain, France and Germany from September 7, 1993 to April 30, 2002 and conducted several different unit root tests including the ADF, PP and KPSS tests. He found the results obtained from these three tests all indicated that the stock price indices in these developed countries contain a unit root.

- Developing stock markets

Similar to the developed stock markets, the traditional unit root tests have also indicated that the developing stock markets are weak-form efficient. For example, Choudhry (1997) conducted the ADF test on the weekly stock price indices in six Latin American countries including Argentina, Brazil, Chile, Colombia, Mexico, and Venezuela from January 1989 to December 1993. The results of the ADF tests suggest that the null hypothesis that these six stock indices contain two unit roots can be rejected while containing a unit root cannot be rejected. It indicates that the stock indices in these six emerging markets are nonstationary and cannot be predicted. In the study of Batuo Enowbi et al. (2009), four African stock markets in Egypt, Morocco, Nigeria, South Africa, and Tunisia were tested by using the ADF, PP and KPSS unit root tests. The stock indices were expressed in local currencies and included 2407 daily observations from the 4th January 2000 to 26th March 2009. The results of the ADF, PP and KPSS unit root tests showed that there is no evidence against the presence of unit roots, which means all of these four stock markets are weak-form efficient. Worthington and Higgs (2005) applied the ADF test, PP test and KPSS test to ten Asian emerging stock markets (China, India, Indonesia, Korea, Malaysia, Pakistan, The Philippines, Sri Lanka, Taiwan and Thailand). The data is composed of market value-weighted equity indices for these ten countries and was obtained from Morgan Stanley Capital International (MSCI). The results of these three tests all indicated the stock indices in these ten markets contains a unit root.Marashdeh and Shrestha (2008) applied the ADF and PP test to examine the daily Emirates stock index over the period 31 August 2003 to 13 April 2008. The results indicated that the Emirates stock index contained a unit root. Syriopoulos (2007) tested the stationarity of the stock indices in the in three emerging central European countries including the Czech Republic, Hungary, and Poland from September 7, 1993 to April 30, 2002 by using the ADF test, PP test and KPSS test. For all of these three tests, the null hypothesis of containing a unit root cannot be rejected.

- China's stock markets

For China's stock market, most of the studies examining the efficiency of their stock markets applied the traditional unit root test which provided strong evidence supporting the theory that China's stock market is weak-form efficient. For example, in the study of Liu et al. (1997), the ADF unit root test was used to examine whether stock prices in Chinese stock markets followed a random walk process from 21 May 1992 to 18 December 1995. The daily data consisted of the stock indices from the Shanghai and Shenzhen Stock Exchanges. They found both stock indices are characterised by the random walk, which means the Chinese stock markets are efficient. Laurence et al et al. (1997) examined the weak-form efficiency of Chinese stock markets from March 8, 1993 to October 31, 1996 using the ADF unit root test. The data is composed of four daily stock indices for Shanghai A shares, Shanghai B shares, Shenzhen A shares, and Shenzhen B shares. They found each stock index is characterised by a unit root, which means Chinese stock markets are weak-form efficient. Mookerjee and Yu (1999) applied a battery of tests to examine the efficiency of the Chinese stock markets. By using the stock index from the Shanghai Stock Exchanges from December 19, 1990 to December 17, 1993 and the stock index of the Shenzhen Stock Exchange from April 3, 1991 to December 17, 1993, and based on the result of the ADF unit root test, there was no evidence supporting the unit root null hypothesis for both stock indices. Cong et al. (2008) applied the PP and KPSS tests to a number of monthly stock indices including two composite indices, 10 classification indices, and four oil price indices in the Shanghai and Shenzhen Stock Exchanges from January 1996 to December 2007. They found that each stock index is a stationary process, which indicated the Chinese stock markets are inefficient. Qian et al. (2008) investigated the behaviour of the monthly Shanghai Stock Exchange Composite (SSEC) index from December 1990 to June 2007 using the ADF, PP and KPSS unit root tests. They found that all the tests indicated that the (SSEC) index is characterized by a unit root, consistent with the efficient market hypothesis. In the study of Kang et al. (2010), ADF, PP and KPSS unit root tests were applied to daily stock indices of the Shanghai A and Shanghai B shares, and Shenzhen A and Shenzhen B shares from January 1998 to December 2007. The results of the three tests indicated that each stock index is a stationary process. Based on the literature using the traditional unit root tests, we can find that both the developed and developing stock markets are weak-form efficient, which is consistent with the EMH. However, this conclusion is not reliable if the structural breaks in the data are neglected. Therefore, I next introduce some studies which use the univariate unit root tests allowing for the structural breaks to see whether the stock markets are still weak-form efficient.

2. Univariate unit root tests with structural breaks

Since Perron (1989) pointed out the importance of the structural breaks in unit root tests, many empirical work studies using a number of unit root tests allowing for the structural breaks has been developed to test the efficiency of the stock markets.

- Developed stock markets

Based on the literature, I find that the studies still suggest that most of the developed stock markets are weak-form efficient, although the structural breaks have been taken into account. For example, Narayan and Smyth (2005) used Zivot and Andrews (2002) one break unit root tests and Lumsdaine and Papell (1997) two break unit root tests to test the unit root null for 15 European stock price indices in Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Netherlands, Norway, Portugal, Sweden, Switzerland and the United Kingdom. The data was obtained from the OECD Main Economic Indicators and the time span is different for each country, which depended on data availability. Based on the results of the tests, they concluded that there is strong evidence supporting the view that the 15 stock price indices are characterized by a unit root. Narayan and Smyth (2007) examined the random walk hypothesis for G7 stock price indices (United State, United Kingdom, Canada, France, Japan, Italy and Germany) by using a number of unit root tests allowing for one or two structural breaks (Zivot and Andrews, 2002, Lumsdaine and Papell, 1997, Lee and Strazicich, 2003). The data is composed of seven stock indices expressed in local currencies for each of the G7 countries. The time span varies between countries depending on data availability. Based on the results of the tests, they found that there is only evidence indicating that the stock price index in Japan is stationary. It means the other six stock price indices followed the random walk process.

- Developing stock markets

Although the studies show that many developing stock markets are weak-form efficient using the unit root tests allowing for sharp structural breaks, there are a number of studies which provide strong evidence that some developing stock markets are inefficient. For example, Lin (2012) applied the Lee and Strazicich (2003) LM unit root tests allowing for two structural breaks to examine the unit root null for six Asian emerging markets in India, Indonesia, Korea, the Philippines, Taiwan and Thailand respectively. The monthly data from January 1986 to December 2010 is composed of six stock price indices for each of these six countries. The results of the tests indicated that the unit root null cannot be rejected for all six stock price indices. In addition, Mishra et al. (2015) tested the random walk null hypothesis for six stock indices in the Indian stock markets by using the Lee and Strazicich (2003) LM two structural break unit root tests. They used monthly data consisting of six stock indices over the period from January 1995 to December 2013. The results indicated that all stock indices were characterized by the random walk. However, Chaudhuri and Wu (2003b) examined the random walk hypothesis for stock prices in 17 emerging markets (Argentina, Brazil, Chile, Colombia, Greece, India, Jordan, Korea, Malaysia, Mexico, Nigeria, Pakistan, Philippines, Taiwan, Thailand, Venezuela, and Zimbabwe) by using the Zivot and Andrews (2002) sequential trend break model which allows for one structural break. The monthly data obtained from International Finance Corporation's Emerging Market Database (IFC-EMDB) spanned from January 1985 to February 1997. Chaudhuri and Wu (2003b) found that the unit root null is rejected for 11 of the 17 stock price indices, supporting mean reversion of stock prices in emerging stock prices.

- China's stock markets

Based on the literature, just a few studies using unit root tests allowing for the structural breaks have been done and provide evidence showing that China' stock market is weak-form efficient. For example, in the study of Tian (2007), Zivot-Andrew tests allowing for one structural break were used to test the unit root null for monthly data on Shanghai's A-share index and Shanghai's B share index from July 1993 and March 2007. The results indicated that both stock indices contain a unit root, which is consistent with the market efficiency hypothesis. From the literature using the unit root tests allowing for the sharp structural breaks, I find that the studies indicated that most of the developed and developing stock markets are all weak-form efficient. However, compared with the results obtained from the traditional unit root tests, the unit root tests allowing for the sharp structural breaks provided more evidence supporting the inefficiency of the stock markets in both the developed and developing countries, which is inconsistent with the efficient market hypothesis. Next, considering that the effect of the structural breaks could be gradual, studies using the unit root tests allowing for smooth structural breaks will be reviewed.

3. Univariate unit root tests with smooth breaks

Based on the literature, there are just a few studies where the unit root tests allowing for the smooth structural breaks have been applied to test the behaviour of the stock prices. Therefore, we can only assess a few studies using these unit root tests allowing for either one gradual structural break or a number of smooth structural breaks.

- Developed stock markets

For the developed stock markets, the studies considering the smooth structural breaks cannot provide clear evidence supporting or against the efficiency of the stock markets. Some studies suggested some developed stock markets are weak-form efficient. For example, Narayan (2006) investigated the behaviour of monthly US stock prices over the period from 1964:06 to 2003:04 using an unconstrained two-regime threshold autoregressive (TAR) model with a unit root developed by Caner and Hansen (2001). The result of this study suggested that the US stock prices were characterised by a unit root process, which is consistent with the weak-form efficient market hypothesis.Kumar Narayan (2005) employed an unrestricted two-regime threshold autoregressive model to test whether or not stock prices for Australia and New Zealand can be characterized by a unit root process. Using the monthly data over the period January 1960 to April 2003 and January 1967 to April 2003 for Australia and New Zealand respectively, the results indicated that both stock prices in Australia and New Zealand were characterised by a unit root, which means the stock markets in these two counties are weak-form efficient. However, there are other studies indicating that some developed stock markets are inefficient. For example, using the nonlinear unit root test procedure recently developed by Kapetanios et al. (2003), Hasanov (2009) found South Korea's stock market was inefficient because the result of the test indicated that the null hypothesis of a unit root cannot be rejected using monthly data from September 1987 to December 2005. In addition, Wang et al. (2015) employed a Lagrange Multiplier (LM) Fourier unit root test proposed by Enders and Lee (2012b) to test the behaviour of the stock prices in Japan, South Korea and Singapore over the period December 1990 to March 2013. The results of the test indicated that the stock prices in all these three stock markets were characterised by a strong mean reversion process, which suggested that these three stock markets are all inefficient.

- Developing stock markets

For the developing stock markets, results about the efficiency of the stock markets are also mixed. For example, Hasanov et al. (2007) examined the weak-form efficiency of eight transition stock markets, namely, Bulgarian, Czech, Hungarian, Polish, Romanian, Russian and Slovakian stock markets. The time span of the data was different for each country. Based on the results of the test, the study suggested that the Bulgarian, Czech, Hungarian and Slovakian stock markets are weak-form efficient and the other four stock markets are inefficient. In addition, using the nonlinear unit root test developed by Kapetanios et al. (2003), Karadagli et al. (2012) examined the stationarity of the stock prices in Bulgarian, Greek, Hungarian, Polish, Romanian, Russian, Slovenian and Turkish over the period from January, 2002 to the May, 2010. The results indicated that the null hypothesis of a unit root for the Russian, Romanian and Polish stock price series cannot be rejected, which implied that these markets are not weak form efficient.

- China's stock markets

For China's stock market, the studies using the unit root tests allowing for the smooth structural breaks provide mixed results. For example, Hasanov et al. (2007) employed a nonlinear unit root test developed by Kapetanios et al. (2003) to examine the behaviour of the Chinese A-share stock price index over the period August, 1991 to December, 2005. The study found that the Chinese A-share stock market was inefficient. However, Wang et al. (2015) employed a Lagrange Multiplier (LM) Fourier unit root test proposed by Enders and Lee (2012b) to test the behaviour of the stock prices in Mainland China, HK, China over the period December 1990 to March 2013. The results of the test indicated that both the stock prices in Mainland and HK stock markets are characterised by a strong mean reversion process, which suggested that these five stock markets are all efficient.

3.2.2.2 Panel unit root tests without structural breaks

1. Panel unit root tests without structural breaks

Compared with each type of the univariate unit root tests, the corresponding panel unit root tests are more powerful in providing inference on the efficiency of the stock prices. Therefore, next I will review the literature in the context of the panel systems. Firstly, the studies using the traditional panel unit root tests will be presented.

- Developed stock markets

For the developed stock markets, the studies provided strong evidence supporting the theory that developed stock markets are efficient, which is the same with the results obtained from the traditional unit root tests. For example, Ludwig and Sløk (2002) used the IPS panel unit root test to examine the unit root null for the stock prices in 16 OEDC countries including Belgium, Denmark, Finland, France, Germany, Italy, Norway, Spain, Australia, Canada, Ireland, Japan, the Netherlands, the United Kingdom, the United States and Sweden. The time span varies between each country depending on the data availability. The IPS test indicated that the unit root null cannot be rejected, which is consistent with the efficient market hypothesis. Narayan and Smyth (2007) examined whether stock prices in G7 countries followed the mean reverting or random walk process by using five panel unit root tests, namely the IPS test, the Levin and Lin test, and the LM test, the seemingly unrelated regression (SUR) test, and the multivariate augmented Dickey Fuller (MADF) test. The data used in this study was obtained from the OECD Main Economic Indicators (DX for Windows) from January 1975 to April 2003. The results of all the tests showed that stock prices for the G7 countries contained a unit root, which is consistent with the efficient market hypothesis. Lu et al. (2010) tested the stationarity of the stock indices in G7 countries by using a number of unit root tests. The sample periods covered January 2000 to December 2007. The IPS panel unit root tests, which are two of the tests used in this study, indicated that the stock markets in G7 countries are efficient because the null hypothesis of non-stationarity for both tests cannot be rejected.

- Developing stock markets

For the developing countries, the studies using the traditional unit root tests also suggested that the stock markets are weak-form efficient. For example, Chaudhuri and Wu (2003a) examined the unit root null of the monthly stock indices in 17 emerging markets from January 1985 to April 2002 by using the SUR panel unit root test. They found that the null hypothesis of a unit root cannot be rejected for 17 emerging stock prices. The 17 countries consist of Argentina, Brazil, Chile, Colombia, Greece, India, Jordan, Korea, Malaysia, Mexico, Nigeria, Pakistan, Philippines, Taiwan, Thailand, Venezuela, and Zimbabwe. Ahmed (2010) applied a battery of unit root tests to examine whether the mean reversion properties held for 15 emerging stock markets, namely, Argentina, Brazil, Chile, Colombia, India, Jordan, South Korea, Malaysia, Mexico, Nigeria, Pakistan, Philippines, Taiwan, Thailand, and Zimbabwe. The results of the LLC, IPS and Hadri tests found that the 15 stock indices were characterised by a unit root, which means the 15 emerging markets in this study are weak-form efficient.Zhang et al. (2012) applied a number of panel unit root tests to examine the weak-form efficient market hypothesis for five African countries (Egypt, Kenya, Morocco, South Africa and Tunisia). The weekly data consisted of five stock indices from January 2000 to April 2011. They concluded that the tests developed by Levin et al. (2002), Im et al. (2003) andMaddala and Wu (1999) cannot reject the unit root null hypothesis, indicating these five African stock markets are weak-form efficient.

- China's stock markets

2. Panel unit root tests with structural breaks

Although the studies suggested that both the developed and developing stock markets are weak-form efficient, it might be unreliable without taking into account the structural breaks. Therefore, the studies using the panel unit root tests allowing for the structural breaks are presented next. In addition, it should be pointed out that there only exist few studies using a panel unit root allowing smooth structural breaks, we just put the studies considering sharp and smooth structural breaks together.

- Developed stock markets

Compared with the studies using the univariate unit root tests allowing for the structural breaks, the studies using the panel unit root tests provided more evidence indicating that inefficiency exists in the developed stock markets. For example, using the panel unit root tests allowing for multiple structural breaks, these studies have found that the developed stock markets are inefficient. For example, Narayan (2008) tested the stationarity of stock prices in G7 countries by using LM panel unit root tests in the presence of one and two structural breaks respectively. The data is composed of 7 stock indices for each of the G7 countries and were obtained from the OECD Main Economic Indicators (DX for Windows) for the period January 1975– April 2003. They found that stock indices in G7 countries were stationary, which is inconsistent with the efficient market hypothesis and this finding was supported using both univariate unit root tests and panel unit root tests without structural breaks. In addition, in the study by Lu et al. (2010), the panel test for stationarity developed by Lluís Carrion-i Silvestre et al. (2005) was applied to examine the stationarity of the stock indices in G7 countries over the period January 2000-December 2007. The result of the test indicated that the null hypothesis of stationarity for all the stock indices cannot be rejected, therefore, the efficient market hypothesis does not hold for G7 countries, which is contrary to the finding obtained by using univariate unit root tests and the panel unit root tests without structural breaks in the same study.

- Developing stock markets

For the developing stock markets, the studies using the panel unit root tests considering the structural breaks indicated that the developing stock markets are inefficient. For example, in the study by Lean and Smyth (2007), LM panel unit root tests developed by allowing for one and two breaks were applied to test the random walk null hypothesis for the stock prices in 8 Asian countries, namely, Hong Kong, Indonesia, Japan, South Korea, Malaysia, the Philippines, Singapore and Thailand. The data was from January 1, 1991 to June 30, 2005 consisting of 8 stock price indices for each country. They found that LM panel unit root tests with one structural break suggested that each stock index is characterized by the random walk, but the LM panel unit root test in the presence of two structural breaks provided evidence that the stock prices are a mean reverting process. In addition, Ahmad et al. (2010) applied the panel stationarity tests by Lluís Carrion-i Silvestre et al. (2005) and the panel unit root tests by Im et al. (2005) to test the stationarity of stock prices in 15 emerging stock markets for the period 1985 to 2006. Based on their results, they concluded that the majority of the stock prices follow a mean reverting process. This is supported by the findings of Chaudhuri and Wu (2003a), but was inconsistent with the findings of Chaudhuri and Wu (2003b).

By allowing a smooth structural break,Suresh et al. (2013) used a nonlinear panel unit root test developed by Ucar and Omay (2009) to examine whether the stock indices of the emerging BRICS (Brazil, Russia, India, China and South Africa) countries over the period 2000M1 to 2010M12. The finding of the study indicated that the stock indices present a nonlinear and stationary property, which support that the stock markets in BRICS countries are inefficient.

- China's stock markets

For China's stock market,Li et al. (2012) employed the panel stationarity test developed by Lluís Carrion-i Silvestre et al. (2005) allowing for multiple sharp structural breaks to examine the stationarity of the monthly real stock price indices from July 2001 to December 2010 for 13 major sectors, namely, Agriculture, Mining, Manufacturing, Utilities, Construction, Transportation, IT, Wholesale & Retail (W&R), Financials, Real Estate, Social services, Media and Conglomerates. The results of the tests showed that each sectoral stock index is nonstationary and contains a unit root, indicating that the Chinese stock markets are efficient. It should be pointed out that there is no study using a panel unit root test allowing smooth structural breaks to investigate the efficiency of China's stock market.

To summarise, in the context of the univariate unit root tests, both the developed and the developing stock markets are weak-form efficient using the traditional unit root tests. When the sharp structural breaks are considered, although most of the studies, especially the studies for the developed stock markets, indicated that stock markets are still weak-form efficient, the literature presented some evidence supporting the inefficiency of the stock markets. When allowing for the smooth structural breaks, especially a number of smooth breaks, the literature is able to show that more stock markets in both the developed and developing countries are inefficient. In the context of the panel unit root tests, the studies using the traditional panel unit root tests provided a strong evidence supporting that both the developed and developing stock markets are weak-form efficient. However, when the panel unit root tests allowing for the structural breaks are employed, the studies provide stronger evidence indicating the stock markets are inefficient in both the developed and developing countries. Therefore, considering the panel unit root tests allowing for the structural breaks are the most powerful among these unit root tests, we can conclude that the existing literature using the unit root tests to examine the efficiency of the stock markets suggested that there are many inefficient stock markets in both the developed and especially developing countries. For China's stock market, there has not many studies been done to investigate the efficiency of the stock market. In addition, the inference on the efficiency of China's stock market provided by existing is mixed and unpersuasive (Qian et al., 2008, Kang et al., 2010, Hasanov et al., 2007, Li et al., 2012, Tian, 2007, Wang et al., 2015).

3.3 Methodology

This study aims to investigate the efficiency of China' stock market by using a number of unit root tests including two groups: one is univariate unit root tests and the other is panel unit root tests. Considering the interplay between the nonlinearity of the deterministic trend of a series and the non-stationarity of the stochastic component of a series, it is essential to find a good approximation to the unknown deterministic component underlying the data prior to investigate the non-stationarity of the series. Because a time series is commonly characterised by a linear time trend, this study will firstly use a test developed by Perron and Yabu, 2009 to test for the presence of a linear time trend. In addition, a time series is commonly characterised by structural breaks and different numbers and types of structural breaks can lead to different types of nonlinearity in the series. Therefore, a number of tests are used to specify the form of the nonlinearity. It should be pointed out that these pre-tests used in this study are able to produce a robust result regardless of whether the series is stationary or contains a unit root, which can further assure the reliability of the inference on the non-stationarity of the series. Then, with the specification of the deterministic trend obtained from the pre-tests, the corresponding univariate and panel unit root tests are employed to investigate the non-stationarity of the series. To be specific, the methodology of this study can be shown as follows (the following steps are applied for both the univariate and panelapproaches):

- A test for a linear trend developed by Perron and Yabu, 2009 is firstly used to specify whether only a constant or both the constant and trend should be included in the other pre-tests and the unit root tests.

- The traditional unit root tests without structural breaks (ADF test; IPS test) are used to make a comparison with the unit root tests considering structural breaks.

- The unit root tests with sharp structural breaks (Lee and Strazicich, 2003, Lee et al., 2004, Im et al., 2010, Lluís Carrion-i Silvestre et al., 2005) are applied. Because the sharp structural breaks are modelled by dummy variables in the tests, there is no need to use a pre-test to examine the existence of the sharp structural breaks.

- A linearity test developed byHarvey et al., 2008 is applied to test for the presence of an ESTAR or LSTAR process which can be used to approximate the nonlinearity caused by a smooth structural break. If the test showed that such a nonlinear process is present in the series, the unit root tests allowing one smooth structural break (Cerrato et al., 2011) would be applied.

- A test developed by Perron et al., 2017 will be used to test for the presence of a Fourier function which can be used as an approximation to a nonlinear process caused by a number of smooth structural breaks. If the test suggested that a Fourier function significantly exists in the series, the unit root tests allowing a number of smooth structural breaks (Enders and Lee, 2012b, Enders and Lee, 2012a, Lee et al., 2016a) would be applied.

Next, the details of all the tests used in this study are presented as follows: the pre-tests are firstly introduced, then the univariate unit root tests are listed, the panel unit root tests are presented in the end. Lee and Strazicich (2003)

3.3.1 Univariate unit root tests

3.3.1.1 Traditional unit root test (ADF unit root test)

The Argumented Dickey-Fuller (ADF) unit root test, developed byDickey and Fuller, 1979 and Dickey and Fuller, 1981, is most commonly used one to examine the nonstationarity of the data series. Compared the DF unit root test, the ADF test allows for the autocorrelation in the dependent variable, which enables the ADF test to have more power in examining the nonstationarity of the data series. If the autocorrelation in the dependent variable could not be fully modelled, the test would suffer from size distortions which will enlarge the probability of rejecting the null hypothesis when the null hypothesis should not actually be rejected. The size distortion can be corrected by adding lags of the dependent variable into the three regression models. There are three specifications for the data generating process:

$$\Delta y_t = \gamma y_{t-1} + \sum_{i=2}^{p} \beta_i \Delta y_{t-i+1} + \varepsilon_t, \tag{3.1}$$

$$\Delta y_t = \alpha_0 + \gamma y_{t-1} + \sum_{i=2}^{p} \beta_i \Delta y_{t-i+1} + \varepsilon_t, \tag{3.2}$$

$$\Delta y_t = \alpha_0 + a_1 t + \gamma y_{t-1} + \sum_{i=2}^{p} \beta_i \Delta y_{t-i+1} + \varepsilon_t. \tag{3.3}$$

The three specifications of the data generating process are distinguished by whether the constant and/or the time trend is included. The null hypothesis is that there is a unit root ($\gamma = 0$) whilst the alternative hypothesis test is that there is no unit root ($\gamma < 0$). What should be noted is that because the data generating process contains a unit root, the test statistics in these cases no longer follow the standard distribution but follow a distribution which is a function of the Brownian process. The distributions and the critical values of the test statistics can be found in Dickey and Fuller, 1979 and Dickey and Fuller, 1981.

3.3.1.2 Unit root tests with sharp structural breaks (Lee et al., 2004, Lee and Strazicich, 2003)

Lee and Strazicich (2003) developed an endogenous two-break LM unit root test, which allows for two changes in the intercept and two changes in the slope of the trend in the DGP. The DGP used in this test is as follows and is similar to the one used in the LM test developed by Schmidt and Phillips (1992):

$$y_t = \delta' Z_t + X_t, \quad X_t = \rho X_{t-1} + \varepsilon_t, \quad \varepsilon_t \sim N\left(0, \delta^2\right) \tag{3.4}$$

where X_0 is taken fixed as an initial value. Z_t consists of exogenous variables. It can be noted that if $Z_t = (1, \text{t})$, this process is actually the same asthe DGP used in Schmidt and Phillips (1992).

When considering two structural breaks in the intercept and the slope of the trend, it can be described by $Z_t = [1, t, \ D_{1t}, \ D_{2t}, \ DT_{1t}, \ DT_{2t}]'$, where $D_{jt} = 1$ for $t \geq T_{Bj} + 1$, $j = 1, 2$ and 0 otherwise. $DT_{jt} = t - T_{Bj}$ for $t \geq T_{Bj} + 1$, $j = 1, 2$ and 0 otherwise. T_{Bj} denotes the date when the breaks occured.

Actually, this DGP can be written as an extended version of the "crash-cum-growth" model which was developed by Perron (1989) and only allows one shift in the intercept and one change in the slope of the trend. Under the null and alternative hypothesis, it can be shown as follows:
The Null Hypothesis:

$$y_t = \mu_0 + d_1 B_{1t} + d_2 B_{2t} + d_3 D_{1t} + d_4 D_{2t} + y_{t-1} + v_{1t}, \tag{3.5}$$

The Alternative Hypothesis:

$$y_t = \mu_1 + \gamma t + d_1 D_{1t} + d_2 D_{2t} + d_3 DT_{1t} + d_4 DT_{2t} + v_{2t} \tag{3.6}$$

where $v_{1t} \ and \ v_{2t}$ are stationary error terms. $B_{jt} = 1$ for $t = T_{Bj} + 1$, $j = 1, 2$ and 0 otherwise. It should be stressed that the meaning of the intercept and the trend are consistent under the null and the alternative. It means a rejection of the null unambiguously implies the series is trend-stationarity.

The procedure to get the test statistics is the same as that in the SPLM test. The first step is to get the following de-trended series:

$$\widetilde{S}_t = y_t - \widetilde{\psi}_X - Z_t \widetilde{\delta} \tag{3.7}$$

where $\widetilde{\delta}$ are the coefficients in the regression of Δy_t on ΔZ_t based on the model $\Delta y_t = \delta' \Delta Z_t + \nu_{1t}$ which is actually the null obtained by imposing the restriction $\rho = 1$ on the DGP and it should be noted that ΔZ_t is used instead of Z_t here and $\Delta Z_t = [1, B_{1t}, B_{2t}, D_{1t}, D_{2t}]$, $B_{jt} = \Delta D_{jt}$ and $D_{jt} = \Delta DT_{jt}$, $j = 1, 2$. $\widetilde{\psi}_X$ is the restricted MLE of φ_X given by $y_1 - Z_1 \widetilde{\delta}$, y_1 and Z_1 are the first observations of y_t and Z_t respectively. By subtracting $\widetilde{\psi}_X$, we can make the de-trended series $\widetilde{S}_t$ start at zero so that any deterministic part in the series y_t is removed.

Then in the second step, based on the LM (score) principle, The LM test statistics can be constructed by regressing the following model:

$$\Delta y_t = \delta' \Delta Z_t + \phi \widetilde{S}_{t-1} + u_t. \tag{3.8}$$

In addition, to correct for aurocorrelation in the error term, we can add a number of augmented terms into the model as in the ADF test.

$$\Delta y_t = \delta' \Delta Z_t + \phi \widetilde{S}_{t-1} + \sum_{j=1}^{k} \phi_j \Delta \widetilde{S}_{t-j} + u_t. \tag{3.9}$$

It can be seen that ΔZ_t is used in both of the models instead of Z_t which is also used in the case of the DF test. Under the null hypothesis $\phi = 0$, The LM test statistics can be given by:

$$\widetilde{\rho} = T\widetilde{\phi} \tag{3.10}$$

$\widetilde{\tau} =$ the usual t-statistic under the null hypothesis $\phi = 0$

The asymptotic distribution of the test statistics were developed by Lee and Strazicich (2003). It should be stressed that Lee and Strazicich (2003) point out that the LM test statistics with two endogenous trend breaks will be effected by the nuisance parameters $\lambda = (\lambda_1,\ \lambda_2)$, $\frac{T_{Bj}}{T} = \lambda_j$, $j = 1, 2$ indicating the location of the breaks and d indicating the magnitude of the breaks**.**

In this study, the model will be estimated with lags. The optimal number of augmented terms can be determined by following the general to specific procedure suggested by Ng and Perron (1995). Specifically, starting from a maximum number of lags of 8, the test looks for the last significant lagged term to determine the optimal number of lagged terms by comparing the t-statistic of this lagged term with the 10 per cent asymptotic critical value of 1.645. After determining the optimal number of lagged terms with each combination of the breaks, we will determine the location of the breaks where the test statistic is minimized over the time interval [0.1T, 0.9T] (to eliminate end points). The test statistics for the minimum can be shown to be as follows:

$$LM_\rho = \underset{\lambda}{ln\,f}\ \widetilde{\rho}\,(\lambda) \tag{3.11}$$

$$LM_\tau = \underset{\lambda}{ln\,f}\ \widetilde{\tau}\,(\lambda) \tag{3.12}$$

3.3.1.3 A unit root test with a smooth structural break (KSS test)

The KSS test, proposed by Kapetanios et al. (2003) can be used to test for the presence of non-stationarity against a nonlinear but globally stationary exponential smooth transition autoregressive (ESTAR) process. The ESTAR model used in this test can be specified as follows:

$$\Delta y_t = \gamma y_{t-1}\left[1 - \exp\left(-\theta y_{t-1}^2\right)\right] + \varepsilon_t \quad (\theta \geq 0) \tag{3.13}$$

where y_t is the demeaned or de-trended time series of interest. ε_t is an i.i.d error with zero mean and constant variance. $1 - \exp\left(-\theta y_{t-1}^2\right)$ is an exponential transition function representing the nonlinear process. The condition, $\theta \geq 0$, can effectively determine the speed of mean reversion. Based on atheESTAR model above, the null hypothesis ($\theta = 0$) that the series contain a unit root is tested against the alternative hypothesis ($\theta < 0$) that the series is a nonlinear but globally stationary ESTAR process. However, because γ is not identified under the null hypothesis, it is not feasible to test the null hypothesis. To address this problem, KSS suggest to reparameterize the model above by computing a first-order Talyor series approximation to the ESTAR model under the null to get an auxiliary regression specified as follows:

$$\Delta y_t = \beta y_{t-1}^3 + \varepsilon_t. \tag{3.14}$$

The regression can be extended to a more general case where there is serial correlation in the error terms:

$$\Delta y_t = \sum_{j=1}^{p} \rho_j \Delta y_{t-j} + \beta y_{t-1}^3 + \varepsilon_t \tag{3.15}$$

where p is the number of the lags which should be selected prior to the test by means of standard model selection criteria or significance testing procedure.

By testing the null hypothesis that $\beta = 0$ against $\beta < 0$, the t-statistic can be constructed as follows:

$$t_{NL} = \frac{\hat{\beta}}{s.e.\left(\widehat{\beta}\right)} \tag{3.16}$$

where $\hat{\delta}$ is the estimated value of δ and $s.e.\left(\hat{\delta}\right)$ is the standard error of $\hat{\delta}$. In addition, the t-statistic in this test does not follow the asymptotic standard normal distribution.

3.3.1.4 A unit root test with a number of smooth structural breaks (Enders and Lee, 2012b)

Enders and Lee (2012b) developed a unit root test where the Fourier function is used as an approximation for the smooth breaks in the data. In addition, they also pointed out that the Fourier function can not only have a good approximation to the smooth breaks but also to the sharp breaks. The DGP used in this test is as follows:

$$\begin{gathered} y_t = \alpha_0 + \gamma t + \alpha_k \sin\left(\frac{2\pi kt}{T}\right) + \beta_k \cos\left(\frac{2\pi kt}{T}\right) + e_t, \quad k \le T/2, \\ e_t = \rho e_{t-1} + \varepsilon_t, \\ \varepsilon_t \sim N\left(0, \delta^2\right) \text{ , } t = 1, \ldots, T \end{gathered} \tag{3.17}$$

where $\alpha_k \sin\left(\frac{2\pi kt}{T}\right) + \beta_k \cos\left(\frac{2\pi kt}{T}\right)$ is the Fourier Fumction.

Based on this DGP, the null hypothesis that the series contains a unit root ($\rho = 1$) is tested on the alternative hypothesis that the series is stationary ($\rho < 1$). In order to make the distribution of the test statistics under the null hypothesis invariant to the magnitudes of the parameters including α_0 , γ

, α_k and β_k , Enders and Lee (2012b) applied a two-step de-trending method. Firstly, a de-trended series can be constructed as follows:

$$\widetilde{S}_t = y_t - \widetilde{\psi} - \widetilde{\delta}_0 t - \widetilde{\delta}_1 \sin\left(\frac{2\pi kt}{T}\right) - \widetilde{\delta}_2 \cos\left(\frac{2\pi kt}{T}\right) \qquad t = 2, \ldots, T \tag{3.18}$$

where $\hat{\delta}_0$, $\hat{\delta}_1$ and $\hat{\delta}_2$ are estimated coefficients based on the following regression model:

$$\Delta y_t = \delta_0 + \delta_1 \Delta \sin\left(2\pi kt/T\right) + \delta_2 \Delta \cos\left(2\pi kt/T\right) + \mu_t \tag{3.19}$$

In addition, $\widetilde{\psi} = y_1 - \widetilde{\delta}_0 - \widetilde{\delta}_1 \sin\left(\frac{2\pi k}{T}\right) - \widetilde{\delta}_2 \cos\left(\frac{2\pi k}{T}\right)$, y_1 is the first observation of y_t . By subtracting $\widetilde{\psi}$, we can make the initial value of the de-trended series $\widetilde{S}_t$ start at zero. Then in the second step, according to the LM principle, we can develop the following regression model:

$$\Delta y_t = \phi \widetilde{S}_{t-1} + d_0 + d_1 \Delta \sin\left(2\pi kt/T\right) + d_2 \Delta \cos\left(2\pi kt/T\right) + \varepsilon_t \tag{3.20}$$

This model can be extended to the following general version where the autocorrelation in the residuals can be corrected by adding a number of lags of $\widetilde{S}_{t-1}$:

$$\Delta y_t = \phi \widetilde{S}_{t-1} + d_0 + d_1 \Delta \sin\left(2\pi kt/T\right) + d_2 \Delta \cos\left(2\pi kt/T\right) + \sum_{j=1}^{p} \Delta \widetilde{S}_{t-j} + \varepsilon_t \tag{3.21}$$

Based on this regression model, the LM test statistic can be shown as follows:

$$\tau_{LM} = t - statistic\, for\, the\, null\, hypothesis\, \phi = 0 \tag{3.22}$$

The distribution of the test statistic depends on the frequency of k. It should be noted that Enders and Lee (2012) pointed out that using a specific frequency k = 1 can often produce a good approximation to the model with structural breaks. In addition, if the data contains several breaks and/or if the breaks are sharp, it seems to be important to include the second frequency in the model.

3.3.2 Panel unit root tests

3.3.2.1 A panel unit root test without cross-sectional dependence (IPS test)

Im et al. (2003) proposed a unit root test for heterogeneous panels. In this test, a standardized t-bar test statistic is constructed by averaging the (augmented) Dickey-Fuller statistics across the groups and follows the standard normal distribution as both T (the time series dimension) and N (the cross sectional dimension) go to infinity. The DGP used for each cross-section unit in the panel is actually the same as those in the DF or ADF tests. In the panel framework, the DGP can be expressed as follows:

$$\Delta y_{it} = \beta_i y_{it-1} + \sum_{j=1}^{p_i} \rho_{ij} \Delta y_{i,t-j} + a_{mi} d_{mt} + \varepsilon_{it}, \quad i = 1, \ldots, N, t = 1, \ldots, T, m = 1, 2, 3 \tag{3.23}$$

where d_{mt} contains the deterministic variables. $d_1 = \{\emptyset\}$, $d_2 = \{1\}$, $d_3 = \{1, t\}$. p_i is the number of lagged terms included in the i-th individual equation. Based on these DGP, the hypotheses are as follows:
The Null Hypothesis:

$$\beta_i = 0, for\ all\ i, \tag{3.24}$$

The Alternative Hypothesis:

$$\beta_i < 0, for\ i = 1, \ldots, N_1, \beta_i = 0, for\ i = N_1 + 1, \ldots, N. \tag{3.25}$$

It should be stressed that the IPS test allows some of the individual series to contain a unit root under the alternative hypothesis. In addition, the fraction of the stationary individual series should be positive, which can be described as follows:

$$\lim_{N \to \infty} \frac{N_1}{N} = \delta \in (0,\ 1)\,. \tag{3.26}$$

Under the null hypotheses and for the fixed T and a sufficiently large N, the test statistic, which is referred to as $\widetilde{t}$ can be constructed as an average of the t-statistic of each individual series:

$$\widetilde{t} - bar_{NT} = \frac{1}{N} \sum_{i=1}^{N} \widetilde{t}_{iT} \left(p_i,\ \rho_i\right) \tag{3.27}$$

where $\widetilde{t}_{iT}\left(p_i, \rho_i\right)$ is the simplified version of the standard ADF test statistic of the test for $\beta_i = 0$, which has been shown Im et al. (2003). $\rho_i = \left(\rho_{i1}, \rho_{i2}, \ldots \rho_{ip_i}\right)$ are the coefficients of the lagged terms included in the individual equation. When T is fixed, the individual ADF statistics depend on the nuisance parameters, $\rho_i = \left(\rho_{i1}, \rho_{i2}, \ldots \rho_{ip_i}\right)$, therefore, it is not practical to use the mean, $E\left[t_{iT}\left(p_i,\ \rho_i\right)\right]$ and variance, $Var\left(p_i,\ \rho_i\right)$ to standardize the test statistics. However, Im et al. (2003) propose an asymptotically valid standardized t-bar statistic which is free of the nuisance parameters and can be shown as follows:

$$Z_{tbar}\left(p, \rho\right) = \frac{\sqrt{N}\left\{t - bar_{NT} - E\left(\eta\right)\right\}}{\sqrt{VAR\left(\eta\right)}} \tag{3.28}$$

where $\rho = \left(\rho_1^{'}, \rho_2^{'}, \ldots, \rho_N^{'}\right)^{'}$, $p = \left(p_1, p_2, \ldots p_N\right)^{'}$. η is the distribution of the ADF statistics as $T \to \infty$, which can be seen in Im et al. (2003). This standardized t-bar statistic has a standard normal distribution as $T \to \infty$, followed by $N \to \infty$.

3.3.2.2 A panel unit root test with sharp structural breaks (Im et al., 2010)

Im et al. (2010) proposed a panel LM unit root test allowing for heterogeneous structural breaks in both the intercept and slope of each cross-sectional unit in the panel. The biggest improvement of this test compared with other panel unit root tests is that the test statistics are no longer dependent on the nuisance parameters around the breaks. If the dependence is ignored, the test in a panel setting will suffer from a serious size distortion even though the bias is negligible in each univariate test. In addition, considering cross-correlations occurring in the innovations of the panel, the test is modified to correct for them by using the cross-sectionally augmented ADF (CADF) procedure of Pesaran (2007).

In the panel framework, firstly, we will get the statistic of each cross-section unit denoted as i by using the following model:

$$\Delta y_{i,t} = \delta'_{i,t}\Delta Z_{i,t} + \phi\widetilde{S}^{*}_{i,t-1} + \sum_{j=1}^{k}\phi_{i,j}\Delta\widetilde{S}_{i,t-j} + u_{i,t}, \quad t = 2, \ldots, T. \tag{3.29}$$

It can be noted that we can regress $\Delta y_{i,t}$ on $\widetilde{S}^{*}_{i,t-1}$ instead of $\widetilde{S}_{t-1}$ as is in the previous equation. The panel test statistic can be constructed based on the following hypotheses:
The Null Hypothesis:

$$\phi_i = 0, for\ all\ i, \tag{3.30}$$

The Alternative Hypothesis:

$$\phi_i < 0, for\ some\ i. \tag{3.31}$$

The panel LM test statistic can be shown to be as follows:

$$LM\left(\widetilde{\tau}^{*}\right) = \frac{\sqrt{N}\left[\bar{t} - \widetilde{E}\left(\bar{t}\right)\right]}{\sqrt{\widetilde{V}\left(\bar{t}\right)}}. \tag{3.32}$$

The panel LM test statistic is the standardized statistic of $\bar{t}$ and has a standard normal distribution. Where $\bar{t}$ is the average of the test statistics of the N cross-section units and $\widetilde{E}\left(\bar{t}\right)$ and $\widetilde{V}\left(\bar{t}\right)$ are the estimated values of the average of the means and variances of $\bar{t}$. They can be calculated as follows:

$$\bar{t} = \frac{1}{N}\sum_{i}^{N}\widetilde{\tau}^{*}_{i}, \tag{3.33}$$

$$\widetilde{E}\left(\bar{t}\right) = \frac{1}{N}\sum_{i=1}^{N}E\left(\bar{t}\left(\widetilde{R}_i, \widetilde{p}_i\right)\right), \tag{3.34}$$

$$\widetilde{V}\left(\bar{t}\right) = \frac{1}{N}\sum_{i=1}^{N}Var\left(\bar{t}\left(\widetilde{R}_i, \widetilde{p}_i\right)\right) \tag{3.35}$$

where $\widetilde{\tau}_i^*$ represents the test statistic of the i-th cross-sectional unit and $\left(\widetilde{R}_i, \widetilde{p}_i\right)$ are the estimated values of the number of structural breaks and the number of lagged terms. Therefore, the test allows the cross-sectional units to have different numbers of breaks and lags. Im et al. (2010) pointed out that the distribution of $\bar{t}$ is dependent on T but independent of N. Moreover, $\bar{t}$ does not depend on the locations of the breaks. As a result, $E\left(\bar{t}\right)$ and $V\left(\bar{t}\right)$ are the same for the different locations of the breaks. Therefore, the test statistics can be constructed and used to address the problem of size distortion, caused by the dependency on the nuisance parameters.

In addition, Im et al. (2010) applied the CADF procedure to correct for the presence of the correlations in the innovations of the cross-sectional units. Specifically, first the error term with a single-factor structural is assumed to be as follows:

$$\mu_{i,t} = \gamma_i f_t + e_{i,t} \tag{3.36}$$

where f_t is the unobserved common effect. Then, the following regression augmented by the cross-section averages of lagged levels and first-differences of the individual series is used to estimate of ϕ_i :

$$\Delta y_{i,t} = \delta_{i,t}^{'} \Delta Z_{i,t} + \phi_i \widetilde{S}_{i,t-1}^{*} + g\overline{S}_{t-1}^{*} + h\Delta S_t^{*} + \sum_{j=1}^{p} g_{i,j}\Delta \overline{S}_{t-j}^{*} + \sum_{j=1}^{p} d_{i,j}\Delta \widetilde{S}_{i,t-j} + u_{i,t}. \tag{3.37}$$

The test statistics can be obtained as the equation and follow the standard normal distribution.

3.3.2.3 A panel unit root test with a smooth structural break (Cerrato et al. (2011))

Cerrato et al. (2011) extended the KSS test to a panel system allowing cross sectional dependence and serially correlated errors. The model is as follows:

$$\begin{aligned} \Delta y_{it} &= \varphi_i y_{i,t-1}\left[1 - \exp\left(-\theta_i y_{i,t-1}^2\right)\right] + \mu_{it}, \theta \geq 0 \\ t \ &= \ 1, 2, \ldots, T \ \ i = 1, 2, \ldots, N \end{aligned} \tag{3.38}$$

where N is the number of cross sections, T is the number of time series observations.

The error term has a one factor structure:

$$\mu_{it} = \gamma_i f_t + \varepsilon_{it}, \quad \varepsilon_{it} \sim \left(0, \delta_i^2\right) \tag{3.39}$$

where f_t is the unobserved common effect, ε_{it} is the i.i.d. error term for the ith series with zero mean and constant variance.

Based on this model, we can test the null hypothesis that all of the series contain a unit root

$$H_0 : \ \theta_i = 0 \ \forall i \tag{3.40}$$

against the alternative hypothesis that some series follow the stationary ESTAR process and part of the series contains a unit root:

$$H_1: \ \theta_i > 0\ ,\ for\ i\ = 1, 2, \ldots, N_1\ and\ \theta_i < 0, for\ i\ = N_1 + 1, 2, \ldots, N. \tag{3.41}$$

The model above can be reparameterized based on a first-order Talyor series approximation to produce an auxiliary regression specified as follows:

$$\Delta y_{it} = \beta_i y_{i,t-1}^3 + \gamma_i f_t + \varepsilon_{it}. \tag{3.42}$$

Cerrato et al. (2011) further suggested using a linear function of mean lagged values of y_{it} to approximate the common factor:

$$f_t \approx \frac{1}{\overline{\gamma}_\omega} \Delta \overline{y}_{\omega,t} + \frac{b}{\overline{\gamma}_\omega} \overline{y}_{\omega,t-1}^3 \tag{3.43}$$

where $\Delta \overline{y}_{\omega,t} = \sum_{i=1}^N \omega_i \Delta y_{i,t}$, $\overline{y}_{\omega,t-1}^3 = \sum_{i=1}^N \omega_i y_{i,t-1}^3$, $\overline{\gamma}_\omega = \sum_{i=1}^N \omega_i \gamma_i$ .Therefore, the equation can be written as the following non-linear cross-sectionally augmented DF (NCADF) regression:

$$\Delta y_{it} = \alpha_i + \beta_i y_{i,t-1}^3 + \rho_i \Delta \overline{y}_t + \sigma_i \overline{y_{t-1}^3} + e_{it} \tag{3.44}$$

where $\overline{y}_t = \sum_{i=1}^N y_{it}$ and $\overline{y_{t-1}^3} = \sum_{i=1}^N y_{i,t-1}^3$. The equation can be extended to a following general case where the serial correlation is present in the error term of each individual series:

$$\Delta y_{it} = \alpha_i + \beta_i y_{i,t-1}^3 + \rho_i \Delta \overline{y}_t + \sigma_i \overline{y_{t-1}^3} + \sum_{j=1}^p \Delta y_{i,t-j} + e_{it} \tag{3.45}$$

where p is the number of lags and can be determined using an information criteria. The test statistic for this panel system can be constructed as follows:

$$\overline{t}\,(N,T) = \frac{1}{N} \sum_{i=1}^N t_i\,(N,T) \tag{3.46}$$

where individual test statistic $t_i\,(N,T)$ is as follows:

$$t_i\,(N,T) = \frac{\hat{\beta}_i}{s.e.\left(\hat{\beta}_i\right)} \tag{3.47}$$

where $\hat{\beta}_i$ is the OLS estimation of β_i and $s.e.\,(\beta_i)$ is the standard error of $\hat{\beta}_i$.

The distribution of $\overline{t}\,(N,T)$ no longer asymptotically follows the standard normal distribution and the critical values have been reported in Cerrato et al. (2011).

3.4 Data and results

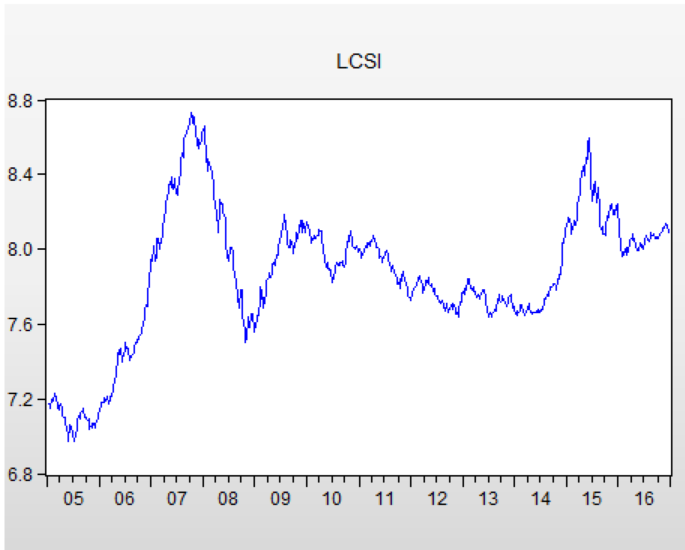
3.4.1 Description of the data

The data used in this study consists of the following two groups: the first group is the weekly data consisting of the SSE A-share composite stock index and ten SSE A-share sectorial stock indices. The indices in the first group include 626 weekly observations from 1/07/2005 to 12/30/2016. The second group is a monthly data consisting of ten SSE A-share sectorial stock indices and five macroeconomic series. All the series in the second group include 144 monthly observations from 01/2005 to 12/2016. It should be pointed out that the sectorial stock indices are available from 01/2005, so the data used in study all start from 2005. In addition, all the above data are collected from Datastream.

The ten sectors included represent the following sectors: Consumer Discretionary, Consumer Stables, Energy, Financials, Heathcare, Industries, Materials, Utilities, Telecommunication Service, Information Technology, respectively. All the ten sectorial stock indices are taken logarithm, denoted as LCHSCDIS, LCHSCONS, LCHSENER, LCHSFINL, LCHSHCRE, LCHSINDL, LCHSMATL, LCHSUTSE, LCHSTSVS, LCHSITEC, respectively. In addition, the composite stock index is in logarithm as well and denoted by LCSI.

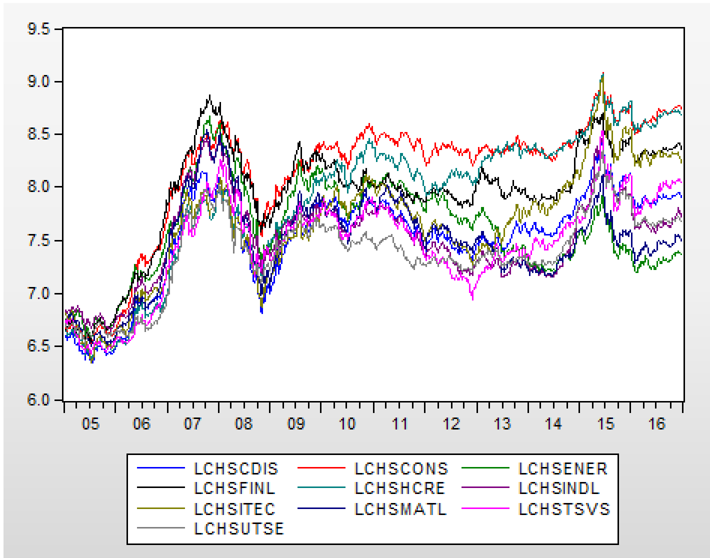
The five macroeconomic series, according to Pesaran et al. (2013) and Lee et al. (2016a), are the consumer price index (CPI_t), exchange rate (ex_t), the long-term rate of interest per annum in per cent (R_t) (typically the yield on ten year government bonds), the price of Brent Crude oil ($poil_t$) and industrial production index (ipi_t), respectively. Based on the need of the tests (Pesaran et al., 2013, Lee et al., 2016a), CPI_t is used to generate the inflation rate (if_t) based on the equation $if_t = lnCPI_t - lnCPI_{t-1}$, R_t is used to generate a monthly interest rate (lr_t) based on the equation $lr_t = 0.25 * ln(1 + R_t/100)$. The other three macroeconomic variables, which are in natural logarithmic form, are denoted to be lex, lpoil and lipi, respectively.

Figure 3.1a and Figure3.1b present the plots of the weekly composite stock index and ten weekly sectorial stock indices (first group). Based on these plots, we find that the trends of sectorial stock indices are very similar with that of the composite stock index, this further indicates these ten sectoral stock indices represent China's stock market reasonably well. In addition, it can also be seen that all these indices start with an intercept but there is not a clear linear time trend in them. This can also be observed based on the descriptive statistics shown in Table 3.1, for each index, both the maximum and minimum just have a small deviation from the mean. This indicates that there seems to be no linear time trend in the indices or that the time trend is very weak.

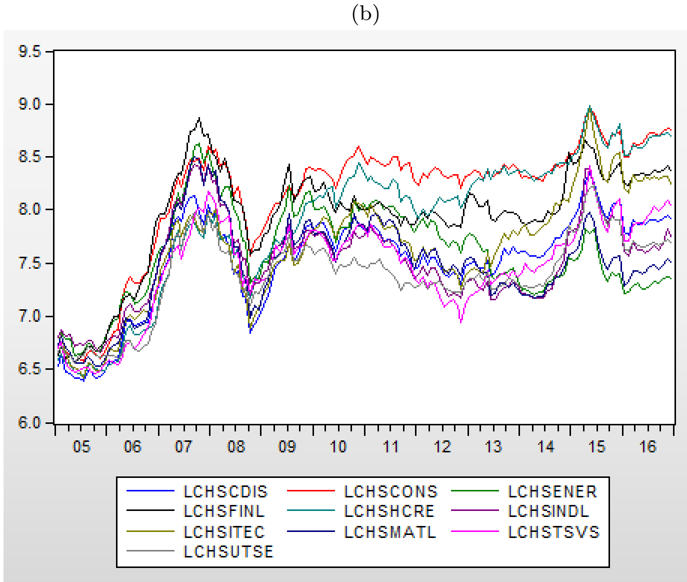


(a)

Figure 3.1: Composite and Sectorial Indices



(b)



(c)

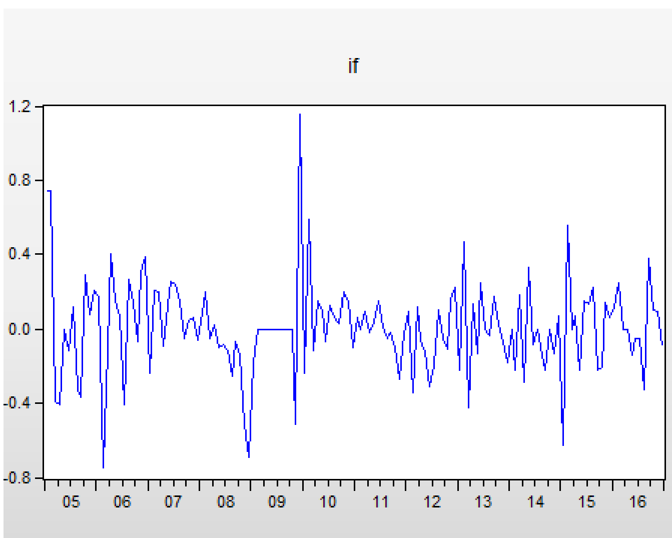
Figure 3.1: Composite and Sectorial Indices

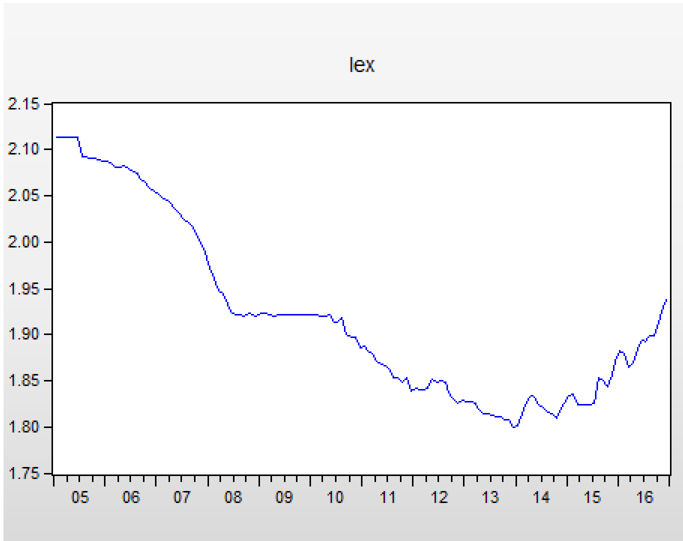
For the second group of data, the properties presented by the plot (Figure 3.1c) and the descriptive statistics of ten monthly sectorial stock market indices (Table 3.1) are similar to the weekly data. For five macroeconomic series, this study only focuses on whether a time trend is contained in them, because when the panel unit root tests (Pesaran et al., 2013,Lee et al., 2016a) are used, if no time trend is contained in sectorial indices, the macroeconomic series containing time trends should first be de-trended. Based on the plots presented in Figure 3.2 and the descriptive statistics shown in Table 3.1, it can be seen that the properties of these five series are quite different. It seems that only exchange rates contain a linear time trend. For the other series, the difference between the minimum and maximum of each series is quite small, therefore, even if there is a linear time trend, it should be very weak.

For both data in the first and second group, the plots and descriptive statistics can only provide some intuitive evidence. A number of tests will be used to provide a robust inference on the nonlinearity and non-stationarity of the indices.

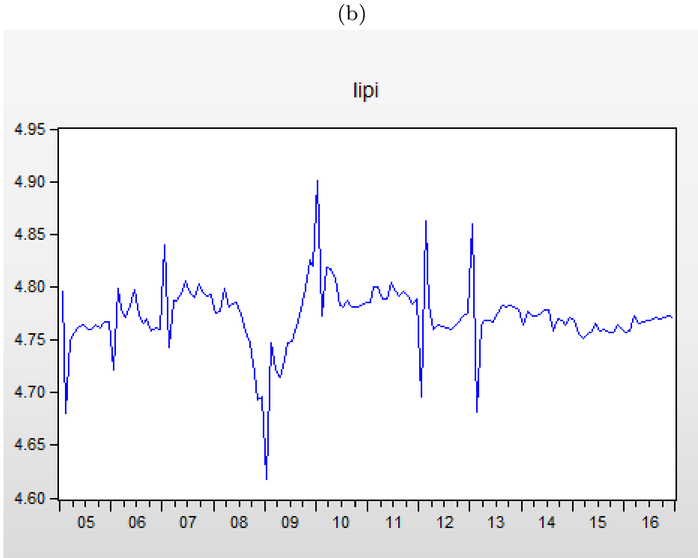
Figure 3.2: Macro Variables

(a)



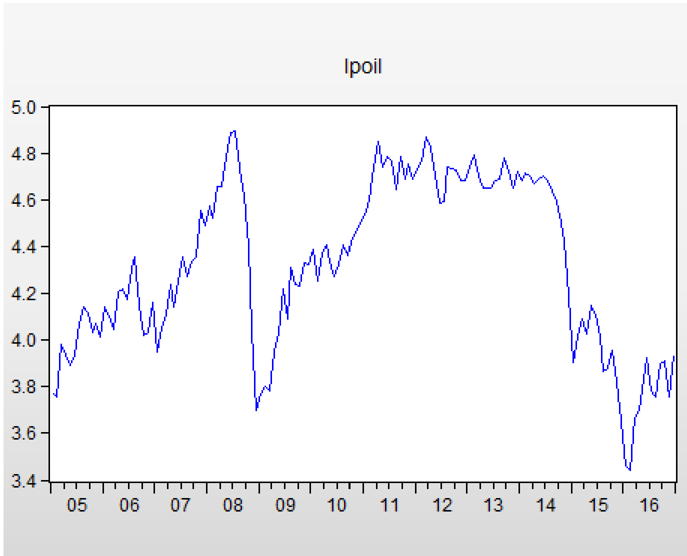


(b)

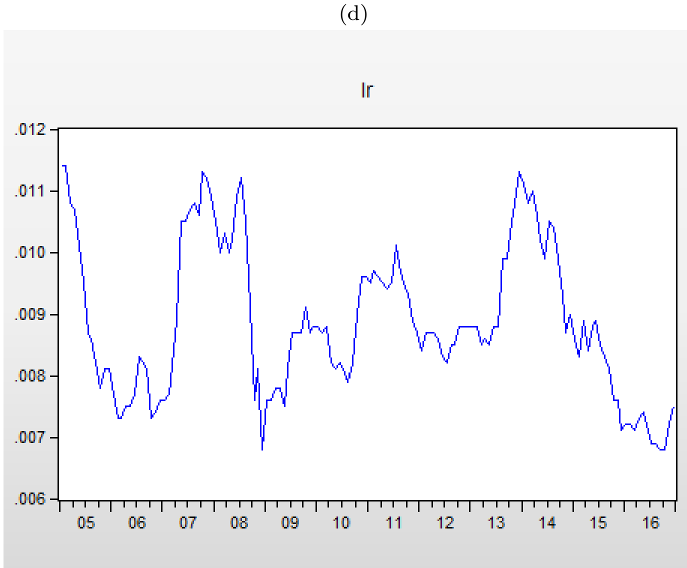


(c)

Figure 3.2: Macro Variables



(d)



(e)

Figure 3.2: Macro Variables

Table 3.1: Data Description

Variable	Obs	Mean	Std. Dev.	Min	Max
Weekly Data					
LCSI	626	7.86069	0.364804	6.969751	8.731816
CHSCDIS	626	7.52195	0.467818	6.346075	8.492872
CHSCONS	626	8.142208	0.604879	6.512844	9.078903
CHSENER	626	7.605632	0.448632	6.567685	8.676904
CHSFINL	626	7.943223	0.523919	6.545062	8.868691
CHSHCRE	626	7.90425	0.670801	6.395228	9.069644
CHSINDL	626	7.521726	0.417136	6.650098	8.475663
CHSMATL	626	7.651047	0.537495	6.340818	9.041395
CHSUTSE	626	7.486993	0.436483	6.501845	8.546035
CHSTSVS	626	7.468311	0.457264	6.433069	8.533519
CHSITEC	626	7.386475	0.388865	6.510422	8.348417
Monthly Data					
CHSCDIS	144	7.518533	0.467707	6.391833	8.338664
CHSCONS	144	8.140868	0.60201	6.564377	8.949627
CHSENER	144	7.600672	0.447295	6.636471	8.626709
CHSFINL	144	7.943196	0.52203	6.566138	8.87406
CHSHCRE	144	7.903921	0.670935	6.432763	8.98584
CHSINDL	144	7.518443	0.41789	6.66014	8.435577
CHSMATL	144	7.646798	0.538464	6.415702	8.951421
CHSUTSE	144	7.481127	0.436364	6.536358	8.495573
CHSTSVS	144	7.468258	0.458233	6.460843	8.418919
CHSITEC	144	7.385483	0.389205	6.556935	8.22618
Macro Data					
if	144	0.005865	0.256165	-0.74721	1.15268
lex	144	1.920092	0.095382	1.80039	2.11342
lipi	144	4.772058	0.031729	4.6177	4.9013
lpoil	144	4.320276	0.359631	3.4401	4.89635
lr	144	0.00887	0.001213	0.0068	0.0114

3.4.2 Univariate unit root tests

3.4.2.1 A test for the linear trend (Perron and Yabu, 2009)

In order to examine whether the stochastic component of a series is stationary or contains a unit root, it is very important to firstly specify correctly the deterministic trend function. Based on Table **??**, the tests for a linear trend indicate that there is a linear trend at the 5% significance level (no trend at the 5% significance level). However, the coefficient of the trend is nearly equal to 0 (0.0008), which implies that if a linear time trend existed, it should be quite weak. This is consistent with the intuition obtained from the plot and descriptive statistics of the composite stock index. In order to make the inference on the property of the stock indexes more robust and due to the ambiguity over whether a trend exists, we will consider both cases where only the constant and both the constant and the trend are included in the unit root test. In addition, it should be pointed out that we refer to the tests with a constant as case 1 and a constant and a linear trend as case 2 and we concentrate on the 5% significance level.

Table 3.2: Linear Trend test for Composite Index

Index	Test statistic	Confidence interval
Composite index	2.0248	$0.0001 < 0.0008 < 0.0014$
		$0.0000 < 0.0008 < 0.0015$
		$-0.0002 < 0.0008 < 0.0018$

The confidence intervals are listed in the third column. If the interval containes zero, it means the null hypothesis that the series doesn't have a trend cannot be rejected. Otherwise, the null hypothesis should be rejected. the first, second and third confidence intervals are obtained at the 1%, 5% and 10%, respectively.

3.4.2.2 Traditional univariate unit root test

The ADF unit root test is firstly applied considering its popularity in the field of unit root tests. Based on Table 3.3, it can be seen that the results of the ADF unit root tests in both cases suggest that the null hypothesis of a unit root cannot be rejected even at the 10% significance level, which implies that the stock market is weak-form efficient.

Table 3.3: ADF test

ADF	Constant	-2.032
ADF	Constant and trend	-1.781

Critical values for the ADF test with only constant are -3.441, -2.866 and -2.569 at 1%, 5% and 10% significance level, respectively. Critical values for the ADF test with both constant and trend are -3.973, -3.417 and -3.131 at 1%, 5% and 10% significance level, respectively.

3.4.2.3 Unit root tests with sharp structural breaks

1. Univariate unit root tests with one sharp structural break

In order to capture the effect of the structural breaks and the deterministic linear trend function, we firstly apply the unit root test allowing for one sharp structural break developed by Lee et al. (2004) to the composite stock index. The test in case 1 detected one significant break and suggested that the composite stock index is characterised by a unit root. It should be pointed out that the structural break (2008:04:18) detected by this test is consistent with the fact there is financial crises in the world occurring during 2007 and 2008. Although the result of the test in case 2 also suggested that the series contains a unit root, it seems difficult to interpret because the structural break in the level and the trend is insignificant. It should be noted that the insignificance of the structural break implies that the probability that the data contains a linear trend is very low, which is consistent with the result from the test for the linear trend.

Table 3.4: Univariate unit root tests with one sharp structural break

Constant	Test statistics	-1.904
	structural break	4.3358***
		(2008:04:18)
Constant and Trend	Test statistics	-2.5624
	Structural break in level	1.2239
		(2007:03:23)
	Structural break in trend	-1.2818
		(2007:03:23)

Critical values for the LM unit root test allowing for one structural break in the level at 10%, 5% and 1% significant levels are -3.211, -3.566 and -4.239 respectively. Critical values for the LM unit root test statistic in presence of one structural break in the level and the trend at 10%, 5% and 1% significant levels are -3.211, -3.566 and -4.239 respectively. Critical values for the coefficients on the structural breaks follow the standard normal distribution.*, **, *** denote statistical significance at the 10%, 5% and 1% levels respectively.

2. Univariate unit root tests with two sharp structural breaks

The unit root test allowing for two structural breaks developed by Lee and Strazicich (2003) is now applied to the composite stock index. Based on Table 3.5, it can be found that both the results of the test in case 1 and case 2 indicate that the unit root null cannot be rejected even at the 10% significance level. The difference is that the structural breaks in case 1 are both significant while only the second structural break with the linear trend is significant in case 2. However, the significance of the second structural break in the linear trend confirms our finding that a relatively weak trend might occur in the data. In addition, it should be pointed that the level significant structural breaks in case 1 and the trend significant structural break in case 2 are consistent with the events that are the financial crises in the world in 2007 and 2008 and China's stock market crush in 2015. Hence, combining the results of the unit root test allowing for one or two structural breaks in the level or the linear trend, we can conclude that the stock market is weak-form efficient.

Table 3.5: Univariate unit root test with two sharp structural breaks

Constant	Test statistics	-1.9933
	First structural break	4.3748*** (2008:04:18)
	Second structural break	2.1646** (2015:08:07)
	Test statistics	-3.3937
Constant and Trend	First structural break in level	-0.5013 (2007:03:09)
	Second structural break in level	1.0051 (2008:07:18)
	First structural break in trend	1.2693 (2007:03:09)
	Second structural break in trend	-2.0646** (2008:07:18)

Critical values for the LM test allowing two structural breaks in the level at 10%, 5% and 1% significant levels are -3.504, -3.842, -4.545. Critical values for the LM unit root test statistic in presence of two structural breaks depend on the location of the structural breaks. In this study, the critical values at 10%, 5% and 1% significance levels are -6.16, -5.59 and -5.27 respectively. Critical values for the coefficients on the structural breaks follow the standard normal distribution.*, **, *** denote statistical significance at the 10%, 5% and 1% levels respectively.

3.4.2.4 Unit root test with a smooth structural break

1. A linearity test (Harvey et al., 2008)

For a time series, where it is possibly characterized by a smooth structural break, then the deterministic component of the series would potentially be a nonlinear process which could be approximated by an ESTAR or LASTAR process. Therefore, the linearity test developed by Harvey et al. (2008) is initially applied to examine the presence of any nonlinearity in the composite stock index. The results of the test shown in Table 3.6 indicate that the composite index is appears to contain a nonlinear process at the 5% significance level (even at the 1% significance level).

Table 3.6: Linearity test

Index	Statistics (W-lam)
Composite index	10.48**(***)

The different cases of critical values are listed in Harvey et al. (2008).*, **, *** denote statistical significance at the 10%, 5% and 1% levels respectively.

2. KSS test

Because of the linearity test showing the presence of a nonlinear ESTAR or LSTART process in the composite stock index, the KSS unit root tests where only one gradual structural break is assumed will be used to test the unit root null against a nonlinear and stationary alternative. The results in both case 1 and case 2 are shown in Table 3.7 indicating that the unit root null cannot be rejected even at the 10% significance level, which is consistent with the weak-form efficient market hypothesis.

Table 3.7: KSS test

KSS	Demeaned	-1.542
KSS	Demeaned and detrend	-1.209

Critical values for the demeaned KSS test at 1%, 5% and 10% significance levels are -3.48, -2.93, -2.66. Critical values for the demeaned and de-trended KSS test at 1%, 5% and 10% significance levels are -3.93, -3.40, -3.13.

3.4.2.5 Unit root tests with a number of smooth structural breaks

1. A test for a Fourier function

Although the test allowing for one smooth structural break has been taken into account, the inference obtained from the test could be unreliable if a number of smooth breaks were present in the composite stock index. If the series contains a number of smooth structural breaks, the nonlinearity of the series can be approximated by a Fourier function. There are mainly three methods which can be used to determine the presence and the specific form of the Fourier function:

- Enders and Lee (2012b) pointed out when n=k=1 (n is the multiple frequency of a Fourier function and k is the particular frequency of a Fourier function) it can serve as a good approximation to the deterministic component of a series containing structural change;
- A test such as Enders and Lee (2012b), Harvey et al., 2008 and Perron et al. (2017) can be used to determine the specific k, the last one is used in this study because it has several advantages over the other two tests (Perron et al., 2017);
- Enders and Lee, 2012b also pointed out that a good approximation can also be achieved using a Fourier function including multiple frequencies ($1 < n \leq 5$, if $n > 5$, it will lead to an overfitting problem (Enders and Lee, 2012b; Enders and Lee, 2012a). The test developed by Perron et al. (2017) can be used to obtain the specific n.

In order to obtain a robust result, this study uses all three methods to specify a Fourier function. Next, the test developed by Perron et al. (2017) is applied to examine the presence of a Fourier function. Based on Table **??**, for case 1, the results show that the particular frequency should be 2 (k=2) at the 5% significance level when a single frequency is used in the Fourier function and the number of multiple frequencies should be 4 (n=4) when the multiple frequency is used in the Fourier function. For case 2, when a single frequency is used, the results indicate that there is no evidence indicating the existence of a Fourier function at the 5% significance level (k=0), in this case, the ADF test with a constant and a linear trend should be applied instead. But when the multiple frequency is used in the Fourier function, the test indicates that the number of multiple frequencies is 2 (n=2) at the 5% significance level. In order to get a more robust result, we applied the unit root test with a Fourier function where k =1, k=2 and n=4 for case 1 and k=1 and n=2 for case 2. The reason for using k=1 as well in the Fourier function follows the suggestions by Enders and Lee (2012b).

Table 3.8: Fourier Function Test

	Constant (case 1)		Constant and trend (case 2)	
Composite index	k	n	k	n
	2	4	0	2

n is the multiple frequency of a Fourier function and k is the particular frequency of a Fourier function.Case 1 means that the series only contain the constant. Case 2 means that the series contain both the constant and trend.

2. Unit root tests with a number of smooth structural breaks

Based on the results of the above test, the unit root tests developed by Enders and Lee (2012b) and Enders and Lee (2012a) are applied to capture the effect of a number of smooth structural breaks. Specifically, the Dickey-Fuller version of the test will be used for case 1 because Enders and Lee (2012a) suggested that it is more powerful than the LM version of the test when there is only level shifts and the linear trend is absent. However, when the series is allowed to contain both a constant and a trend, Enders and Lee (2012b) pointed out that the LM version of the test has better size and power properties than the DF version of the test. Therefore, the LM version of the test is used for case 2. Based on the results shown in Table **??**, in case 1, the series is suggested to contain a unit root at the 5% significance level in all three cases where k=1, k=2 and n=4, respectively. In case 2, the unit root null cannot be rejected at the 5% significance level in both situations where k=1 and n=2, respectively. Therefore, the results of Enders and Lee (2012a) unit root tests allowing a number of smooth structural breaks provides strong evidence supporting China's stock market being weak-form efficient.

Based on the results of all the univariate unit root tests, we can conclude that all the tests provide strong evidence that the stock market is weak-form efficient.

Table 3.9: Unit root tests with a number of smooth structural breaks

Constant (case 1)	Enders and Lee (2012b)	-2.050 (k=1)
	Enders and Lee (2012b)	-2.229 (k=2)
	Enders and Lee (2012b)	-3.227 (n=4)
Constant and linear trend (case 2)	Enders and Lee (2012a)	-2.427 (k=1)
	Enders and Lee (2012a)	-2.580 (n=2)

In case 1, when k=1, the critical values are; In case 2, when k=1, the critical values are -4.80, -4.27 and -4.00 at 1%, 5% and 10% significance levels, respectively, when n=2, the critical values are -5.48, -4.95 and -4.68 at 1%, 5% and 10% significance levels. In case 2, when k=1, the critical values are -4.56, -4.03 and -3.77 at 1%, 5% and 10% significance levels, respectively, when k=2, the critical values are -4.15, -3.54 and -3.22 at 1%, 5% and 10% significance levels, respectively, when n=4, the critical values are -5.89, -5.38 and -4.13 at 1%, 5% and 10% significance levels, respectively.

3.4.3 Panel unit root tests

3.4.3.1 A test for the linear trend (Perron and Yabu, 2009)

Based on Table **??**, the results of the test for the sectorial indices show that there is no trend in any sectoral index at 5% significance level (even at 1% significance level). This is also consistent with the suggestion provided by the plot and descriptive statistics of the sectoral indices. Therefore, in the following panel unit root tests only a constant is included in the trend function.

Table 3.10: Linear Trend Test for Sectorial Indices

Sectoral index	Test statistic	Confidence interval
		-0.0021 < 0.0021 < 0.0063
CHSCDIS	0.8272	-0.0029 < 0.0021 < 0.0071
		-0.0044 < 0.0021 < 0.0087
		-0.0002 < 0.0033 < 0.0068
CHSCONS	1.5635	-0.0008 < 0.0033 < 0.0075
		-0.0021 < 0.0033 < 0.0088
		-0.0025 < 0.0010 < 0.0044
CHSENER	0.4561	-0.0031 < 0.0010 < 0.0051
		-0.0044 < 0.0010 < 0.0063
		-0.0011 < 0.0027 < 0.0065
CHSFINL	1.1930	-0.0018 < 0.0027 < 0.0072
		-0.0032 < 0.0027 < 0.0087
		0.0002 < 0.0033 < 0.0063
CHSHCRE	1.7638	-0.0004 < 0.0033 < 0.0069
		-0.0015 < 0.0033 <0.0081
		-0.0018 < 0.0014 < 0.0047
CHSINDL	0.7316	-0.0024 < 0.0014 < 0.0053
		-0.0036 < 0.0014 < 0.0065
		-0.0026 < 0.0012 < 0.0050
CHSMATL	0.5301	-0.0033 < 0.0012 < 0.0057
		-0.0047 < 0.0012 < 0.0071
		-0.0012 < 0.0021 < 0.0054
CHSUTSE	1.0664	-0.0018 < 0.0021 < 0.0060
		-0.0030 < 0.0021 < 0.0072
		-0.0020 < 0.0015 < 0.0051
CHSTSVS	0.7108	-0.0027 < 0.0015 < 0.0058
		-0.0040 < 0.0015 < 0.0071
		-0.0020 < 0.0023 < 0.0065
CHSITEC	0.8705	-0.0028 < 0.0023 < 0.0073
		-0.0044 < 0.0023 < 0.0089

The confidence intervals are listed in the third column. If the interval containes zero, it means the null hypothesis that the series doesn't have a trend cannot be rejected. Otherwise, the null hypothesis should be rejected. the first, second and third confidence intervals are obtained at the 1%, 5% and 10%, respectively.

3.4.3.2 A panel unit root test without cross-sectional dependence (IPS test)

The IPS unit root test, one of most traditional panel unit tests, is firstly applied. As shown in Table 3.11, the result of the test indicates the unit root null is rejected at 5% significance level by using the IPS test which is inconsistent with the result of the ADF test for the composite stock index.

Table 3.11: IPS test

IPS	Constant	-1.7617**
		(0.0391)

The different cases of critical values are listed in Im et al. (2003).*, **, *** denote statistical significance at the 10%, 5% and 1% levels respectively.

3.4.3.3 A panel unit root test considering cross-sectional dependence (Pesaran et al., 2013)

1. A test for a linear trend (Perron and Yabu, 2009)

However, because all sectorial stock indices are collected from China's stock market, there should be a strong dependence between these sectorial stock indices. Considering that an ignorance of cross-sectional dependence in the IPS test would lead to an unreliable inference, this study uses a test developed by Pesaran et al. (2013) where cross-sectional dependence is eliminated by adding some additional regressors. However, considering that no linear time trend is contained in the sectoral stock indices, the additional variables used in this panel unit root test should be de-trended if a linear time trend exists in these additional variables (Pesaran et al., 2013). Therefore, a test for a linear time trend is firstly applied for these additional variables. The results shown in Table **??** indicate that only the industrial production index contains a linear time trend. Therefore, the de-trended industrial production index is used in the panel unit root tests.

Table 3.12: Linear Trend Test for Macro Variables

Additional regressors	Test statistic	Confidence interval
		-0.0011 <-0.0003 < 0.0004
if	-0.7578	-0.0012 <-0.0003 < 0.0005
		-0.0015 <-0.0003 < 0.0008
		-0.0039 <-0.0012 < 0.0014
lex	-0.7563	-0.0044 <-0.0012 < 0.0019
		-0.0054 <-0.0012 < 0.0029
		-0.0014 <-0.0009 <-0.0004
lipi	-3.0410	-0.0015 <-0.0009 <-0.0003
		-0.0017 <-0.0009 <-0.0001
		-0.0150 <-0.0001 < 0.0148
lpoil	-0.0101	-0.0178 <-0.0001 < 0.0176
		-0.0233 <-0.0001 < 0.0231
		-0.0001 < 0.0000 < 0.0000
lr	-0.7622	-0.0001 < 0.0000 < 0.0000
		-0.0001 < 0.0000 < 0.0001

The confidence intervals are listed in the third column. If the interval containes zero, it means the null hypothesis that the series doesn't have a trend cannot be rejected. Otherwise, the null hypothesis should be rejected. the first, second and third confidence intervals are obtained at the 1%, 5% and 10%, respectively.

2. Pesaran et al. (2013)

After including the additional variables, the panel unit toot test developed by Pesaran et al. (2013) is applied and it can eliminate cross-sectional dependence by adding additional regressors to the model. The results of this test are summarized in Table 3.13. It should be noted that we set the maximum of m_0 equal to 4. This choice is made according to the recent literature which suggests that 2–6 unobserved common factors are sufficient to explain variations in most macroeconomic variables, see, for example, Stock and Watson (2002b) and Eickmeier (2009), among others. The number of additional regressors $h = m_0 - 1$. Therefore, when $m_0 = 1$, no additional regresssor is included in the model and it will become the panel unit root test developed by Pesaran (2007). Based on the results, when the CIPS test is used, the unit root null cannot be rejected at the 1% significance level for any combination of the additional regressors. When the CBS test is used, it can be found that the evidence supporting the rejection of the unit root null becomes stronger as the number of additional regressors increases, especially when three additional regressors are used, 6 out of 10 cases suggest the unit root null can be rejected at the 5% significance level. Because Pesaran et al. (2013) pointed out that the CSB test performs better than the CIPS test for smaller sample sizes, considering the sample size used in this study is relatively small (n=10), the CBS test should be more reliable, that is to say, there is more evidence showing that China' stock market is inefficient based on this test.

Table 3.13: Pesaran et al. (2013) Test

m_0	$\bar{x_t}$	$CIPS\,(\hat{\rho})$	$CSB\,(\hat{\rho})$
1	0	-1.9589	0.5672
2	if	-1.6141	0.5198
	lex	-1.9150	0.3158*
	lipi	-1.5998	0.5838
	lpoil	-1.8293	0.5927
	lr	-1.7222	0.4566
3	if, lex	-1.9061	0.2879
	if, lipi	-1.3521	0.5526
	if, lpoil	-1.7099	0.5626
	if, lr	-1.5326	0.4272
	lex, lipi	-1.8336	0.3416
	lex, lpoil	-1.7707	0.3514
	lex, lr	-1.9520	0.2069***
	lipi, lpoil	-2.2880	0.1769***
	lipi, lr	-1.5979	0.4647
	lpoil, lr	-1.5972	0.5131
4	if, lex, lipi	-1.6244	0.3063
	if, lex, lpoil	-1.5795	0.3258
	if, lex, lr	-1.9912	0.1963**
	if, lipi, lpoil	-1.9920	0.1682***
	if, lipi, lr	-1.3550	0.4464
	if, lpoil, lr	-1.5630	0.5013
	lex, lipi, lpoil	-2.1344	0.1433***
	lex, lipi, lr	-1.9264	0.2096**
	lex, lpoil, lr	-1.8111	0.2315**
	lipi, lpoil, lr	-2.1976	0.1692***

m_0 is the number of common factors shared by the dependent variables and additional regressors used in the model. The variable $\bar{x_t}$ indicates the regressors used for cross section augmentation in addition to the average of the dependent variable in the model. For the selected lag order $\hat{p} = \left[4\,(T/100)^{\frac{1}{4}}\right]$. For $CIPS\,(\hat{\rho})$ test, when $m_0 = 1$, the critical values at 1%, 5% and 10% significance level are -2.53, -2.32 and -2.21; when $m_0 = 2$, the critical values at 1%, 5% and 10% significance level are -2.54, -2.36 and -2.26; when $m_0 = 3$, the critical values at 1%, 5% and 10% significance level are -2.71, -2.53 and -2.43; when $m_0 = 4$, the critical values at 1%, 5% and 10% significance level are -2.84, -2.65and -2.54. For $CSB\,(\hat{\rho})$ test, when $m_0 = 1$, the critical values at 1%, 5% and 10% significance level are 0.241, 0.288 and 0.316; when $m_0 = 2$, the critical values at 1%, 5% and 10% significance level are 0.224, 0.269 and 0.296; when $m_0 = 3$, the critical values at 1%, 5% and 10% significance level are 0.208, 0.250 and 0.276; when $m_0 = 4$, the critical values at 1%, 5% and 10% significance level are 0.192, 0.233 and 0.257.

3.4.3.4 A panel unit root test with sharp structural breaks (Im et al., 2010, Lluís Carrion-i Silvestre et al., 2005)

Considering ignorance of structural breaks, the results of the IPS test could be unrelaible. Therefore, the panel unit root test allowing for sharp structural breaks is employed to provide potentially stronger evidence. It should be pointed out that the panel unit root tests where the structural breaks are allowed to occur in the trend dos not contradict the no trend findings by the test for the linear trend, because it is very flexible and can satisfy different cases. If there is no structural breaks in the trend, it will be automatically reduced to the other specifications of a panel unit root test such as a panel unit root test allowing for structural breaks in the level or no structural breaks. According to the results reported in Table 3.14, the results of the panel unit root test indicate that the unit root null cannot be rejected at the 5% significance level. It should be pointed out the statistics is a complex number when cross-sectional dependence is considered in this panel unit root test and this is useless. The results of the stationarity indicate that the stationarity null hypothesis cannot be rejected at the 5% significance level in both the homogeneous case and heterogeneous case. It should be noted that the critical values of this stationarity test are obtained from the bootstrap distribution computed to take into account cross-sectional dependence of the statistic. Based on the results above, it can be found that both the panel unit root and stationarity tests allowing for sharp structural breaks provide strong evidence supporting that China's stock market is inefficient.

Table 3.14: Panel Unit Root Tests with Sharp Structural Breaks

Panel unit root test			Panel stationarity test		
Lee et al. (2010)	TR-LM	-15.8415	Carrion-i-Silvestre et al. (2005)	homogeneous	1.629
	CA-TR-LM	0.0000 + 12.8421i		heterogeneous	2.185

The critical values for the panel unit root test developed by Lee et al. (2010) at 10%, 5% and 1% significance level are -3.934, -4.191 and -4.698. The critical values for the panel stationarity test developed by Carrion-i-Silvestre et al. (2005) in homogeneous case at 10%, 5% and 1% significance levels are 6.822, 7.475 and 8.617, respectively. For the heterogeneous case, the critical values at 10%, 5% and 1% significance levels are 5.240, 5.738 and 7.093.

3.4.3.5 A panel unit root test with a smooth structural break

1. Linearity test

Next, a linearity test (Harvey et al., 2008) is used to examine whether there is an ESTAR or LSTAR process in sectorial stock indices. The results of the test shown in Table 3.15 indicate that all sectorial indices are suggested to contain a nonlinear process at the 5% significance level (even at the 1% significance level).

Table 3.15: Linearity Test for Sectorial Indices

Sectorial index	Statistics
CHSCDIS	58.63**(***)
CHSCONS	66.00**(***)
CHSENER	149.00**(***)
CHSFINL	63.58**(***)
CHSHCRE	89.63**(***)
CHSINDL	79.29**(***)
CHSMATL	95.75**(***)
CHSUTSE	85.24**(***)
CHSTSVS	85.68**(***)
CHSITEC	119.68**(***)

The different cases of critical values are listed in Harvey et al. (2008).*, **, *** denote statistical significance at the 10%, 5% and 1% levels respectively.

2. Cerrato et al. (2011)

The results reported in Table 3.16 show that the unit root null cannot be rejected at the 5% significance level (even at the 10% significance level), it implies that China's stock market is weak-form efficient.

Table 3.16: Cerrato et al. (2011) Test

Sectorial stock indices	lag	Test statistics
CHSCDIS	0	-2.9162
CHSCONS	0	-2.6185
CHSENER	0	-0.1684
CHSFINL	0	-2.5435
CHSHCRE	0	-1.3108
CHSINDL	0	-1.7206
CHSMATL	0	-0.6172
CHSUTSE	0	-2.2340
CHSTSVS	0	-2.9207
CHSITEC	0	-1.5203
Panel	0	-1.8570

For the individual case, critical values at 1%, 5% and 10% significance level are -3.72, -3.15 and -2.85. For the panel case, critical values at 1%, 5% and 10% significance level are -2.50, -2.33 and -2.25.

3.4.3.6 A panel unit root test with a number of smooth structural breaks (Lee et al., 2016a)

Because the test has been designed to use a single frequency in the Fourier function and applies a data-driven method to select the specific frequency k, the test (Perron et al. (2017)) used for the univariate case is no longer employed for this test. Based on the results shown in Table 3.17, it can be found that k is specified to be 1in a majority of cases, which is consistent with the suggestion provided by Enders and Lee (2012b) that when k=1 is used in a Fourier function, it can often serve as a good approximation to the series. In addition, the number of lags used to eliminate serial dependence is specified to be 1 for each sectorial stock index based on the minimum sum of squares. The CD statistics indicate that there is cross-sectional dependence in sectorial indices, which means that it is feasible to use additional regressors to eliminate cross-sectional dependence. Based on the $BCIPS(p)$ statistics, it can be found that there is no evidence supporting a rejection of the unit root null at the 5% significance level. It implies that China's stock market is weak-form efficient.

To summarize, based on the results obtained from the panel unit root tests, we can conclude that the panel unit root tests allowing for no structural breaks and sharp structural breaks suggest that China's stock market is inefficient, however, the panel unit root tests allowing for smooth structural breaks provide strong evidence that China' stock market is weak-form efficient. Next, this study will present some evidence suggesting the inference obtained from the panel unit root tests allowing for smooth structural breaks are more reliable.

Table 3.17: Lee et al. (2016a) Test

m_0	$\bar{x_t}$	$\left(\hat{p},\hat{k}\right)$	$CSB\left(\hat{p}\right)$	$BCIPS\left(\hat{p}\right)$
1	0	(1, 1)	61.6626	-1.7307
	if	(1, 1)	61.6626	-2.4162
	lex	(1, 2)	61.4886	-2.6004
2	lipi	(1, 1)	61.6626	-2.4262
	lpoil	(1, 1)	61.6626	-2.2923
	lr	(1, 1)	61.6626	-2.8478
	if, lex	(1, 2)	61.4886	-2.4506
	if, lipi	(1, 1)	61.6626	-2.3692
	if, lpoil	(1, 4)	61.0561	-1.8209
	if, lr	(1, 1)	61.6626	-2.8103
3	lex, lipi	(1, 2)	61.4886	-2.6353
	lex, lpoil	(1, 1)	61.6626	-2.6624
	lex, lr	(1, 1)	61.6626	-3.0548
	lipi, lpoil	(1, 1)	61.6626	-2.4779
	lipi, lr	(1, 1)	61.6626	-2.8990
	lpoil, lr	(1, 1)	61.6626	-2.8082
	if, lex, lipi	(1, 2)	61.4886	-2.4424
	if, lex, lpoil	(1, 4)	61.0561	-2.2344
	if, lex, lr	(1, 1)	61.6626	-2.9454
	if, lipi, lpoil	(1, 1)	61.6626	-2.5002
	if, lipi, lr	(1, 1)	61.6626	-2.8560
4	if, lpoil, lr	(1, 1)	61.6626	-2.7914
	lex, lipi, lpoil	(1, 1)	61.6626	-3.1309
	lex, lipi, lr	(1, 2)	61.4886	-2.8829
	lex, lpoil, lr	(1, 1)	61.6626	-3.0972
	lipi, lpoil, lr	(1, 1)	61.6626	-2.9789

m_0 is the number of common factors shared by the dependent variables and additional regressors used in the model. The variable $\bar{x_t}$ indicates the regressors used for cross section augmentation in addition to the average of the dependent variable in the model. CD is the cross-sectional dependence test of Pesaran (2004). For the $CIPS\left(\hat{p}\right)$ test, when $m_0 = 1$,$k = 1$, the critical values at the 1%, 5% and 10% significance level are-3.21, -3.03 and -2.94 respectively; when $m_0 = 2$,$k = 1$, the critical values at the 1

3.5 Discussion

The following is evidence supporting smooth structural breaks as being more likely to be contained in China's stock indices, thus the panel unit root test allowing for smooth structural breaks are the most appropriate ones for investigating the efficiency of China's stock market.

- It should be noted that the data used in this study starts from 2005. In 2005, the Chinese government carried out a significant non-tradable shares reform which aimed to reduce the government's control on China's stock market by making all non-tradable shares tradable gradually. It is generally viewed as a reform significantly improving the degree of efficiency in China's stock market. In addition, a series of policies have been carried out by the government in the following years aiming to improve the efficiency of China's stock market. In order to maintain stability of the stock markets, these polices aim to have a gradual effect on China's stock market, which could lead to a number of smooth structural breaks in the stock price indices. The key events has been labeled by the red lines in Figure 3.3. Specifically, in Figure 3.3a, 8May2005, 8Jun2005, 23Aug2005, 04Sep2005: policies about non-tradable shares reforms introduced. 02Jun2006: IPO resumed. Oct2006: PetroChina joined the reforms. In Figure 3.3b, 28Aug2008: CSRC encouraged large shareholders to increase shareholdings; 19Sep2008: Imposed stock stamp duty unilaterally; SASAC support central enterprises to increase shareholdings in listed companies; Central Huijin Investment Ltd. increased shares of BOC, CCB and ICBC. 10Nov2008: Four trillion investment plan. 28Nov2008: Investing of Social Security Fund in stock markets. In Figure 3.3c, 26Apr2013: The SFC canceled the guidance on the margin trading window. 09May2014, The State Council promulgated the "Opinions of the State Council on Further Promoting the Healthy Development of the Capital Markets". 22Nov2014: Reduced benchmark interest rate on loans and deposits. 05February2015: Reduced deposit reserve ratio. 28Mar2015: One Belt One Road policy. 19Apr2015: Reduced deposit reserve ratio. In Figure 3.3d, 27Jun2015: Cut reserve ratio and interest rate. 01Jul2015: Adjust securities margin trading. 03Jul2015: Provide liquidity support. 04Jul2015: Suspension of IPO. 05Jul2015: Limit on stock selling. 09Jul2015: Encouraged stock buying. 07Sep2015: Circuit Breaker introduced.

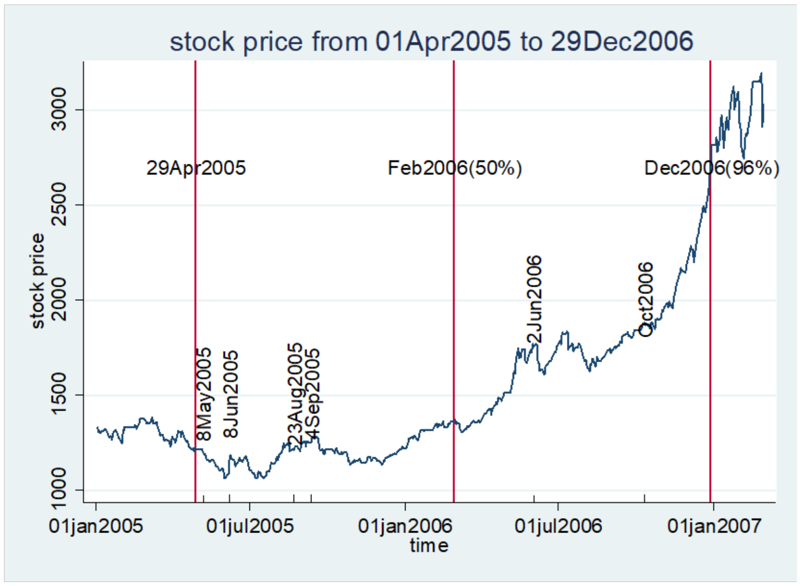
- Im et al. (2010) pointed out that a series with more than two breaks might best be modelled as a non-linear process. It can be found from the tests (Lluís Carrion-i Silvestre et al., 2005), as shown in **??** all the sectorial stock indices contain four or five sharp structural breaks. Therefore, it is better to use a nonlinear process to model China's stock indices, which is further support in favour of the reliability of the panel unit root tests allowing for the smooth structural breaks.

- Although it has been found that a nonlinear process approximated by a Fourier function significantly exists in the composite index based on the tests, according to the method suggested by Enders and Lee (2012b), a group of plots showing a close fit between the time-varying mean of the estimated series and the actual series are presented to obtain a better understanding of the nature of the Fourier approximation process. It should be pointed out that a time trend is allowed in the regression model, which aims to keep the starting point of the plots different from the end point. The green line is obtained using n=k=1, the blue line is obtained using a particular k selected according to Perron et al. (2017), the red line is obtained using a multiple frequency determined using Perron et al. (2017). Table **??** shows results on k and n obtained from the test (Perron et al., 2017) for the composite index. Based on Figure 3.4, it can be found that when n=k=1 is specified in the Fourier function, it can generate a good approximation, which is consistent with the suggestion of Enders and Lee (2012b). However, when a particular k is used, it seems the fit with the actual data is not good. When a multiple frequency is applied, it can generate quite a good approximation to the actual data. Overall, based on these plots, a Fourier function with n=k=1 or a multiple frequency are able to serve as a good approximation to the deterministic component of the series. Therefore, this further enhances the reliability of the inference obtained from the panel unit root tests allowing for a number of smooth structural breaks.

Therefore, based on the above three points, this study believes the conclusions regarding the efficiency of China's stock market from the panel unit root tests allowing for smooth structural breaks especially the one using a Fourier function are the most reliable, which means this study suggests China's stock market is weak-form efficient. This finding is consistent with the conclusion made by Wang et al. (2015). They also suggested that Chinese stock market is weak-form efficient using LM Fourier unit root test proposed by Enders and Lee (2012b). In addition, Li et al. (2012) provided evidence supporting Chinese stock market is weak-form efficient using the panel stationary test allowing for multiple structural breaks developed by Lluís Carrion-i Silvestre et al. (2005), which is inconsistent with the finding in this paper using this same test but consistent with the suggestion provided by the panel unit root tests allowing for smooth structural breaks. Because this study is the first one to use the panel unit root test allowing smooth structural breaks to investigate the efficiency of Chinese stock market, there has not yet other studies which can be compared with the finding of this study.

Figure 3.3: Key Events

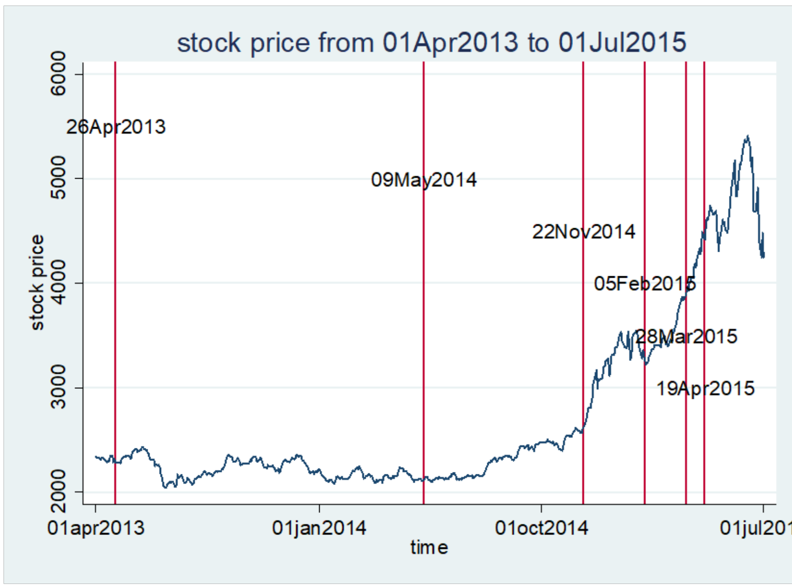
(a)



(b)

Figure 3.3: Key Events

(c)



(d)

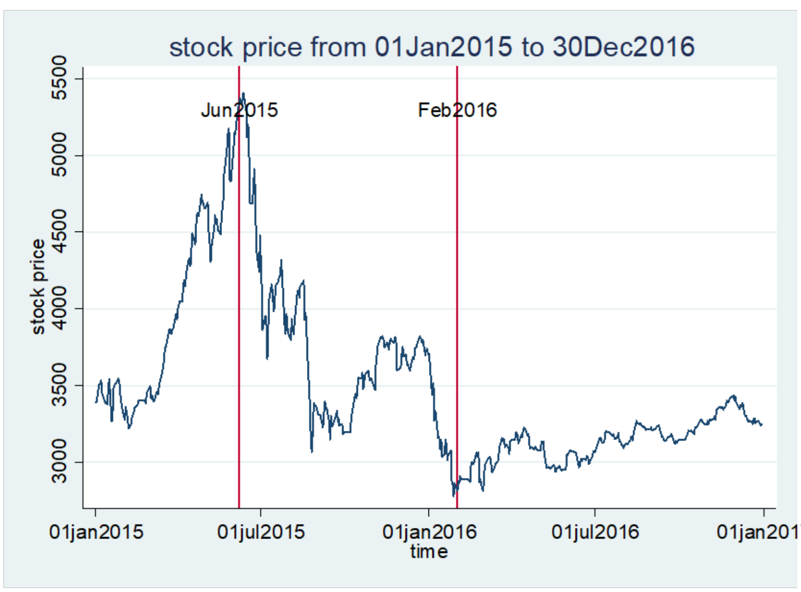
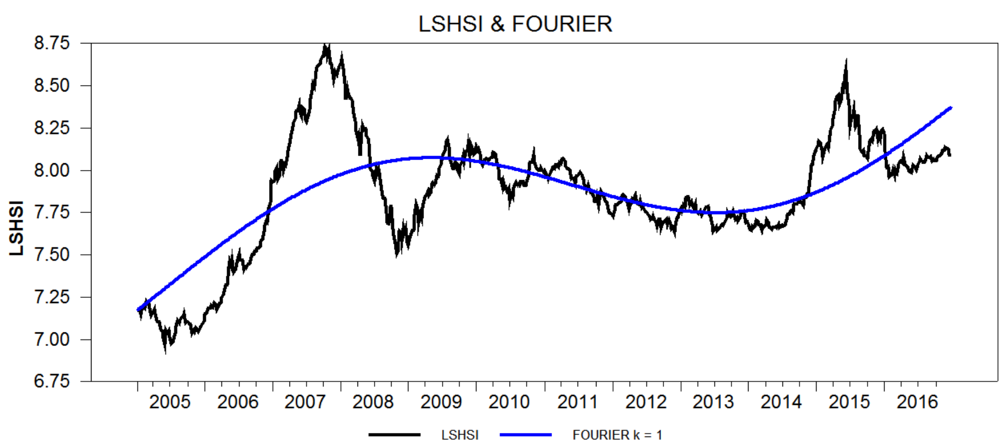


Figure 3.4: Fourier Function Approximation

(a)



(b)

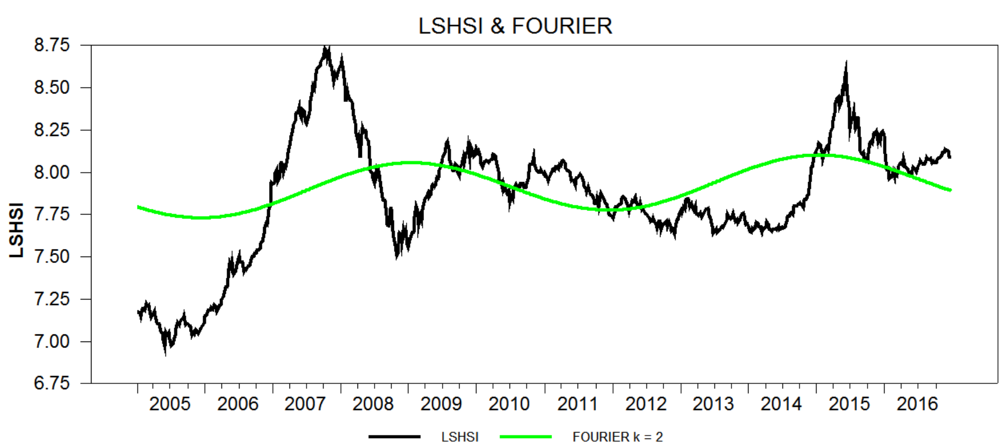


Figure 3.4: Fourier Function Approximation

(c)

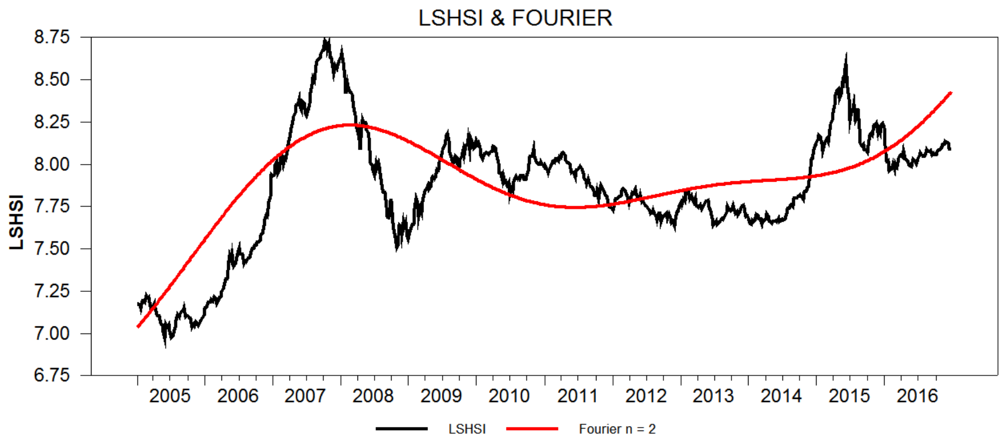


Table 3.18: Break Points Test

Sector	P values	Break Locations
CHSCDIS	0.017**	20/04/2007, 06/02/2009, 26/11/2010, 07/12/2012, 06/03/2015
CHSCONS	0.017**	10/11/2006, 22/08/2008, 04/06/2010, 06/02/2015
CHSENER	0.013**	20/07/2007, 05/02/2010, 11/02/2011, 28/11/2014
CHSFINL	0.026**	13/07/2007, 24/04/2009, 07/12/2012, 28/11/2014
CHSHCRE	0.018**	06/04/2007, 16/01/2009, 07/01/2011, 11/01/2013, 13/03/2015
CHSINDL	0.016**	13/04/2007, 20/03/2009, 02/09/2011, 05/12/2014
CHSMATL	0.013**	20/04/2007, 13/03/2009, 02/09/2011, 28/11/2014
CHSUTSE	0.012**	13/10/2006, 25/07/2008, 19/11/2010, 28/12/2012, 20/03/2015
CHSTSVS	0.017**	30/03/2007, 06/02/2009, 29/07/2011, 05/12/2014
CHSITEC	0.014**	30/03/2007, 30/01/2009, 12/11/2010, 09/11/2012, 13/03/2015

This test allows for at most five structural breaks. *, **, *** denote statistical significance at the 10%, 5% and 1% levels respectively.

3.6 Conclusion

Although China's stock markets have experienced the unprecedented development and have been playing an increasingly important role in the domestic and international financial markets over the last thirty years, especially since 2005 China deeply promoted the stock markets' development and openness, there has not yet a consensus in the literature on the market efficiency. Therefore, this paper investigated the nonlinearity and nonstationarity of China's stock market by applying a series of nonlinearity and nonstationarity tests into both the market-level and sector-level data since 2005.

Compared with the previous literature, which applied traditional unit root tests and/or unit root tests only accounting for sharp structural breaks to investigateg the weak-form efficiency of China's stock markets, this chapter contributed to the literature by accounting for: smooth structural breaks in the unit root tests, which characterized China's stock indices and can be well modeled by the Fourier Function based on three different criteria (Enders and Lee, 2012b, Harvey et al., 2008 and Perron et al., 2017), and cross-section dependence captured by incorporating the common information contained the macroeconomic variables into the shocks.

The panel unit roots test Lee et al. (2016a) , allowing the smooth structural breaks modeled by the fourier function and, is applied into ten sectorial stock return indices. The results showed China's stock market is weak-form efficient, which is consistent with the conclusion made by Wang et al. (2015), who showed that Chinese stock market is weak-form efficient using LM Fourier unit root test proposed by Enders and Lee (2012b). The other unit root and stationary tests used in this study produced mixed results, which is in line with the findings in the literature and suggests that the results tend to be mixed if the nonlinearity cannot be modeled accurately and nonstationarity is accessed using different types of techniques.

This result suggests that the development of the Chinese stock markets over the last thirty years has taken China's stock market from a casino to a weak-form efficient market. This development has been brought about through various reforms and the liberalization of transactions and stock ownership. Therefore, the Chinese government should continue to develop and open the financial markets. For example, the restrictions regarding the entrance and investment into China's stock market on the foreign investors should be further released to enable more foreign investors to invest in China's stock market, though the QFII and RQFII schemes stock connections has been established and well developed. Although Shanghai-Hong Kong and Shenzhen-Hong Kong stock connections have been well established, more investment channels connecting China's stock market and other countries' stock markets should be connected to internationalize China's stock market, which enable both domestic and foreign investors to well manage their wealth and risk, and thus achieve an efficient capital allocation. In order to connect China's stock market with the international capital market, China must develop the business environment by revised existing or set new relevant regulations and policies. For example, Chinese government should continue reduce the subsidy to State Owned Enterprises (SOEs) and the interference of SOEs into the financial market, which can improve the capital allocation and create more fair market environment attracting more private investors including the foreign investors (Ljungqvist et al., 2015).

The limitation of this chapter is using only the unit root tests to examine the efficiency of China's stock market, the future study could try other methods (e.g. Bai et al., 2016; Carpenter et al., 2020) to investigate the informativeness of China's stock market.

Chapter 4

Identifying Drivers of China's Stock Price Volatility and Investigating Their Effects

This declaration concerns the article entitled:			
Identifying Drivers of China's Stock Price Volatility and Investigating Their Effects			
Publication status (tick one) **Draft manuscript** ✔ **Submitted** ☐ **In review** ☐ **Accepted** ☐ **Published** ☐			
Publication details (reference)			
Copyright status (tick the appropriate statement) I hold the copyright for this material ✔ Copyright is retained by the publisher, but I have been given permission to replicate the material here ☐			
Candidate's contribution to the paper (provide details, and also indicate as a percentage)	The candidate contributed to / considerably contributed to / predominantly executed the… Formulation of ideas: 100% Design of methodology: 100% Experimental work: 100% Presentation of data in journal format: 100%		
Statement from Candidate	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature.		
Signed	Yuexian Tang	**Date**	30/08/2020

4.1 Introduction

The Chinese stock markets have been experiencing a unprecedented development over the last thirty years, especially since China joined in the World Trade Organization (WTO) at 2001. Both China's economy and stock markets are now the second largest in the world. This development has been brought about through various reforms and the liberalization of transactions and stock ownership, as well as the allowing of derivative products and practices such as short selling.

However, it is still common to witness abrupt market fluctuations and jumps generated by insider trading, financial fraud, or government economic policies uncertainty. For example, China's stock market turbulence in 2015 brought about substantial losses to both domestic and foreign investors and caused instability to both China's and the international financial markets. In addition, a comprehensive financial risk aversion system has not been established. For example, the derivative market is still in the initial stages of the development and investors have limited tools to manage the financial risks. Therefore, it is of great importance for the risk managers and investors to get an accurate prediction of the Chinese stock market risks considering the instability and immaturity of China's stock market.

There are substantial studies in the literature on modeling asset volatilities that are crucial in risk measures such as Value-at-Risk (VaR) or Expected Shortfall. One of the most successful of these volatility modeling is the Autoregressive Conditional Heteroscedasticity (ARCH) model introduced by Engle (1982) and has since become an extensively researched area in the field of financial econometrics. Stochastic volatility (SV) models, another class of volatility models in the literature, are also applied wildly to model the time-varying volatility in option pricing, portfolio allocation and risk management. Apart from the ARCH-family models and SV models, the realized volatility, which is a relatively new volatility modeling technique and developed by Andersen et al. (2001) and Barndorff-Nielsen and Shephard (2002), has enjoyed a increasing popularity in modeling asset volatilities using high-frequency intra-day asset returns. Using these volatility models, many studies have been conducted to model and predict China's stock return volatility. However, China's stock markets have been gradually evolving from a highly speculative market in the nineties, being thus at times comparable to a casino (Girardin and Joyeux, 2013), to a relatively efficient market attributed to a number of deep informs in the last twenty years. As a result, the macroeconomic and financial information is gradually playing an increasingly important role in the assets pricing. Therefore, it is necessary to capture the information contained in the macroeconomic and financial variables when modeling and predicting the stock price volatility.

The examination of the role played by macroeconomic and financial variable in modeling stock volatility can be dated back to the seminal work by Schwert (1989) where the author posed a question: what drives the variation in the US stock return volatility? Although the author only provided weak evidence supporting the usefulness of these macroeconomic and financial variables in driving the US stock return volatility, this study suggested that the US stock volatility is negatively related with the business cycle. Similar with the findings from Schwert (1989), Paye (2012) applied linear estimation models to examined the ability of macroeconomic and financial variables in predicting the US stock return volatility. The finding suggested that there was no additional information that can be exploited by the forecasting models or methods to improve the forecasting accuracy.

Compared with the findings form Schwert (1989) and Paye (2012) , there are papers reporting more encouraging evidence. Employing the Generalized Autoregressive Conditional Heteroscedasticity-spline (GARCH-spline) model, Engle and Rangel (2008) found that the low-frequency component of volatility can be predicted by exploiting the information contained in the macroeconomic variables. Engle et al. (2013) applied the Generalized Autoregressive Conditional Heteroscedasticity-Mixed Data Sampling (GARCH-MIDAS) model that can incorporating directly incorporate macroeconomic to predict the US stock return volatility. They showed that the inflation rate and industrial production rate are useful for predicting the long-horizon US stock return volatility. Christiansen et al. (2012) used a large pool of potential predictors to predict the US stock return volatility in Bayesian model-averaging (BMA) framework and found that forecasts were improved using the model incorporating macroeconomic and financial variables compared with autoregressive benchmarks. Mittnik et al. (2015) applied the same macroeconomic and financial variables as Christiansen et al. (2012) but a boosting approach (Freund et al., 1996; Friedman, 2001) to model volatility and showed that these risk drivers affect the future stock volatility.

There have as well emerged a number of studies considering showing the usefulness of the macroeconomic and financial variables in modeling and predicting China's stock price volatility. For example, inspired by Engle et al. (2013), Girardin and Joyeux (2013) applied GARCH-MIDAS model to investigate the influence of volume and macroeconomic fundamentals on the long-term volatility of the Chinese stock markets. The empirical findings confirmed the speculative characteristic in the Chinese stock markets before WTO entry in late 2001. But they also showed that after that date macroeconomic fundamentals, especially CPI inflation, has been playing an increasing role in the Chinese stock market and the speculative characteristic attenuated substantially as indicated by the influence of volume on the Chinese stock markets. However, they did not find the evidence supporting the significant influence of macroeconomic fundamentals on the Chinese long-run stock volatility. However, Cai et al. (2017) compared the forecasting performance of the AR (1) model and the predicative regression including both the lag of stock volatility and macroeconomic and financial variables. They found that the augmented model outperformed the benchmark AR (1) model, suggesting that the information contained in the macroeconomic and financial variables is useful for predicting the Chinese stock price volatility.

Given these evidence supporting the usefulness of the information contained in macroeconomic and financial variables and the development of the Chinese stock markets, It is necessary to find the determinants of the Chinese stock volatility prior to model and predict the stock volatility. However, firstly, the literature is too limited to draw a conclusion on which variable can provide forecasts on Chinese stock volatility. Secondly, the literature can be difficult to compare, as there are relatively different studies examine different forecasting variables and apply different econometric approaches. Therefore, this paper firstly aims to find the determinants of the Chinese stock volatility from a large set of potential macroeconomic and financial variable using the penalized regression techniques and the corresponding significance tests.

Specifically, the GARCH-MIDAS model is used as filter on the realized volatility (Schwert, 1989) to produce a less noisy monthly Chinese stock volatility. Based on the literature on both developed stock markets and Chinese stock markets, the potential variables are classified into three categories: international variables, macroeconomic and financial variables and the variables representing characteristics of the Chinese stock markets. Then the Least Absolute Shrinkage and Selection Operator (LASSO) based on the Least-Angle regression (LARS) algorithm and Gradient decent algorithm are used to select the important variables from these potential variables. Further, the Post-LASSO, Truncated Gaussian and CovTest significance tests are applied to find the variables having statistically significant effect on the Chinese stock markets. The results showed that VIX is the most significant driver among these potential drivers of the Chinese stock volatility, which lead to the other question this paper aimed to investigate that is how the VIX index affects the Chinese stock volatility over time.

Given the importance of the relationship between China and the US for the economy and finance of both countries and even the whole world, there have existed a number of studies investigating the influence of the US stock market on the Chinese stock volatility. For example, Moon and Yu (2010) examined the short-run return and volatility spillovers effects between the the Shanghai Stock Exchange (SSE) index in China and Standard & Poor's (S&P) 500 stock index in the US using the Generalized Autoregressive Conditional Heteroscedasticity-Mean (GARCH-M) model. Their empirical finding showed that since December 2005, volatility spillover from the US to China's stock market is both symmetrical and asymmetrical but only symmetrical from China to the US. Sarwar (2012) investigated relationships between Chicago Board Options Exchange (CBOE) market volatility index (VIX) and stock market returns in Brazil, Russia, India, and China (BRIC) and found that there was a significant negative contemporaneous relationship between VIX and China's and Brazil's stock returns. The findings also showed evidence for a strong asymmetric relation between innovations in VIX and China's and Brazil's stock returns. Although such studies provides some evidence suggesting the US stock market has significant influence on the Chinese stock volatility, these studies have been confined to only providing the constant influence measured by the coefficient of the variable representing the US stock market.

Based on the literature, the Bayesian Time-Varying Structural Vector Autoregressive (TV-VAR) model proposed by Primiceri (2005), which allows for both heteroskedasticity of the shocks and time variation in the simultaneous relationships between the variables in the model, can be applied to address this issue. The TV-VAR model has been popularly used to analyze the time-varying structure of the macroeconomy. For example, Benati (2008) applied the TV-VAR model to to assess the source of the "Great Stability" in the United Kingdom as well as uncertainty for inflation forecasting. Baumeister et al. (2008) applied TV-VAR model to assess the effects of excess liquidity shocks on macroeconomic variables in euro area. An increasing number of studies have examined the TV-VAR models to provide empirical evidence of the dynamic structure of the economy (see e.g., Baumeister and Benati, 2010 and Clark and Terry, 2010). In order to provide more reliable evidence, this study applied TV-VAR model to firstly investigate if the innovations of the VIX index is changed over time, secondly analyze how these shocks to the VIX index affect the Chinese volatility over time through the impulse function and thirdly compare the influence of the US stock market on the Chinese stock market among three China-US presidency periods.

This paper contributes to the existing literature on volatility modeling and the information transmission between the US and Chinese stock markets in several ways. First, this paper considered a large set of potential drives of the Chinese stock volatility, especially, considered the variables representing the development, openness and ownership structure of the Chinese stock markets. Second, the application of LASSO regression and the corresponding significant tests can not only select the most correlated drivers but also can provide the statistically inference on these selected drives. To the best of my knowledge, this is the first application so far in both the developed stock markets and Chinese stock markets. Third, the results showed that Chinese stock volatility is primarily driven by the the international factor such as the VIX index and variable representing characteristics of the Chinese stock markets, which confirmed the important role played by the integration of the Chinese economy with the world economy and the development and openness of the stock markets. Fourth, the TV-VAR model is the first time applied to analyze the influence of the US markets on the Chinese stock volatility and even any issues associated with financial markets. The application of TV-VAR model can produce more realistic and reliable evidence for the influence of the US stock markets on the Chinese stock markets. The interesting finding is that the US stock markets have the strongest effect on the Chinese stock volatility during the Jinping Xi and Donald Trump presidency, which is in line with the fact that the China-US trade war happened during this period.

4.2 Literature Review

4.2.1 Stock Volatility Measurement

Time-varying volatility is arguably among the most important areas of research in empirical asset pricing finance and risk management. This has been the case for a long time according to early comments including Mandelbrot (1963) and Fama (1965). It was also clear that assuming volatility to be constant for convenient simplification was unrealistic, e.g. Black et al. (1972) wrote "... there is evidence of non-stationarity in the variance. More work must be done to predict variances using the information available." It is necessary to allow heterogeneity instead of assuming homogeneity for both the theory and practice of financial economics and econometrics.

Moreover, it is beneficial to develop stochastic volatility models considering that the market risks are changing over time as implied by the asset pricing theory that an asset with higher returns is always exposed to more systematic risk. In addition, the well-known stylistic fact, the smile effect, which has been documented in the empirical literature on the Black-Scholes implied volatilities also produces the requirement to build time-varying volatility models. More generally, time-varying volatility are more consistent with the empirical reality of financial market, therefore, modeling time-varying volatility can inspire new approaches and enable investors to make better decisions.

One of the most successful time-varying volatility models is the ARCH model introduced in the seminal paper by Engle (1982). It has since enjoyed unprecedented empirical success because the phenomenon of clustering volatility has been successfully modeled with it. Thereafter, a myriad of extensions have been developed based on ARCH model. The GARCH model, a generalization of ARCH model, was developed by Bollerslev (1986) and was widely applied for modeling volatility. In addition, a series of other ARCH related models were developed by considering other financial characteristics, for example, EGARCH (Nelson and Cao, 1992) and GJR-GARCH (Glosten et al., 1993) models were developed to incorporate the leverage effect; IGARCH model was developed by allowing the unit root in the GARCH process. Apart from these univariate volatility models, multivariate GARCH models (MGARCH) were developed to model the volatilities or co-volatilities across several financial assets or markets. According to, MGARCH models can be non-mutually classified into three categories with regards to the approached for constructing these models: the first category is the direct generalizations of the univariate GARCH model such as the VEC, BEKK and factor models; the second category is the linear combinations of univariate GARCH models such as generalized orthogonal models and latent factor models; the third category is the nonlinear combinations of univariate GARCH models such as dynamic conditional correlation models, the general dynamic covariance model and copula-GARCH models.

Stochastic volatility (SV) models, another class of volatility models in the literature, are also applied widely to model the time-varying volatility in option pricing, portfolio allocation and risk management. SV models were firstly built in the discrete-time setting although the modern treatment of SV models are situated in continuous-time setting. The time-varying volatility cast in a discrete-time setting was originated by specifying the asset price as a function of random process of information arrival by Clark (1973). Later Tauchen and Pitts (1983) extended this work by allowing temporary dependence in information arrival instead of i.i.d. information arrival as in Clark (1973). A well-known discrete-time SV model developed by Taylor (2008) explicitly modeled volatility clustering and was an alternative to the ARCH model. In addition, Breidt et al. (1998) and Harvey (2007) developed discrete-time models where the log volatility was specified as a fractionally integrated process to account for long memory characteristic. In addition to these univariate discrete-time SV models, Harvey et al. (1994) put forth a discrete-time multivariate SV model where the martingale components are given as a direct rotation of a p-dimensional vector of univariate SV processes.

Further studies in SV models took researchers into continuous-time SV models for addressing portfolio choice and derivatives pricing. Johnson (1979) firstly applied continuous-time SV models when studied option pricing using time-varying volatility. The more well-known application of continuous-time SV models was conducted by Hull and White (1987) who allowed the spot volatility process of the underlying asset in option pricing to follow a general diffusion process. Further studies like Merton (1976) and Bates (1996) improved these initial continuous-time SV models by adding discrete jumps into the asset price process since the theory argued that discrete jumps in asset price should occur when significant new information is revealed.

Moreover, empirical work like Andersen et al. (2002) and Eraker et al. (2003) using SV models allowing jumps in asset price process showed significant improvements in model performance. In addition, improvements in modeling continuous-time SV models were also achieved by allowing jumps in diffusive volatility process, e.g., Eraker et al. (2003) who thought this extension was critical for an adequate model fit and Barndorff-Nielsen and Shephard (2001) who build continuous-time SV models with pure jump processes. Another extension to initial continuous-time SV models involved modeling log volatility as a fractionally integrated process to account for long memory characteristic, e.g., Comte and Renault (1998) and Barndorff-Nielsen (2001). Apart form these univariate continuous-time SV models, Diebold and Nerlove (1989) developed a continuous-time multivariate SV model cast in the factor structure used in many areas of asset pricing. Related empirical papers using this model include King et al. (1994) and Fiorentini et al. (2004).

The models mentioned above include ARCH models, stochastic volatility models and the implied volatilities from options or other derivatives prices. However, the validity of these volatility models generally depends upon specific distributional assumptions. Andersen et al. (2003) directly pointed out the limitations of these standard volatility models from an empirical point. First, the standard volatility model specified for modeling daily level volatility cannot accommodate the information incorporated in high-frequency intra-day data which has a significant impact on the modeling of, say, daily return volatility. Meanwhile, models used directly for the high-frequency intraday data generally cannot capture the longer interdaily volatility movements sufficiently well. Consequently, although higher frequency data are available, standard practice still applies daily return observations to produce volatility forecasts.

Second, although many multivariate GARCH and stochastic volatility models are available (see, for example, the surveys by Bollerslev et al., 1994 and

Ghysels et al., 1996), those models generally can only model low-dimensional volatilities because of a curse-of-dimensionality problem. As a result, those models are severely constrained in the situations where more than a few assets need to be dealt with simultaneously. The limitations of these traditional models motivated the use of the approach of realized volatility by Andersen et al. (2001). They summed squares and cross-products of high-frequency intraday returns to get ex post realized daily volatilities. Volatilities constructed in this way are model-free and are also shown to be free from measurement error theoretically as the sampling frequency of the returns approaches infinity. This approach is directly consistent with earlier work by Poterba and Summers (1986), French et al. (1987) and Schwert (1989), who constructed monthly realized stock volatilities using primarily daily return observations but did not provide a formal justification for such an approach.

Since the high-frequency intra-day data is not available across the sample time span in this paper, the monthly realized volatility can be constructed using daily returns observations. However, according to Barndorff-Nielsen and Shephard (2002), monthly realized volatilities are a very noisy measure of volatility. However, as Engle et al. (2013) suggested, the GARCH-MIDAS model can be used to filter realized volatility in order to produce a smooth long-term volatility.

4.2.2 Determinants of stock price volatility

4.2.2.1 International Determinants

There exists a substantial literature investigating how news from one stock market affects other stock markets' performances. Early studies predominantly concentrated on analyzing the relationships between the returns and volatilities among developed stock markets. For example, Hamao et al. (1990) found that there were stock volatility spillover effects from the New York stock markets have the volatility spillover effect on both Tokyo and London stock markets, and London stock markets have the volatility spillover effect on Tokyo stock markets. Lin et al. (1994) found that US and Japanese stock markets influenced each other using a signal extraction model with GARCH process.

Later a number of studies investigating how volatility spillovers from developed markets to emerging markets has emerged in the literature with an increasingly important effects on emerging markets. For example, Miyakoshi (2003) investigated how returns and volatilites spillover from Japan's and the US stock market to seven Asian stock markets using a bivariate EGARCH model and found that the US stock markets have more influence on the volatility of the Asian markets than Japan's stock markets. However, using the ARMA-GARCH model, Liu and Pan (1997) found that the spillover effect from the US stock market is more influential than that from Japan's stock markets on the four Asian markets of Hong Kong, Singapore, Taiwan, and Thailand.

Using ARMA-GARCH and ARMA-GJR-GARCH models, Wang and Firth (2004) investigated the relationships between the Greater China's stock markets including the stock markets of Hong Kong, Taiwan, Shanghai A and Shenzhen

A and the three developed markets of New York, London and Tokyo in terms of volatility and return spillovers. They provided evidence that the contemporaneous return generally spillovers unidirectionally from the developed stock markets to the Great China's stock markets and there were bi-directional volatility spillover effects between Greater China's stock markets and these three developed markets. Wang and Wang (2010) examined the return and volatility transmissions between the Great China's stock markets and the US and Japan's stock markets using the GJR–BEKK–GARCH model which can incorporate the return and volatility interaction between the markets. The findings form Wang and Wang (2010) suggested that volatility spillover effects are stronger than returns spillover effects between the Great China's stock markets and the US and Japan's stock markets.

In contrast to the findings from Wang and Firth (2004) , they did not find any evidence supporting the dominance effect of developed markets over developing markets. In addition, they found that the extent of influence by developed markets on the Great China's stock markets is positively related with the degree of financial openness of the Great China's stock markets. Hua and Sanhaji (2015) explored daytime and overnight return and volatility transmissions between Chinese and Asian, European and North American main stock markets using the dynamic conditional correlation GARCH model. The empirical findings indicated that the daytime information transmissions in terms of stock returns and volatilities between China's and Asian stock markets are stronger than those between China's and non-Asian markets, whereas the overnight information transmissions have an inverse relationship between these markets.

Zhou et al. (2012) measured the directional volatility spillovers between China's and the world equity markets using forecast-error variance decompositions in a generalized vector autoregressive framework. Their empirical findings indicated China's stock markets volatility has had a significantly positive influence on other markets since 2005. Specifically, China's stock volatility interacted more with the stock markets of Hong Kong and Taiwan than with the Western, and other Asian markets. In addition, during the subprime mortgage crisis, the US stock volatility have a dominant effect on other stock market but China's stock markets were not influenced in terms of stock volatilities.

Moon and Yu (2010) examined the short-run return and volatility spillovers effects between the the Shanghai Stock Exchange (SSE) index in China and Standard & Poor's (S&P) 500 stock index in the US using a GARCH-M model. Their empirical finding showed that since December 2005, the volatility spillovered both symmetrically and asymmetrically from the US to China's stock market but only symmetrically from China to the US. Sarwar (2012) investigated relationships between the CBOE market volatility index (VIX) and stock market returns in Brazil, Russia, India, and China (BRIC) and found that there was a significant negative contemporaneous relationship between VIX and China's and Brazil's stock returns. The findings also showed evidence for a strong asymmetric relationship between innovations in the VIX and China's and Brazil's stock returns.

4.2.2.2 Macroeconomic and Financial Determinants

In this study, the potential determinants of the low-frequency volatility have been selected with regard to economic theory, previous empirical evidence and the characteristics specific to the Chinese stock market. Conceptually, the conditional variance of the market returns depends upon the conditional variances of future cash flows, the conditional variances of discount rates, and conditional covariances between these two series. Under a constant discount rate, the conditional variance of aggregate return depends only on the conditional variances of future aggregate cash flows. According to Engle et al. (2008), levels as well as fluctuations of economic variables are potential factors affecting the uncertainty of future cash flows and risk premiums and their impact on stock volatility might depend also on the state of the economy.

Previous research has emphasized the relationship between volatilities and the business cycle; for example, Schwert (1989) find economic recessions to be the most important factor influencing US stock-return volatility. Engle et al. (2008) considered the growth rate of GDP to account for the changes in the real economy. However, we use the growth rate of industrial production instead considering the unavailability of monthly GDP data.

In addition Engle et al. (2008) argued that predictors of economic factors or future states of the economy might be important explanatory variables of low-frequency volatility. For example, variables associated with monetary policy decisions and future economic growth are helpful in evaluating future uncertainty about interest rates and cash flows. Based on the previous literature, factors such as the inflation rate and money supply are widely used to explain stock return volatility (Schwert (1989); Engle et al. (2008); Paye (2012); Engle et al. (2013)). In particular, as Engle et al. (2008) argued, many macroeconomic reforms in developing economies have been intended to improve institutional control of inflation (and to open the economies to trade). Therefore, we also consider using the inflation rate and money supply to forecast Chinese stock price volatility. In addition, we also include some associated factors, including the interest rate, long-term government bond yield, the spread between them and the exchange rate (Engle et al. (2008); Welch and Goyal (2008); Christiansen et al. (2012)).

Volatility and uncertainty about fundamentals are also potential factors affecting market volatility. For example, Gennotte and Marsh (1993) derive returns volatility and risk premia based on stochastic volatility models of fundamentals; David and Veronesi (2008) identify inflation and earnings uncertainty as sources of stock market volatility. The empirical literature also suggests the relationship between market volatility and macroeconomic volatility (see Officer, 1973; Schwert, 1989; Engle et al., 2008; Paye, 2012; Engle et al., 2013). Therefore, we also consider measures of macroeconomic volatility to account for this uncertainty. According to Engle et al. (2013), we fit the following autoregressive model with 12 monthly dummy variables D_{jt} and square the estimated residuals to be the monthly macroeconomic volatility (for any variable X):

$$X_t = \sum_{j=1}^{12} \alpha_j D_{jt} + \sum_{i=1}^{12} \beta_i X_{t-i} + \varepsilon_t$$
$$VOL = (\hat{\varepsilon}_t)^2 \tag{4.1}$$

In addition to consider macroeconomic determinants of the stock volatility, this paper also account for financial determinants which are shown to have predictability on stock returns but are also considered as determinants of stock price volatility (see Mele, 2005, 2007; Paye, 2012). According to Christiansen et al. (2012), we consider well-known equity factors, such as the earnings price ratio and Fama–French factors. Other variables such as trading days and trading volume (Schwert, 1989) are also used in paper. In addition, as Paye (2012) has argued, stock market liquidity is one of the channels affecting stock price volatility, also the Pastor-Stambaugh liquidity factor (Pástor and Stambaugh, 2003 and Christiansen et al., 2012) is used as a measure of the Chinese stock market liquidity.

Apart from the literature on the US stock markets, this study also refers to the literature on the Chinese stock markets in order to capture more potential macroeconomic and financial variables. For example, Girardin and Joyeux (2013) applied the GARCH-MIDAS model to investigate the influence of volume and macroeconomic fundamentals on the long-term volatility of the Chinese stock markets. The empirical findings showed that macroeconomic fundamentals, especially CPI inflation, has been playing an increasingly important role on the Chinese stock markets. However, they did not find any evidence supporting the significant influence of macroeconomic fundamentals on the Chinese long-run stock volatility. Cai et al. (2017) compared the forecasting performance of the AR (1) model and the predicative regression including both the lag of stock price volatility and macroeconomic and financial variables. They found that the augmented model outperformed the benchmark AR (1) model, suggesting that the information contained in the macroeconomic and financial variables is useful for predicting the Chinese stock price volatility.

However, such studies are primarily inspired by the papers on the US stock markets and thus macroeconomic and financial determinants are almost the same as the those used in the US markets. One unique characteristic in the Chinese economy is the relationship between the Chinese stock market and real estate market, which also motivated a number of studies. For example, Ding et al. (2014) found that there is a significant causal relationship between these two markets using the quantile causality test. Therefore, this chapter also focus on using the macroeconomic and financial variables which are available for the Chinese stock markets and have been considered in the literature on the US stock markets.

4.2.2.3 Variables representing China's Economic and Financial Characteristics

In order to take into account the potential effect of the development and increased openness of the Chinese stock market on the stock price volatility, several variables are used in this study based on the relevant literature and the Chinese data's availability. The growth rate of the market capitalization of SHSE A-shares, the growth rate of the number of listed companies with the SHSE A-share and the SHSE A-share turnover growth rate are used as the measures of stock market development (Bartram et al., 2012). Considering there is no explicit measurement of Chinese stock market openness, we use the growth rate of the number of QFII as well as the growth rate of approved investment funds trading QFII as an approximate measurement of the Chinese stock market openness. As China's financial openness has increased, some studies (Martin and Morrison, 2008) have suggested that 'hot money' (HM) (Chari and Kehoe, 2003) is an important driver of stock market volatility. Considering there is no official data for HM, we follow the method used in the literature to construct the variable HM. In addition to this measurement of HM, we have also used the spread between China's benchmark rate and the Federal Fund Rate as a measurement of hot money. Apart from the variables above, we also take into account the potential effect of the ownership structure on stock volatility. The growth rate of market cap of both state and home legal person owned Non-tradable Shares in the SHSE are used as a measurement of the ownership structure (Sun and Tong, 2003).

4.2.3 Penalized regressions

Linear regression is a widely used technique in many areas, but it not only provides the effects of the variables of interests as measured by the estimated coefficients, but also can quantify the uncertainty for these effects relying on some relevant statistical inference. However, it is common for a practitioner to encounter a situation where a large pool of candidate variables is available but the relevance of these variables with respect to the variables of interest are unknown. In particular, when there are more candidate variables than observations, this problem becomes more serious because the model is unidentifiable. One common practice to deal with the situation where the number of variable is not too large is to firstly fit the model with all variables included, and then refit the model only using the significant variables selected in the first step. However, the problem with this approach is that the significance of variables selected at some specific significance level in the first step is not reliable since the model with all variable included is overfitted and the p-values can no longer be trusted. In order to deal with such situation, penalized regressions are developed to select a subset of candidate variables.

The Least Absolute Shrinkage and Selection Operator (LASSO), introduced by Tibshirani (1996), has been widely used to shrink the large data set to a more manageable number of the most significant variables by imposing the L1penalty function on the regression coefficients. However, LASSO has two problems as highlighted by Zou and Hastie (2005). First, if the number of regressors p are more than the number of the observations n , LASSO selects at most n variables. Second, if there is a group of variables with high pairwise coefficients, LASSO tends to select only one variable from the group and does not care which one.

These concerns suggest that a convex combination of ridge and LASSO estimation might be desirable. The result is the 'elastic net' (EN) estimator of Zou and Hastie (2005). The idea behind the elastic net is to stretch the fishing net that retains all the 'big fish'. Like LASSO, the EN simultaneously shrinks the estimates and performs model selection to ensure only the most relevant variables are selected. The Least Angle Regression developed by Efron et al. (2004) is another well-known variables selection technique.The advantage of LARS compared with LASSO and Elastic-Net is that it is able to produce the ranking of the variables according to the degree of correlation of these variables with the variable of interest. According to Efron et al. (2004), the well-known forward stage wise regressions are in fact special cases of LARS, but LARS is more cautious than the forward stage selection regressions as it takes smaller steps towards the final model (Efron et al., 2004; Bai and Ng, 2008). In addition, LARS can also be regarded as an algorithm to solve LASSO and Elastic Net (Efron et al., 2004).

These penalized regressions have been widely applied in the empirical literature. For example, Bai and Ng (2008) used LASSO, LARS and Elastic-Net based on the LARS algorithm to select the targeted predictor from a large set of candidate predictors as the input of factor estimation in the problem of forecasting of inflation rate. They argued that using these penalized regressions can reduce the noise existed in the original large set of predictors and then the inflation rate forecasting performance can be improved. Inspired by Bai and Ng (2008), Schumacher (2010) conducted a study to predict the German GDP using national and international data. The finding that the factor forecasts using pre-selection data by Elastic-Net outperform the factor forecasts using all the data, suggesting pre-selection of predictors help exploit the additional information contained in the large data. Kim and Swanson (2014) empirically compared the predictive accuracy of a large group of data reduction models. They found that hybrid combination of factor and shrinkage method such as LARS model often produce superior predictions. Li et al. (2015) provided evidence supporting the predictability of economic fundamentals for the exchange rates in the out-of-sample forecasting framework using the kitchen-sink regression where the predictors are selected by the Elastic-Net shrinkage model. In addition, the empirical findings also showed that their approach outperforms alternative models including the individual exchange rate models, the random walk model , a kitchen-sink regression estimated with ordinary least squares, standard forecast combinations.

4.2.3.1 Significant tests for the LASSO

Although these penalized regressions mentioned above have a strong theoretical background and have enjoyed great popularity in empirical work, they get severely constrained for a long time when used in the as estimation procedure. Specifically, there isn't the usual constructs in these penalized regressions, such as the p-values, confidence intervals, etc., for researchers to make statistical inference. This limits our ability to make statistical inference and has produced a growing literature attempting to construct the required statistics for statistical inference.

One area of the literature is dedicated to developing the statistical inference for the true regression coefficients, or some subset of these coefficients, using the lasso regression with some fixed regularization parameter. For example, Zhang and Zhang (2014) constructed confidence intervals for contrasts of high-dimensional regression coefficients, by using the usual score vector instead of the residual from a relaxed projection. Bühlmann et al. (2013) started with a ridge regression and then applied a bias correction term that uses lasso. As a result, p-values for coefficients in high-dimensional regression models can be constructed for statistical inference.

More recent work, e.g., Van de Geer et al. (2014), Javanmard and Montanari (2014) developed approaches to get debiased lasso estimates, which are asymptotically normal such that marginal p-values for each predictor coefficient can be constructed. However, these methods were criticized by Lee et al. (2016b) as they cannot address post-selection inference. Specifically, the p-values or confidence intervals are constructed for the true coefficients in the high-dimensional regression models rather than the estimated coefficients in the selected sparse regression models. Although inference for the true coefficients is more attractive, it is difficult to satisfy the assumptions about the correctness of model linearity and sparsity. In the spirit of Berk et al. (2013) and Miller (2002), Lee et al. (2016b) derived inference for the selected lasso regression model which can be regarded as a linear approximation to the true lasso regression model. This idea of post-selection inference for selected models firstly appeared in Pötscher (1991), although the notion of inference conditional on certain relevant subsets dates back to Fisher (1956).

Another growing area of the literature carried out inference for lasso regression models in the path context. The tests proposed in this literature focus on testing sequential steps taken by the LARS algorithm in constructing the lasso path. For example, Lockhart et al. (2014) proposed the covariance test (CovTest)to test the significance of the predictor variable entering the current lasso model in the sequence of models visited along the lasso solution path and showed that the covariance test statistic has an specific asymptotic distribution under the null hypothesis that all truly active variables are contained in the current lasso model when the true model is linear. In addition, Taylor et al. (2014) extended the covariance test to derive the exact finite sample inference for lasso regression models based on the lars algorithm. The Truncated Gaussian (TG) test developed by Taylor et al. (2014) is the conditional test at any step taken by the LARS algorithm for the true underlying regression coefficient.

Empirically, there a number research applied these significance tests based the penalized regressions to study the medical issues (Heiskanen et al., 2015; Tibshirani et al., 2016; Dhaese et al., 2018). However, there are very few studies applying these techniques in the other research areas. McNeish (2015), which is the only one paper I found, applied the CovTest (Lockhart et al., 2014) into the behavioral sciences. To the best of my knowledge, there has as yet been no empirical study applying these significance tests in the economic and financial literature. This study is the first attempt to apply these tests to study economic and financial problems.

4.2.4 Bayesian time-varying structural VAR model (TV-VAR)

The Bayesian time-varying structural VAR model was proposed by Primiceri (2005) and it allows both the time-varying coefficients and the heteroschadestistic innovations of the variables in the system. It has been widely used to analyze macroeconomic issues duo to its ability to capture the potential time-varying nature of the underlying structure in the economy in a flexible and robust manner. Primiceri (2005) developed this model and conducted empirical research with it to explain the US high inflation and unemployment episodes between 1965 and 1980. The findings indicated that the non-systematic monetary policy played more important role than the systematic monetary policy in explaining the US high inflation and unemployment during this time period between 1965 and 1980. Baumeister and Benati (2010) found that a compression in the long-term bond yield had a strong impact on the macro economy in terms of output growth and inflation within the context of the Great Recession of 2007-2009 using the TV-VAR model.

Clark and Terry (2010) applied the TV-VAR model to explore time-varying passthrough of energy inflation to core inflation in the US. They found that the impact of energy inflation on core inflation had been declined, which can be attributed to the lower response of the monetary policy to energy inflation starting around 1985. D'Agostino et al. (2013) used the TV-VAR model to capture the structural change in predicting the inflation rate, unemployment rate and interest rate in the US. The findings indicated that the three variables can be accurately predicted using the TV-VAR model. In particular, the forecasting performance of the TV-VAR model on the inflation rate are much better than the other competing models such as fixed coefficients VARs, time-varying autoregressions and the random walk model.

Benati and Surico (2008) applied the TV-VAR model to investigate the underlying causes of the Great Moderation in the United Kingdom and found that the monetary policy has only had a limited impact on the Great Inflation episode while the non-policy shocks played a dominant role in explaining the high inflation during the Great Inflation period. In addition to its use in analyzing macroeconomic issues, the TV-VAR model has also been as well applied to investigate the other issues. For example, Lopreite and Mauro (2017) applied the TV-VAR model to assess the impact of population aging on healthcare expenditure in Italy. They found that there is a positive relationship between the health expenditure and the longevity, suggesting that more efficient plans are required to provide better support for the elderly.

4.3 Models

4.3.1 The GARCH-MIDAS model

In recent years realized volatility has been widely applied to measure long-term volatility (Merton, 1980; Schwert, 1989; Paye, 2012). However, according to Barndorff-Nielsen and Shephard (2002), monthly realized volatilities are a very noisy measure of volatility. As Engle et al. (2013) suggested, the GARCH-MIDAS model can be used to filter realized volatility in order to produce a smooth long-term volatility. In this paper, GARCH-MIDAS model is used to model the monthly stock volatility. According to Engle et al. (2013), stock volatility can be decomposed into two components. One is the short-term volatility modeled by a GARCH (1,1) process:

$$g_{i,t} = (1 - \alpha - \beta) + \alpha \frac{(r_{i-1,t} - \mu)^2}{\tau_t} + \beta g_{i-1,t} \tag{4.2}$$

Where it is assumed that the starting value of expectation of short-term component, $E_{t-1}(g_{i,t})$, is equal to its unconditional expectation, $E_{t-1}(g_{i,t}) = 1$. In addition, the condition $\alpha + \beta < 1$ is imposed to ensure the model is stationary and $\alpha > 0, \beta > 0$ is imposed to ensure the positivity of volatility.

The other component is the long-term component modeled by filtering realized volatility using a MIDAS regression:

$$\tau_t = m + \theta \sum_{k=1}^{K} \varphi_k(\omega_1, \omega_2) RV_{t-k} \tag{4.3}$$

$$RV_t = \sum_{i=1}^{N_t} r_{i,t}^2 \tag{4.4}$$

Where RV stands for realized volatility. K is the number of the lagged months, quarters or annuals. The weight scheme $\varphi_k(\omega_1, \omega_2)$ [1]is a Beta lag structure (Ghysels et al., 2006) which can be shown as below:

$$\varphi_k(\omega) = \frac{(k/K)^{\omega_1 - 1}(1 - k/K)^{\omega_2 - 1}}{\sum_{j=1}^{K}(j/K)^{\omega_1 - 1}(1 - j/K)^{\omega_2 - 1}} \tag{4.5}$$

[1]Engle et al. (2013) also provided exponentially weighting function, however, they mentioned that exponentially weighting function is able to yield the same practical purpose as beta lag structure. Hence, as Engle et al. (2013) did, we adopt bata lag structure to obtain weight scheme.

Where the weights sum to 1. Under the beta lag structure, the weighting scheme can be either monotonically increasing or decreasing or hump-shaped[2]. It should be noted that Engle et al. (2013) pointed out that optimal ω_1 is always 1 such that the weights decrease monotonically in GARCH-MIDAS models with RV. Hence, in this paper, ω_1 is set to be 1 for GARCH-MIDAS models with RV. Consequently, only one parameter, ω_2, remains in beta lag structure. In addition, a larger ω_2 leads to a faster decrease in the rate of weights.

The long-term volatility above is based on a fixed span. As opposed to a fixed-span RV, a rolling window RV is introduced to make the series to a daily frequency. The GARCH-MIDAS model with a rolling window RV can be defined as follows:

$$RV_i^{(rw)} = \sum_{j=1}^{N'} r_{i-j}^2 \tag{4.6}$$

Where N' represents the length of the rolling window. Specifically, for monthly rolling windows, $N' = 22$[3], It should be noted that RV is changed at daily frequency. Based on the rolling window RV, the τ process can be defined as follows:

$$\tau_i^{(rw)} = m^{(rw)} + \theta^{(rw)} \sum_{k=1}^{K} \varphi_k(\omega_1, \omega_2) RV_{i-k}^{(rw)} \tag{4.7}$$

Following this setup, the constructed volatilities of the macroeconomic variables are listed in Table 4.3.

4.3.2 Penalized regression (LASSO)

Considering the following model:

$$y_t = \alpha + \rho y_{t-1} + \sum_{p=1}^{P} \beta_j x_{t-1,p} + \varepsilon_t. \tag{4.8}$$

To simplify it, let $x_{t-1,1} = y_{t-1}$, the equation can be reduced into as follows:

$$y_t = \alpha + \sum_{j=1}^{J} \beta_j x_{t-1,j} + \varepsilon_t. \tag{4.9}$$

This high-dimensional time series model with a huge number of parameters has been studied before in the literature, with Bayesian shrinkage estimations and factor models being employed (Bai and Ng, 2008, De Mol et al., 2008).In this

[2]Ghysels et al. (2006) provided further details with respect to the various shapes of weights scheme with beta lag structure

[3]For quarterly and biannual rolling window, $N' = 65$ and 125, respectively. In this paper, we only consider the monthly rolling window.

study, let $\hat{\beta} = (\hat{\beta}_1, \hat{\beta}_2, \ldots, \hat{\beta}_P)$, the coefficients are estimated using the LASSO. The lasso estimate $(\hat{\alpha}, \hat{\beta})$ is defined by

$$\frac{1}{2}\sum_{t=1}^{T}(y_i - \alpha - \sum_{j=1}^{J}\beta_j x_{ij})^2, \tag{4.10}$$

subject to

$$\sum_{j=1}^{J}|\beta_j| \leqslant t,$$

for some $t > 0$, which is equivalent to minimizing the following penalized least squares for some $\lambda > 0$:

$$\frac{1}{2}\sum_{t=1}^{T}(y_i - \alpha - \sum_{j=1}^{J}\beta_j x_{ij})^2 + \lambda\sum_{j=1}^{J}|\beta_j| \tag{4.11}$$

where λ is a tuning parameter which will be determined using cross validation method in this study. The regression problem is traditionally estimated using the ordinary least squares (OLS). However, the OLS is criticized by delivering poor prediction accuracy owing to the overfitting problem and fails to help researchers to interpret the model when there are a large number of predictors. Ridge regression can efficiently solve the overfiting problem by penalizing the coefficients with L2 norm (Zou and Hastie, 2005). But it cannot produce a sparse model since L2 norm can only shrink coefficients instead of setting any coefficients to be 0. Using L1 norm constraint on the regression coefficients, the lasso can not only avoids overfitting problem and hence deliver an accurate prediction, but give a sparse solutions by setting some coefficients to be 0 and hence the model is easily interpreted.

4.3.3 CovTest

The covariance test statistic proposed by Lockhart et al. (2014) is constructed from the lasso solution path. The lasso path can be computed by the well-known LARS algorithm of Efron et al. (2004).

The covariance test targets at testing the significance of the variable that enters the active set. The test statistic defined at the kth step of the path can be shown as follows:

$$\tilde{\beta}_A\left(\lambda_{k+1}\right) = \underset{\beta_A \in \mathbb{R}^{|A|}}{argmin}\frac{1}{2} \parallel y - X_A\beta_A \parallel_2^2 + \lambda_{k+1} \parallel \beta_A \parallel_1 \tag{4.12}$$

where A is the active set which is just before λ_k. $\tilde{\beta}_A\left(\lambda_{k+1}\right)$ is the solution of the lasso problem using only the active predictors X_A, at $\lambda = \lambda_{k+1}$. Therefore, the covariance test statistic can be defined as follows:

$$T_k = (< y, X\hat{\beta}(\lambda_{k+1}) > - < y, X_A\beta_A(\hat{\lambda}_{k+1}) >)/\delta^2. \tag{4.13}$$

Intuitively, the covariance statistic is a function of the difference between $X\hat{\beta}$ and $X\beta_A$.

It is possible that the other functions are also appropriate here, but the covariance form has a distinctive advantage: the null distributions of this statistic is simple and exact asymptotic. under the null hypothesis that all truly active variables, $A \supset supp(\beta*)$, are contained in the current lasso model:

$$T_k \xrightarrow{d} Exp(1). \tag{4.14}$$

It means that T_k is a standard exponential random variable and has a asymptotically distribution.

4.3.4 Bayesian Time Varying Structural Vector Autoregressions

Following Primiceri (2005), regarding the model:

$$y_t = c_t + B_{1,t}y_{t-1} + \cdots + B_{k,t}y_{t-k} + u_t \tag{4.15}$$

where y_t is an $n \times 1$vector of observed endogenous variabels; c_t is an $n \times 1$vector of time varing intercepts; $B_{i,t}, i = 1, \ldots k$,are $n \times n$ matrices of time varing coefficients; u_t are heteroscedastic unobservable shocks with a time-varying variance covariance matrix Ω_t which can be decomposed in the following way:

$$A_t \Omega_t A' = \Sigma_t \Sigma_t' \tag{4.16}$$

where A_t is a lower triangular matrix that models the contemporaneous interactions among the endogenous variables

$$A_t = \begin{bmatrix} 1 & 0 & \cdots & 0 \\ \alpha_{21,t} & 1 & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ \alpha_{n1,t} & \cdots & \alpha_{nn-1,t} & 1 \end{bmatrix} \tag{4.17}$$

and Σ_t is a diagonal matrix that contains the stochastic volatility

$$\Sigma_t = \begin{bmatrix} \sigma_{1,t} & 0 & \cdots & 0 \\ 0 & \sigma_{2,t} & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & \sigma_{n,t} \end{bmatrix}. \tag{4.18}$$

Equation (4.16) can be written as follows:

$$\begin{gathered} y_t = X_t' B_t + A_t^{-1} \Sigma_t \varepsilon_t, \\ X_t' = I_n \otimes \left[1, y_{t-1}', \ldots, y_{t-k}'\right], \\ I_n = V(\varepsilon_t) \end{gathered} \tag{4.19}$$

where all the R.H.S coefficients in Equation (4.17) are stacked into B_t, the symbol $\otimes$denotes the Kronecker product. A decomposition of the variance covariance matrix resulting in Equation (4.19) is common, especially in the literature considering the problem of efficiently estimating covariance matrices (see, for instance, Pinheiro and Bates, 1996; Pourahmadi, 1999; Pourahmadi, 2000 ;Smith and Kohn, 2002).

The drifting coefficients are meant to capture possible nonlinearities or time variation in the lag structure of the model. The multivariate time-varying variance-covariance matrix allows for heteroskedasticity of the shocks and time variation in the simultaneous relationships between the variables in the system. Allowing for time variation in both the coefficients and the variance covariance matrix, leaves it up to the data to determine whether the time variation of the linear structure comes from changes in the size of the shock and its contemporaneous impact or from changes in the propagation mechanism.

Following Primiceri (2005), let α_t be the vector of non-zero and non-one elements of the matrix A_t and $\sigma_t$be the vector of the diagonal elements of the matrix Σ_t. The dynamics of the model's time varying parameters is specified as follows:

$$\begin{aligned} B_t &= B_{t-1} + \nu_t, \\ \alpha_t &= \alpha_{t-1} + \zeta_t, \\ log\sigma_t &= log\sigma_{t-1} + \eta_t. \end{aligned} \tag{4.20}$$

It implies that the elements of B_t are modeled as random walks, as are the free elements of the matrix A_t. The standard deviations (σ_t) are assumed to evolve as geometric random walks, belonging to the class of models known as stochastic volatility models. This constitutes an alternative to the ARCH models. The crucial difference is that the variances generated by (7) are unobservable components. In addition, all the innovations in the model are assumed to be jointly normally distributed with the following assumptions on the variance covariance matrix:

$$V = Var\left(\begin{bmatrix} \varepsilon_t \\ \nu_t \\ \zeta_t \\ \eta_t \end{bmatrix}\right) = \begin{bmatrix} I_n & 0 & 0 & 0 \\ 0 & Q & 0 & 0 \\ 0 & 0 & S & 0 \\ 0 & 0 & 0 & W \end{bmatrix} \tag{4.21}$$

where $I_n$is an n-dimentional identity matrix, Q, S and W are positive definite matrices. As Primiceri (2005) pointed out, there are no necessary restrictions on the structure of V and all zeros blocks could be relpaced by non-zeros blocks.

Based the model setup above, Bayesian methods are used to evaluate the posterior distributions of the parameters of interest with assuming normal priors on the entile sequences of the B's, α's and logσ's (conditional on Q,$W$and S).

4.4 Data and Results

4.4.1 Long-term Volatility Estimated from the GARCH-MIDAS Model

In this paper, the daily Shanghai A-share index from 28th December 2004 to 28th December 2018[4] is used to estimate the GARCH-MIDAS model with a fixed window RV and also with a rolling window RV. The long-term volatility from the model with the smallest SIC is used as the dependent variable in the subsequent forecasting equation. For each GARCH-MIDAS model, Firstly, the beta lag structure will be determined; Secondly, the optimal number of lags used in the long-term volatility specification will be determined according to the SIC criteria; Thirdly, each model above will be estimated with the optimal number of lags. In order to get the long-term component of the conditional volatility, the specification of the beta lag structure needs to be determined. Engle et al. (2013) pointed out that the optimal ω1 is always 1 such that the weights decrease monotonically in the GARCH-MIDAS models with RV.

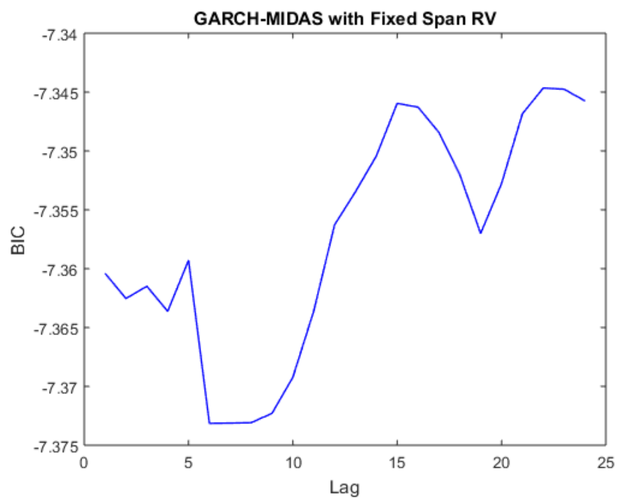
According to Figure 4.1a, Figure4.1b and Table 4.1, the GARCH-MIDAS with a fixed span and rolling window RV produce the smallest BIC at the seventh and sixth lags by allowing the maximum number of lags to be 24, respectively. It should be noted that taking lags in model estimates leads to a loss of observations, as a result, both the short-term and long-term volatility obtained from the GARCH-MIDAS with a Fixed Span RV and Rolling Window RV start from 01/08/2005[5].

[4] The stock return series starts from the 4th January 2005 which is the beginning of trading days to 28th December 2018. The long-term volatility is calculated from the GARCH-MIDAS model using daily stock return series, so the the daily Shanghai A-share index from 28th December 2004 to 28th December 2018 is collected.

[5] In this paper, monthly rolling window RV is used in GARCH-MIDAS with Rolling Window RV model. As a result, the first month data will be abandoned and hence the data actually starts from 01/02/2005. Therefore, the long-term volatility from GARCH-MIDAS with rolling window RV starts from 01/08/2005 considering the optimal number of lags is six.

Figure 4.1: BIC

(a) LV with Fixed Span LRV



(b) LV with Rolling Window LRV

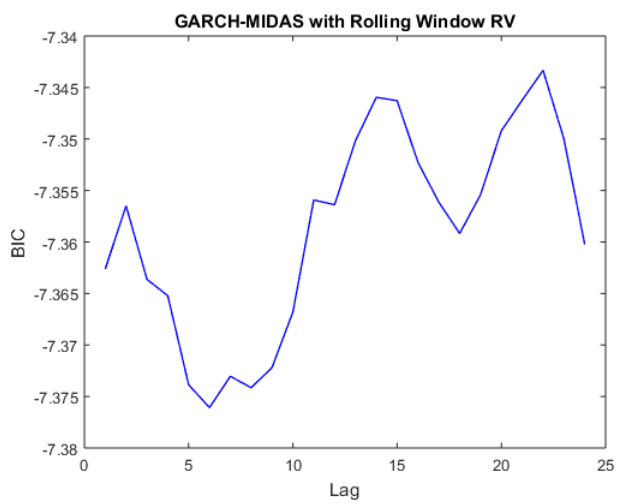


Table 4.1: Optimal Number of Lags

GARCH-MIDAS with Fixed Span RV	GARCH-MIDAS with Rolling Window RV
7	6

BIC is used to determine the optimal number of lags.

According to Table 4.2, most of the parameter estimates in these two models are significant at the 1% significance level. It can be seen firstly that the covariance stationarity conditions are satisfied in the GARCH components of both the GARCH-MIDAS fixed span RV and rolling window RV because $\alpha + \beta < 1$. According to Figure 4.2a and 4.2b, the weighting schemes of these two models are monotonically decreasing which means that the recent information contained in the realized volatility are more important than older information with respect to the long-term volatility by allowing more weights. As Conrad et al. (2014) suggested, monotonously decreasing weighting schemes imply that the variables are lagging or coincidental. Another parameter θ, which is of most interest, determines how realized volatility affects long-term volatility. The significance of θ suggests that information contained in both the fixed span and rolling window realized volatility has a significant effect on the long-term volatility.

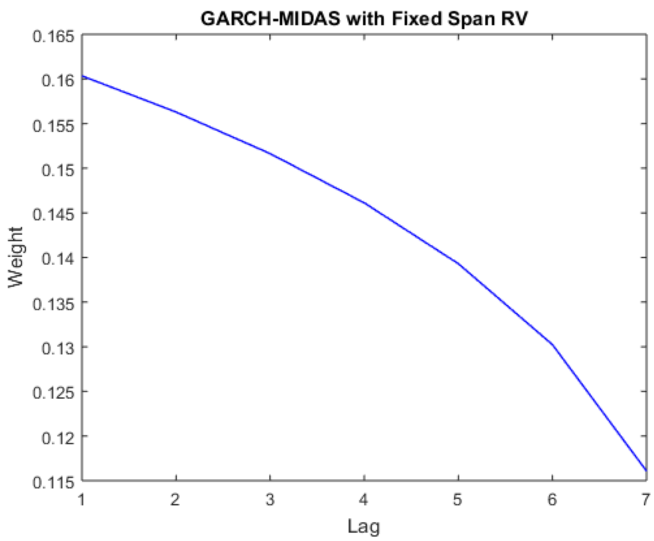
Table 4.2: Parameter Estimates

	μ	α	β	θ	ω	m	BIC
LLV_Fixed	0.0001	0.0636***	0.9147***	0.1966***	1.166***	0.0032***	-7.3731
	(1.5754)	(8.8327)	(75.3731)	(11.8492)	(4.4535)	(4.8225)	
LLV_Rolling	0.0001	0.0660***	0.9069***	0.2048***	1.0053***	0.0029***	-7.3761
	(1.6556)	(8.0431)	(72.088)	(12.933)	(13.422)	(5.0687)	

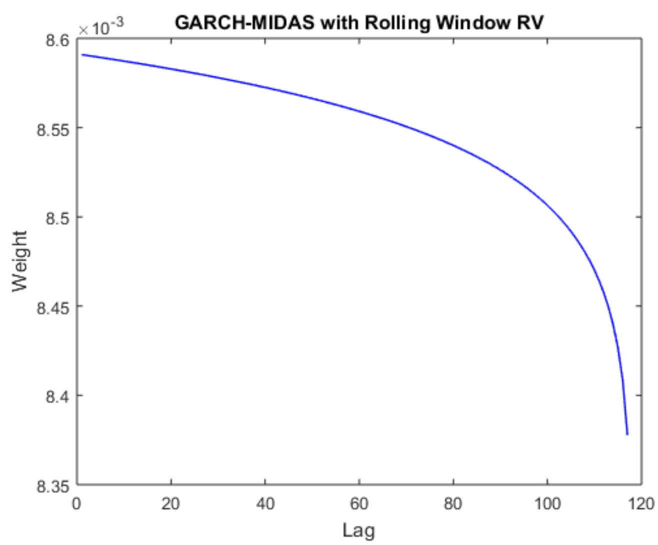
*** means that the variable is significant at 1% significance level, the values in the parentheses are test statistic, BIC stands for the Bayesian Information Criterion. μ, α and β are parameters in Equation (4.2), θ, ω and m are parameters in Equation (4.3). LLV_Fixed and LLV_Rolling stands for GARCH-MIDAS with fixed span LRV and rolling window LRV, repectively.

Figure 4.2: Weighting Scheme

(a) LV with Fixed Span LRV



(b) LV with Rolling Window LRV

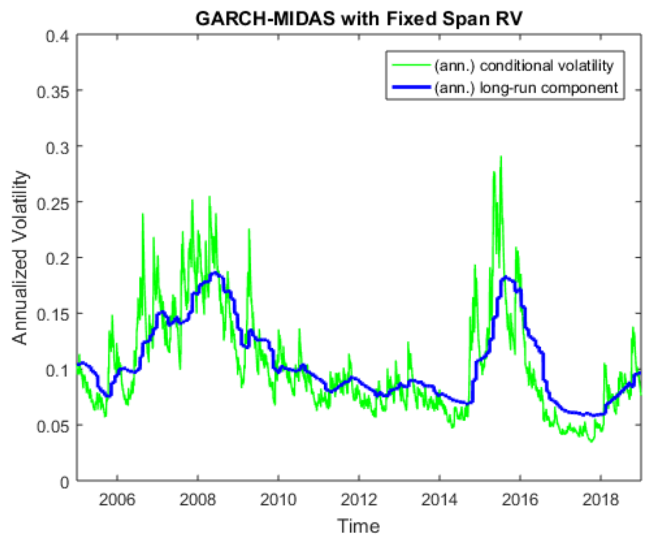


Each model indicates that the long-term volatility is much smoother than short-term volatility. As Engle et al. (2013) suggested, it can be seen from both Figure 4.3a and 4.3b that the long-term volatilities from the GARCH-

MIDAS models are smoother than the realized volatilities. In addition, The BIC of the GARCH_MIDAS model with a rolling window RV is less than that of the GARCH-MIDAS model with a fixed window RV. Therefore, the long-term volatility from the GARCH-MIDAS model with a rolling win- dow is used. It should be mentioned that the GARCH-MIDAS with a rolling window RV model produced the lowest frequency daily volatilities. Therefore, as with Engle et al. (2008), a measure of the low-frequency volatility used in this paper can be defined as the average of the daily low-frequency volatilities over a long-term horizon—namely, one month.

Figure 4.3: Volatility and Long-term Volatility

(a) LV with Fixed Span LRV



(b) LV with Rolling Window LRV

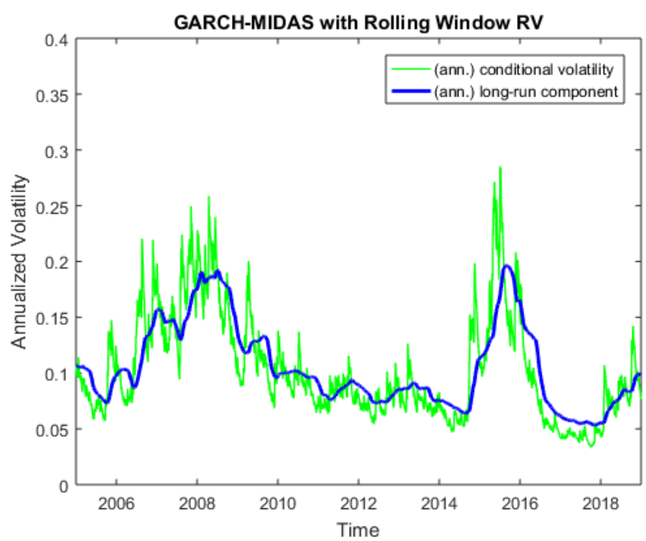
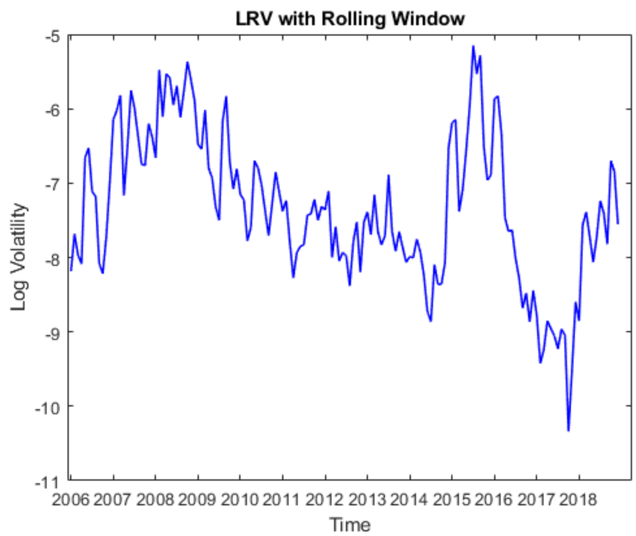


Figure 4.4: Long-term Volatility with Rolling Window

(a) RV with Rolling Window



(b) LV with Rolling Window

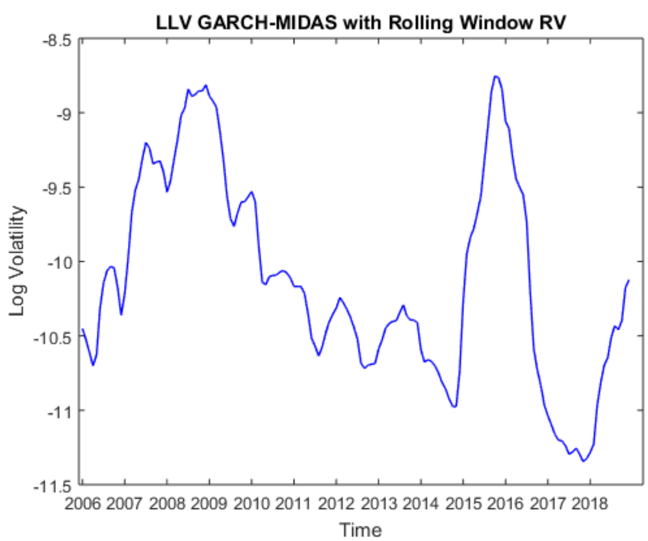
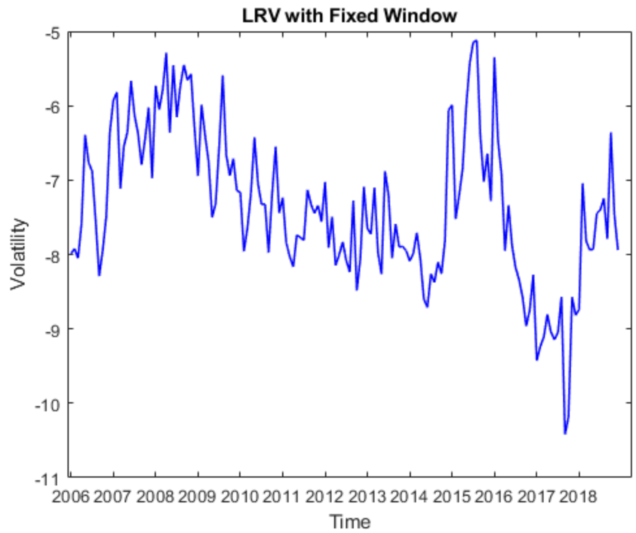


Figure 4.5: Long-term Volatility with Fixed Window

(a) RV with Fixed Window



(b) LV with Fixed Window

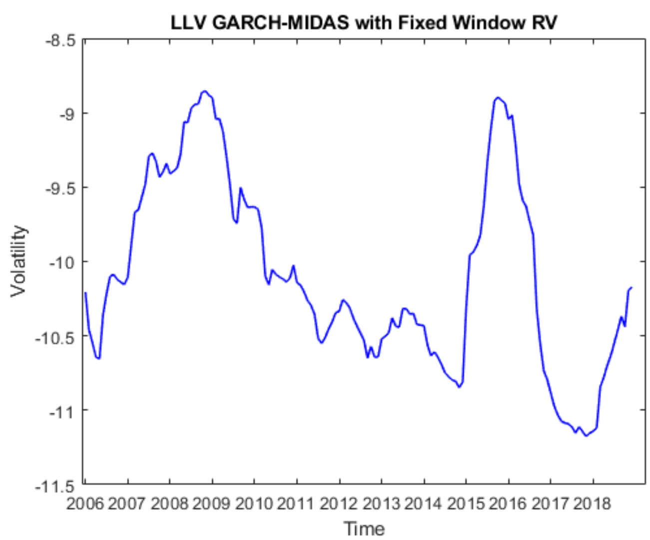


Table 4. 3: Data Sources, Transformation and Definitions

Raw Data	Source	Trans.	Variable

Dependent variable			
SHSE A-share Composite Index	CSMAR	Equation (4.3) Equation (1.4)	LLV LRV
Independent variables			
A. Macroeconomic Variables			
Industrial Production Index	CSMAR	Δln Equation (4.1)	IPI IPIV
Industrial Purchasing Manager Index	CSMAR	Δln Equation (4.1)	PMI PMIV
Property Price	CSMAR	Δln Equation (4.1)	RP RPV
National Real Estate Climate Index	CSMAR	Δln Equation (4.1)	RECI RECIV
Consumer Price Index	CSMAR	Δln Equation (4.1)	CPIM CPIVM
Money Supply (M2)	CSMAR	Δln Equation (4.1)	M2M M2VM
Government Expenditure	CSMAR	Δln Equation (4.1)	GE GEV
Investor Sentiment Index	CSMAR	Δln Equation (4.1)	IS ISV
China Policy Uncertainty Index	Baker et al. (2016)	Δln Equation (4.1)	CPUI CPUIV
Brent Crude Oil Price	Datastream	Δln Equation (4.1)	BOP BOPV
Three-Month Shanghai Interbank Offered Rate (SHIBOR)	CSMAR	lv (Δlv)	SB
Long-term Goverment Bond Rate	Datastream	lv (Δlv)	LTBY
Exchange Rate US DOLLAR (USD) to CHINA RENMINBI (CNY)	CSMAR	Δln	RU
B. Financial Variables			
Fama–French's market factor of SHSE A-share	CSMAR	lv	MER
Fama–French's SMB factor of SHSE A-share	CSMAR	lv	SF
Fama–French's HML factor of SHSE A-share	CSMAR	lv	VF
Fama–French's short-term reversal factor of SHSE A-share	RESSET	lv	STRF
Pastor-Stambaugh liquidity factor of SHSE A-share	CSMAR	lv	PS
Trading days of SHSE A-share	CSMAR	ln	TD
Trading Volumn of SHSE A-share	CSMAR	Δln	TV
Price Earnings Ratio of SHSE A-share	CEIC	Δln	PE
S&P 500 Index	Datastream	Δln Equation (4.1)	SP SPV
Hang Seng Index	Datastream	Δln Equation (4.1)	HS HSV
CBOE Market Volatility Index	CBOE	ln	VIX

C. Stock market development, openess and ownership structure			
C1. Stock Market Development			
Market Capitalization of SHSE A-share	CSMAR	Δln	MC
Number of listed company of SHSE A-share	CSMAR	Δln	NUMC
Turnover of SHSE A-share	CSMAR	Δln	TN
C2. Stock Market Openness			
QFII: Approved Investment Fund	CEIC	Δln	QFII
Number of QFII	CEIC	Δln	NUMQFII
Hot Money	CSMAR	lv	HM
Spread between China's benchmark rate and the Federal fund rate	CEIC Federal Fund Board Website	lv (Δlv)	DF
C3. Ownership Structure			
Market Cap of State owned Non-tradable Share in SHSE	CEIC	Δln	NSG
Market Cap of Domestic Legal Person owned Non-tradable Share in SHSE	CEIC	Δln	NSL

Table A.3 lists description of series, source, transformations and variables abbreviations. The first column is the raw data chose based on the economic theory, previous empirical research and Chinese economic and financial characteristics. The sources of these data are listed in the second column, namely, China stock Market and Accounting Research (CSMAR) database, RESSET database, CEIC database, and Datastream database. CSMAR and RESSET are Chinese databases and are widely used in the academic research (e.g., Fan et al. (2007); Firth et al. (2016);Lo et al. (2010); Li et al. (2015); Lyon et al. (2013). CEIC is an Asia database and also used widely (e.g., Chen et al. (2010);Fernald et al. (2014)). Apart from using these database, Federal fund rate is collected from the official website of Federal fund Board; CBOE Market Volatility Index is collected form the official website of Chicago Board Options Exchange (CBOE); China Policy Uncertainty Index is collected from the website of Economic Policy Uncertainty and the construction method is developed by Baker et al. (2016). In the third column, Δln denotes the first difference of the logarithm and transforms series into growth rate or return, lv denotes the level of the series; Δlv denotes the first difference of the series. lv(Δlv) denotes that level of the series contain a unit root and thus the first difference is taken on the series. As shown in the table above, PP test suggests that Shibor, long-term government bond rate and spread between China's benchmark rate and federal fund rate all contain one unit root, and thus these three series are differenced (Bai and Ng, 2008). Apart from these three series, the others are all stationary. Equation (4.1) is applied to produce the volatility of the series. The last column present the variables denotations used in this paper. In addition, Shibor only starts from the October of 2016, so we use the China's three month interbank offered rate from December of 2014 to September of 2016. Because hot money flows quickly and is poorly monitored, there is no well-defined, direct method for estimating the amount of hot money flowing into a country during a period of time. Following Martin and Morrison (2008) and Zhang and Fung (2006), we calculate the amount of hot money inflow as follows: (change in foreign exchange reseLRVes) minus (trade and service balance) minus (foreign direct investment). In the analysis, the HM is the hot money inflow measured in billion dollars in the preceding month. DF is the difference between the China one-year lending rate which is regarded as benchmark rate and the three month federal fund rate.

4.4.2 Data Description

Table 4.3 lists the description of the data series, their source, transformations and any variable abbreviations. The first column is the raw data based on economic theory, previous empirical research and the Chinese economic and financial characteristics. Considering the data availability and increased development and openness experienced by China's stock market in recent years, we only collect these monthly raw series over recent years starting from December of 2004 to December of 2018, to ensure that the growth rate or return of these series can start from January of 2005. However, we lose 12 observations when calculating the volatility of the macroeconomic variables according to Equation (4.1). Therefore, the final dataset is from December of 2006 to December of 2018.

The sources of the data are listed in the second column, namely, China's stock Market and Accounting Research (CSMAR) database, the RESSET database, the CEIC database, and Datastream. CSMAR and RESSET are Chinese databases and are widely used for academic research (e.g., Fan et al., 2007; Lo et al., 2010; Lyon et al., 2013; Li et al., 2015; Firth et al., 2016). CEIC is an Asian database and also used widely (e.g.,Chen et al., 2016b; Fernald et al., 2014). Apart from using these databases, the US Federal fund rate is collected from the official website of the Federal Fund Board; the CBOE Market Volatility Index is collected form the official website of the Chicago Board Options Exchange (CBOE); China's Policy Uncertainty Index is collected from the website of Economic Policy Uncertainty.

In the third column, Δln denotes the first difference of the logarithm and transforms the series into growth rate or return, lv denotes the level of the series; Δlv denotes the first difference of the series; lv (Δlv) denotes that level of the series containing a unit root and thus the first difference is taken on the series. As shown in the Table above, the Philips-Perron (PP) test suggests that the Shibor, long-term government bond rate and spread between China's benchmark rate and federal fund rate all contain one unit root, and thus these three series are differenced (Bai and Ng, 2008). Apart from these three series, the others are all stationary. Equation (4.1) is estimated to produce the volatility of the series.

The last column presents the variable denotations used in this paper. In addition, since PMI is only available since January of 2005, we take the average of the 12 months' PMI in 2005 as the value in December of 2004. Shibor only starts from October of 2006, so we use China's three month interbank offered rate from December 2004 to September of 2006. Because the trading using the hot money is frequent and is poorly monitored, there is no well-defined, direct method for estimating the amount of hot money flowing into a country during a period of time. Following Martin and Morrison (2008), we calculate the amount of hot money inflows as follows: (the change in foreign exchange reserves) minus (the trade and service balance) minus (foreign direct investment). In the analysis, the HM is the hot money inflow measured in billions of dollars in the preceding month. DF is the difference between the Chinese one-year lending rate which is regarded as the benchmark rate and the three month federal fund rate.

4.4.3 Results

4.4.3.1 What drives the stock volatility?

Since this study aims to investigate the drivers of the variation of China's stock volatility using a large set of macroeconomic and financial variables, as discussed before, the penalized regression models, like LASSO, LARS and Elastic-Net, have superiority in selecting the most important regressors in terms of addressing the overfitting problem. Furthermore, a number of the statistical inferences based on the these penalized regressions have been developed, like CovTest, Post-selection test and PG test. Therefore, this study will apply these tests to not only find the most important drivers, but also provide the statistical significance of these variables.

Figure 4.6 and Figure 4.7 present the coefficients path of LASSO regression at the using coordinate decent and LARS algorithms. The tune parameter lambda is selected by minimizing the cross-validated mean squared error. Along with the determination of the lambda, the most important variables driving the stock price volatility are also selected with the corresponding coefficients. The sub-figures (a) show the plots of the cross-validated MSE against the negative log lambda. The sub-figures (b) and (c) show the path of coefficients of all the variables and the path of coefficients of the selected variables, respectively.

Figure 4.6: LASSO LLV

(a)

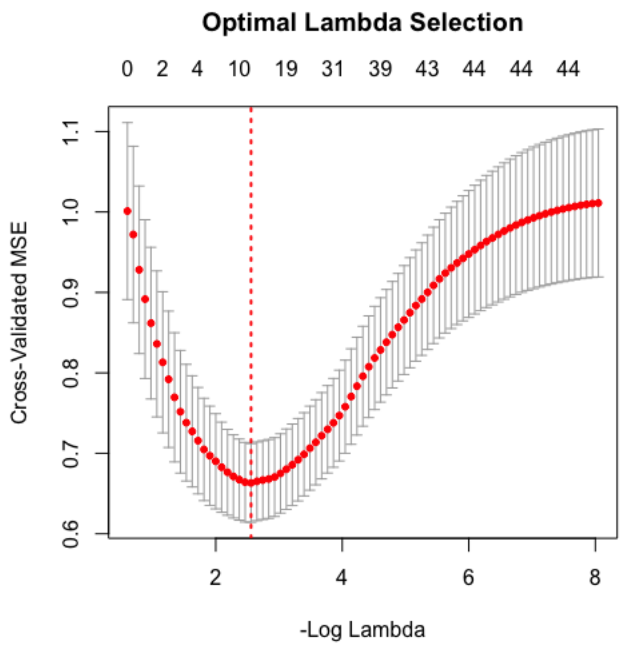
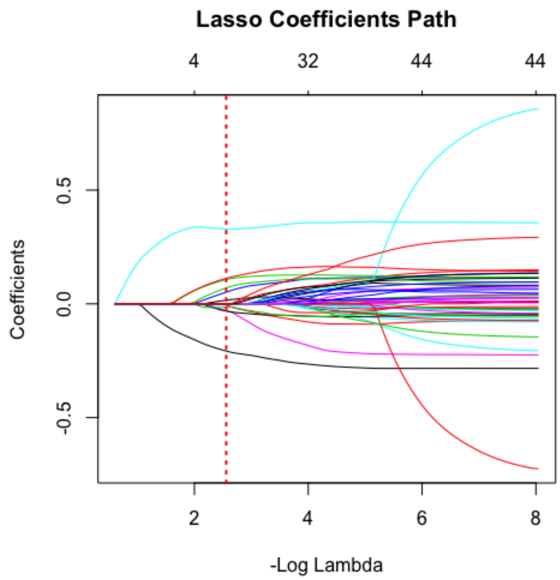


Figure 4.6: LASSO LLV

(b)



(c)

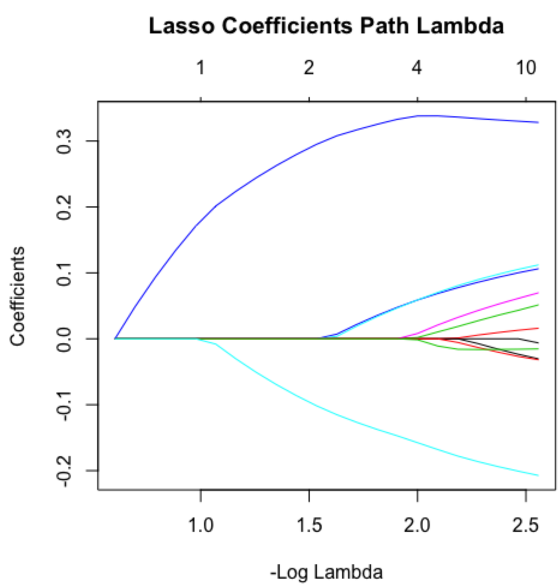
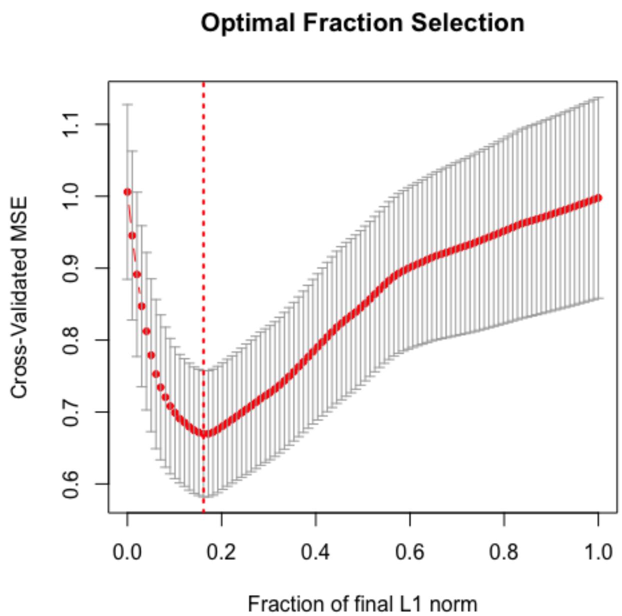


Figure 4.7: LARS-LASSO LLV

(a)



(b)

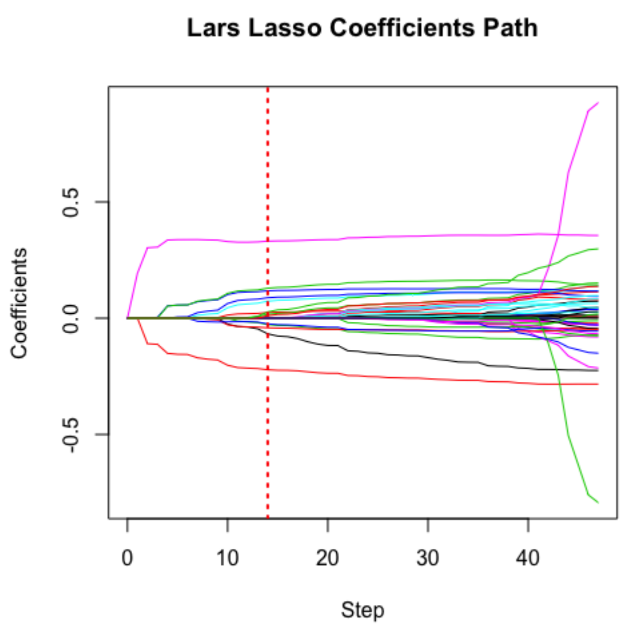
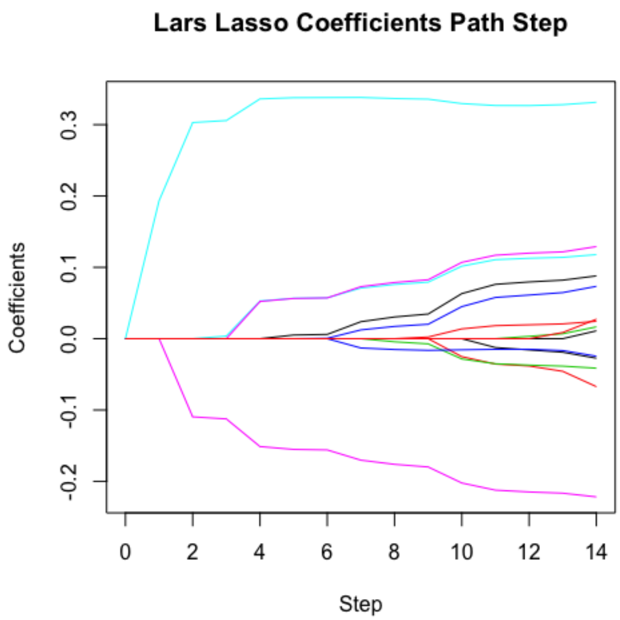


Figure 4.7: LARS-LASSO LLV

(c)



According to Table4.4, LARS ranked the variables from the most correlated to the least correlated with China's stock volatility. Generally, it can be seen that international factors are shown to be most correlated with China's volatility most, especially, the VIX index is shown by all three significance tests to have the most significant effect on China's stock volatility. Secondly, the variables representing China's stock markets characteristics are also strongly correlated with the stock volatility. e.g. NUMC and DF are shown to have statistically significant effects according the CovTest and Post-Selection tests. Thirdly, Financial variables such as PS, SF and STRF have a weaker correlation with China's stock volatility and there is no evidence showing the significant effect. Most of macro variables have slightly lower correlation with the stock volatility and show no statistically significance on China's stock volatility.

	LASSO	Post-Selection Test		LARS	TG	CovTest
Selected Vars	Coefs	P_Values	Ranked Vars	Coefs	P_Values	P_Values
PMIV	0.1013	0.0686*	VIX	0.4111	0.0000***	0.0000***
RECI	0.0658	0.2161	NUMC	-0.3186	0.7274	0.0117**
RECIV	0.0208	0.7583	PS	0.1662	0.2096	0.1936
M2	0.0732	0.2708	SF	0.0574	0.9872	0.1345
M2V	-0.0141	0.7238	STRF	0.0730	0.9725	0.9818
ISV	0.0233	0.7169	DF	0.1363	0.0043***	0.7171
CUPIV	-0.0373	0.4024	NSL	0.3059	0.5400	0.9199
RF	-0.0694	0.1335	ISV	0.0147	0.0216**	0.8590
RU	0.058	0.3337	PMIV	0.1543	0.9831	0.9893
SF	0.0464	0.5350	NSG	0.1594	0.1411	0.9331
STRF	0.0884	0.1439	RECIV	0.0265	0.2546	0.7223
PS	0.1489	0.0155**	QFII	-0.1983	0.8958	0.8797
TD	0.0259	0.5153	M2	0.1301	0.8114	0.9896
PE	-0.0104	0.7825	RECI	0.0696	0.0265**	0.9526
VIX	0.3638	0.0071***	RU	0.0780	0.0731*	0.6389
NUMC	-0.2413	0.0007***	CUPIV	-0.0982	0.3233	0.9843
TN	-0.0398	0.3650	RF	-0.1481	0.9225	0.5732
QFII	-0.0973	0.0469	HM	-0.1833	0.2849	0.7540
HM	-0.0538	0.2984	TN	-0.3198	0.0370**	0.7949
DF	0.0966	0.1055	TD	0.0790	0.9748	0.8651
NSL	0.0837	0.1767	M2V	-0.0944	0.0578*	0.8852
NSG	0.0975	0.4149	PE	-0.0672	0.9420	0.7780
			HSI	0.1438	0.9105	0.9946
			MER	-0.2866	0.7375	0.7971
			HSV	0.0250	0.6557	0.9984
			IPI	-0.0405	0.1441	0.9374
			SP	0.0623	0.5752	0.8487
			BOP	0.0389	0.5431	0.9488
			RPV	0.0350	0.1590	0.9811
			HML	0.0430	0.8389	0.9481
			ITBY	-0.0148	0.8587	0.9974
			IS	0.0225	0.6024	0.9987
			GE	0.0319	0.3925	0.9992
			GEV	0.0244	0.1554	0.9432
			PMI	0.0209	0.7590	0.9987
			CPIV	-0.0060	0.3177	0.9995
			IPIV	-0.0143	0.7194	0.9824
			NUMQFII	0.0245	0.2553	0.9934
			BOPV	0.0001	0.4079	0.9986
			MC	0.0190	0.2994	0.9888
			TV	0.2880	0.8799	0.7163
			SPV	0.0110	0.7678	0.9982
			CPUPI	-0.0015	0.3295	0.9994
			CPI	0.0016	0.0773*	0.9980
			RP	0.0000	0.3203	0.9976

Table 4.4: Significance Test LLV

1. International Factors

VIX, referred to by market participants as the “investor fear gauge” (Bollerslev et al. 2015), is most correlated with China’s stock volatility with a positive coefficient (0.4111) and has a significant effect on China’s stock volatility even at 1% significance level under both TG and CovTest tests. It means that an increasing fear in US stock markets will significantly increase China’s stock volatility, which is not surprised considering the economic and financial connection between China and US that are two largest economies in the world.

2. China’s stock market characteristics

- Stock market development

It can be seen as well that NUMC representing the development of China’s stock market is the second most correlated variable with stock volatility with a negative coefficient (-0.3186) and drives stock volatility significantly at 5% significance level under CovTest test but has no significant effect under TG test. In addition, TN, another indicator of the development of China’s stock markets, is shown to have a negative correlation with China’s stock volatility (-0.3198) and have a statistically significant effect on China’s stock volatility under the TG test but not the CovTest test. These show that the development in China’s stock market over the years has a significant effect in decreasing the stock price volatility, which implies that the risks are getting increasingly diversified as more and more companies listed in the stock markets and China’s stock markets are becoming gradually more efficient as well. This accords with the argument of Bartram et al. (2012) that higher economic and financial development are associated with lower stock volatility.

- Hot Money

DF, the change of difference between China’s benchmark interest and Federal fund rate representing the change of Hot Money, is shown to positively drive the stock volatility with a coefficient (0.1363) and have a significant effect on China’s stock volatility at 1% significance level under TG test but have no effect under the CovTest test. It implies that China’s stock returns become more volatile as Hot Money becomes increasingly volatile. However, HM, another measurement of Hot Money, is shown to have a negative correlation with China’s stock volatility, which implies that China’s stock volatility gets decreased as more Hot Money inflows into China’s stock market. This is inconsistent with the findings of the literature using the same measurement for Hot Money (Wei et al., 2018 and Guo and Huang, 2010), but both CovTest and TG tests show that the correlation is not statistically significant even at 10% significance level. Therefore, it is can be concluded with more confidence that Hot Money increases China’s stock market volatility.

- Stock market openness

As measurements of stock market openness, QFII is shown to negatively correlated with China's stock volatility, which means the increasing openness over the years drives stock volatility down. But neither CovTest nor TG tests shows a statistically significant effect. Another indicator of stock market openness, NQFII, however, is found to positively correlated with China's stock volatility implying the stock volatility is driven up as the market becomes more open. Meanwhile, there is no evidence showing a statistically significant effect of NQFII on stock volatility. Therefore, it is difficult to draw a conclusion about how the stock market openness affect China's stock volatility. However, as Huo and Ahmed (2018) found, the introduction of QFII scheme reduced the volatility of China's stock index futures market and thus reduced the spot stock market volatility through the transmission mechanism between the futures market and spot market.

- Ownership structure

For variables representing ownership structure, both NSL and NSG are shown to drive stock volatility positively, which implies that stock volatility will get decreased as more and more stocks become tradable. Since the non-tradable shares reform was implemented in 2005, 97% shares have become tradable by the end of 2007. In addition, the state and the legal person have been reducing the ownership of untradable share in the following years.Therefore, the overall policies and actions taken on ownership structure should take the effect of decreasing China's stock volatility in the long-run. However, as both the TG and Covtest have suggested, these effects are not statistically significant. Related studies, e.g., Sun and Tong (2003), also provided evidence supporting the positive impact of the privatization on China's stock markets.

3. Macroeconomic and Financial variables

Most of the Macroeconomic variables have low correlation with stock volatility and no statistically significant effect on stock volatility, which are consistent with the findings of some other studies, e.g., Schwert (1989); Paye (2012). Among them, ISV, the volatility of investor sentiment, is shown to positively and significantly drive the stock volatility, which is in line with the findings of Lee et al. (2002) and Chi et al. (2012). In addition, RECI is also shown to drive stock volatility positively and significantly at 5% significance level, which means China's real estate market has a significant effect on China's stock market. Specifically, when China's real estate market perform well, investments will be attracted into real estate market form stock markets. As a result, the decline in stock prices will lead to an increased stock volatility. Related studies e.g., Ding et al. (2014) also provided evidence supporting the significant relationship between Chinese stock markets and the real estate market.

In summary, the results of both the CovTest and TG tests show that VIX is the most correlated variable with China's stock volatility and positively and significantly driving China's stock volatility, which shows the economic and financial connection between China and US. Secondly, the Chinese stock market characteristics such as NUMC in particular drive stock volatility strongly and/or significantly. It provides evidence showing the success of a series of policies and reforms implemented in China's stock markets in terms of stock market development, openness and ownership structure (As discussed in Chapter 2). In addition, some of the financial variables show a strong correlation with stock volatility but most of theses are not statistically significant. Lastly, most of the macroeconomic variables only have a weak and insignificant correlation with stock volatility, which is consistent with the findings of othes in US literature (Schwert, 1989; Paye, 2012).

Apart from the CovTest and TG tests based on LARS regression, the post-selection significance test based on Lasso is also applied for robustness check. LASSO is not able to rank the variables based on correlation, but it can be seen that VIX is shown to have a positively significant effect on China's stock market at 1% significance level, which is in line with the findings of CovTest and TG tests. NUMC is shown to be negatively and significantly driving stock volatility at the 1% significance level, which is a stronger evidence compared with that provided by the CovTest and TG tests. In addition, some new findings show that PS representing the stock market liquidity and PMIV representing the volatility of PMI positively and significantly drive stock volatility at the 5% and 1% significance levels.

4.4.3.2 How does VIX affect stock volatility?

Based on the results of all three tests, VIX is the most important driver of stock volatility in terms of both correlation and statistical significance. Meanwhile, considering the importance of the relationship between China and the US to the worldwide economy and financial sector, it is necessary to investigate how the VIX drives China's stock volatility over the past years. As China's economy and the US economy are increasingly related with each other especially since China join in the WTO in 2001 and China's stock markets have become gradually more efficient due to a prolonged increase in development and openness, it is therefore likely that the information transmission mechanism between two economies has been increasing over time. Apart from time-varying information transmission mechanism, the shocks to economies are changing over time as well such as the development of technology, political elections, extreme events in financial markets, among other events. Therefore, this study implements a time-varying structural VAR model which allows for both time-varying parameters and heteroscadestistic shocks.

Firstly, only LLV and VIX are allowed in the BSVAR model, denoted as BSVAR1. Then, considering omitted variable bias, NUMC, which is shown to be slightly lower correlated with stock volatility and drive stock volatility significantly at 5% or 1% significance level under different tests, is added into in the existing model BSVAR1 to get model BSVAR2. In addition, in this study, the first 36 observations are used to estimate the prior parameters. For both BSVAR1 and BSVAR2 models, we start with getting the response function to see how the LLV response to the shock to the VIX over time. Then, the standard deviation of the shock to the VIX is analyzed to determine whether the shock is varying over time.

Next, in order to analyze if the transmission mechanism changes over time, the estimation period from Jan of 2009 to Dec of 2018 is divided into three subperiods according to the presidency in both China and the US: the first period is from Jan. 2009 to Dec. 2012 where Jintao Hu is the president of China and Barack Obama is the president of the US, the second period is from Jan. 2013 to Dec. 2016 where Jinping Xi and Barack Obama are the presidents of China and the US respectively; The third period is form Jan. 2017 to Dec. of 2018 where the Jinping Xi and Donald Trump are the presidents of China and the US respectively.

The state of economies in both countries and the relationship between China and US are heavily dependent on the president's plans and objectives, for example, Xijin Ping proposed the ideology "Chinese Dream" : the great rejuvenation of the Chinese nation, the objective "Two Centenaries" , a series of development strategies such as "Belt and Road Initiative (BRI)", "Made in China 2025". Donald Trump in 2018 began setting tariffs and other trade barriers on China's export with the goal of forcing it to make changes to what the U.S. says are "unfair trade practices", which is known as the China–United States trade war. All of these have a significant impact on economies of each country and the economic and financial connection between China and US. Therefore, it is natural to compare the response of LLV to VIX in these three different periods to check whether the transmission mechanism is changing over time.

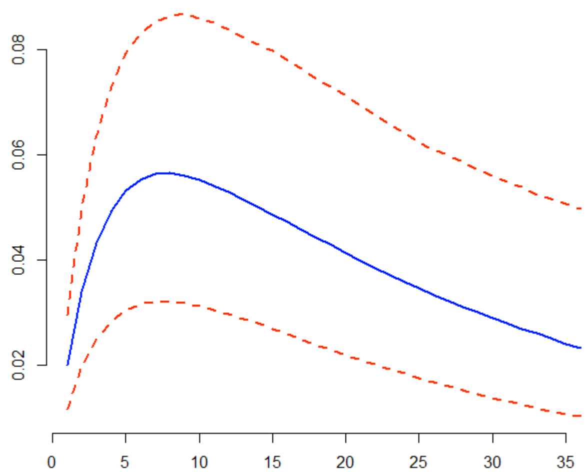
4.4.3.3 Impulse Response Function

Firstly, according to Figure 4.8 showing the response of LLV to VIX in both the BSVAR1 and BSVAR2 models, the VIX is shown to have a persistent effect on China's stock volatility and the effect of the shock to the VIX on LLV peaks after about seven months in both of the two models. It is not surprising to find that the US stock markets have a persistent and significant effect on the Chinese stock market.

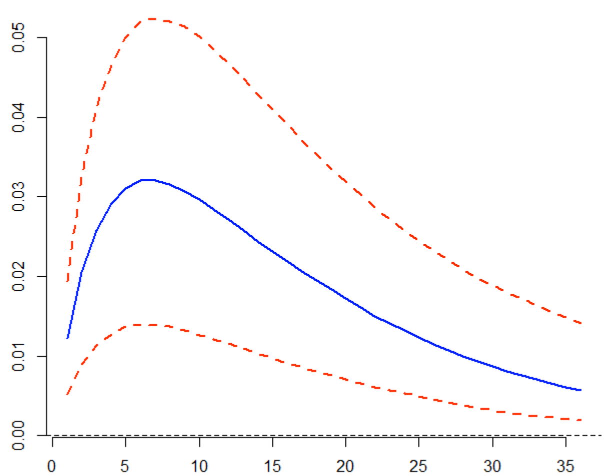
In addition, it shows that magnitude of the response of LLV to VIX in BSVAR2 model is almost half of that in BSVAR1 model. It implies that the NUMC also plays an important role in driving LLV, which is consistent with the finding of the significance tests.

Figure 4.8: Response of LLV to VIX

(a)



(b)



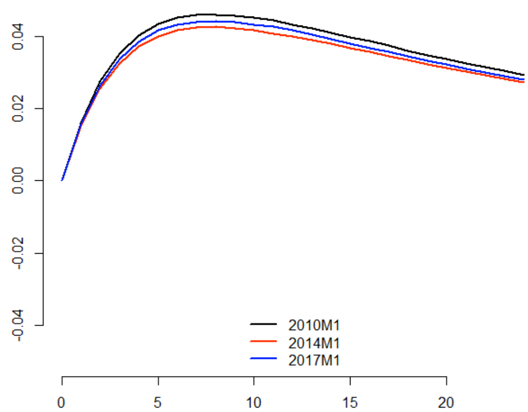
4.4.3.4 time-varying parameters

Next, we investigate whether the information transmission mechanism between the US and China is changing over time by comparing the response of LLV to VIX in three different presidential periods in China and US. The changes in the effects of VIX in BSVAR1 and BSVAR2 are summarized in Figures 4.9 and 4.10. Figures 4.9(a) and Figures 4.10(a) plot the impulse responses of LLV to a VIX shock in three different dates of the sample. The other graphs of Figures 2 and 3 represent pairwise differences between impulse responses in different dates with the 16-th and 84-th percentiles.

Clearly, in BSVAR1, these responses do not vary much over time, indicating that the estimated coefficients do not show much time variation. However, in BSVAR2, there is clear evidence showing that these responses in different periods vary substantially over time. Specifically, the effects of VIX on LLV during the Jinping Xi and Donald Trump presidency is more significant than the other two. This is strongly consistent with the fact that the China-US trade war has a significant impact on the economy and finance. Because of the China-US trade war, China's stock market is more sensitive to the US stock market and is affected by the information in US stock markets more strongly. It also can be found the effects of VIX on LLV are smallest during the Jinping Xi and Barack Obama presidency compared with the other two.

Figure 4.9: time-varying Parameters BSVAR1

(a)



(b)

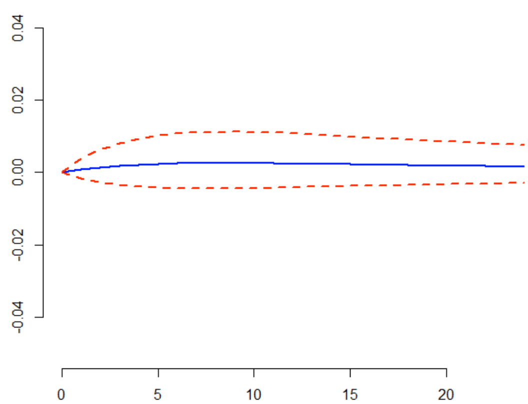
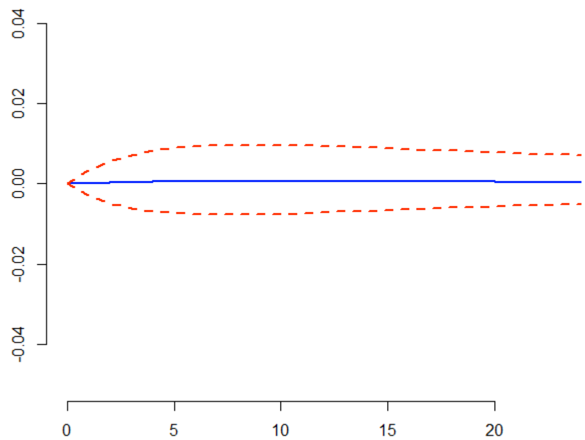


Figure 4.10: time-varying Parameters BSVAR1

(c)



(d)

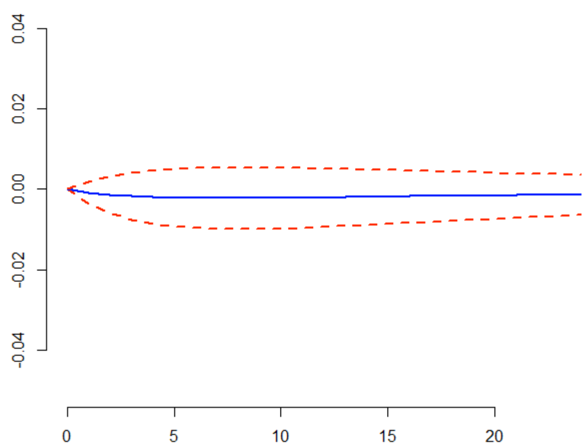
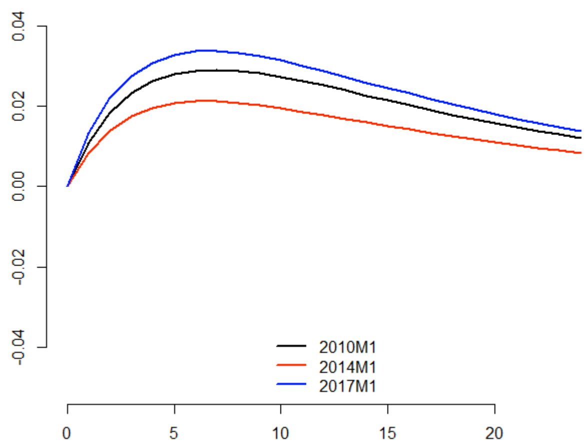
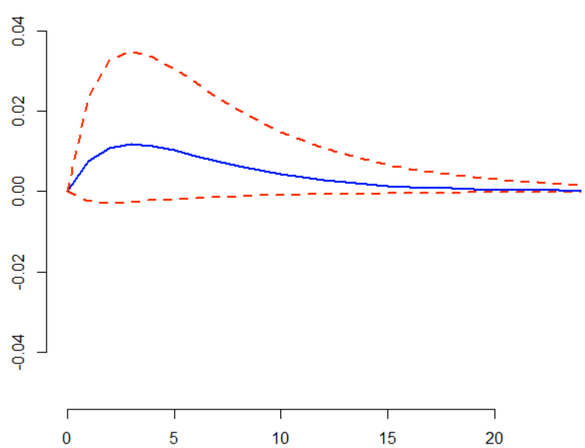


Figure 4.10: time-varying Parameters BSVAR2

(a)



(b)

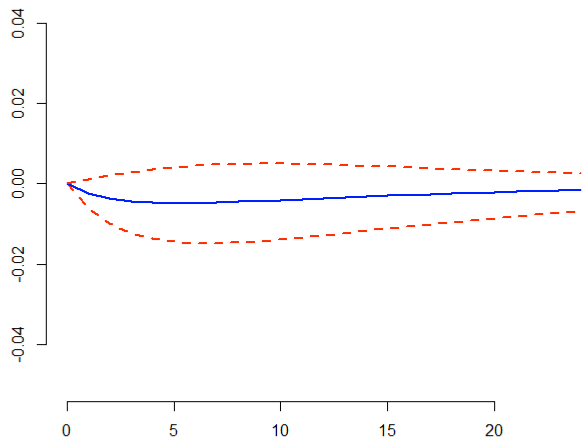


4.4.3.5 Time-Varying shocks

In addition, this study also investigates if the shock to the VIX have been changing over time. Figure4.11 shows that the shock to the VIX is varying over time in both of the two models. There are several outstanding characteristics corresponding to the specific events. For example, the shock peaks in around Aug of 2011, which is due to the S&P downgrading the U.S. by one notch to "AA+" at Aug. 2011, removing the world's largest economy from the Triple A-club for the first time ever. It is obvious that the shock is very volatile during the 2015 to 2016 periods which is attributed to China's stock market crash. It can be seen as well that the standard deviation of the shock to VIX has been increasing since 2018, which is attributed to the China-United States trade war that started in Mar. of 2018. In addition, it can be found that the shock to the VIX in BSVAR2 model is much smoother than that in the BSVAR1 model. It provides evidence showing that NUMC has the power to explain VIX, some of the unexplained part are due to the NUMC such that the residual of VIX has been reduced.

Figure 4.11: time-varying Parameters BSVAR2

(c)



(d)

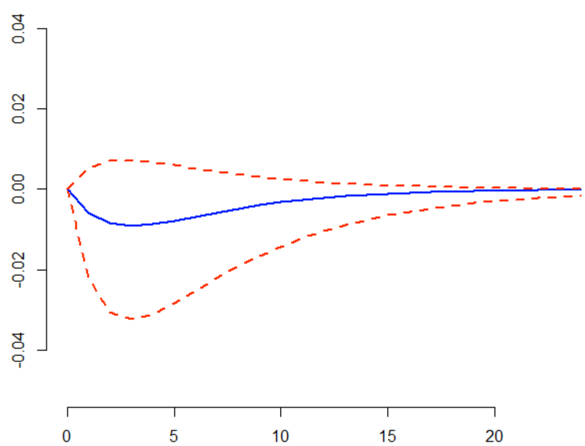
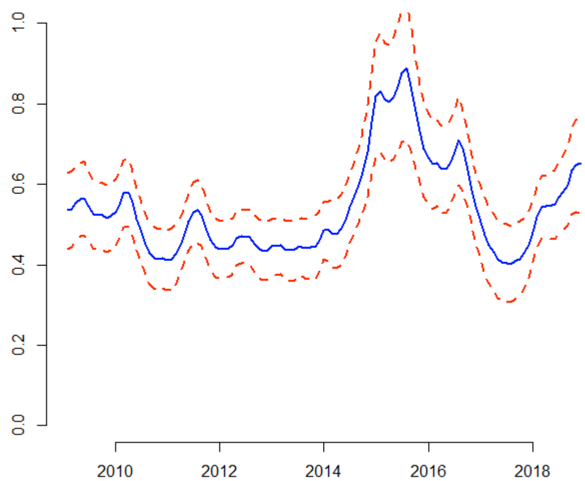
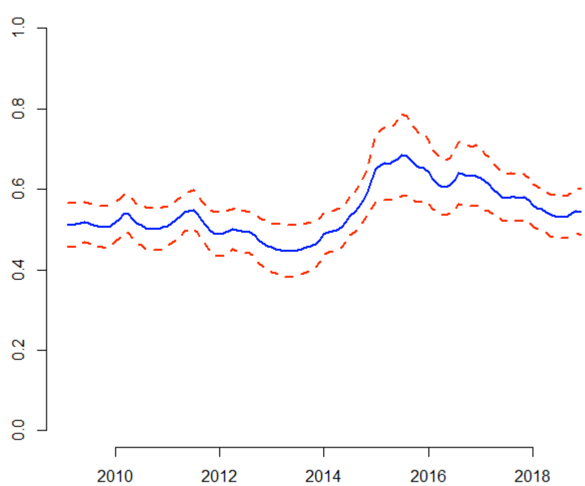


Figure 4.11: Shocks to VIX

(a)



(b)



4.5 Conclusion

Why does stock market volatility change over time? Since Schwert (1989), and the few related studies, that have emerged, there is no consensus reasons. However, some encouraging evidence has been recently presented to support the usefulness of the information contained in macroeconomic and financial variable in modeling and predicting the stock volatility. Given the importance of the Chinese stock markets for the Chinese economy and even the world's economy as well as the co-existing opportunities and risks in the Chinese stock markets, this chapter aims to investigate the drivers of China's stock price volatility. As a by-product of this objective, another question arises on how the VIX index measuring the degree of the US market fear drives the Chinese stock volatility given the VIX is shown to be the most significantly correlated with China's stock volatility.

Driven by these two questions, this paper firstly applied the well-known LASSO regression model into the large potential drivers including the international factors. macroeconomic and financial variables and drivers related to several dimensions of Chinese stock markets such as the development, openness and ownership structure. The variables selected by the LASSO regression are then further examined by three significance tests to present their statistically significance in driving the stock volatility. The results of these two procedures show that the international factors and drivers related to the characteristics of the Chinese stock market stand out as the two most important drivers of the stock volatility while macroeconomic and financial drivers failed. The most outstanding driver VIX, which we have to mention due to the role it has played in the US stock market and thus the potential impact it has on the Chinese stock markets though the information transmission mechanism between the two largest stock markets, shows the most significant effect among these factors.

Using the well-known TV-VAR model, this paper discovered the persistent effect of the VIX index on the Chinese stock volatility though analyzing the impulse response functions generated from the TV-VAR model. More interestingly, this chapter also found the VIX has the strongest impact on the Chinese stock volatility over the Jinping Xi and Donald Trump presidency period, suggesting that the China-US trade war which has occurred in the 2018 and is still ongoing have had provided another path for information to be transmitted between the two stock markets. Based on these results, the suggestions we can provide are that the Chinese government should continue to develop and open the stock markets and pay more attention on the effect of the US markets, by which the risks the Chinese stock market can be managed more effectively and there are can be a gradual and stable move forward to maturity similar to that which the developed stock markets have reached.

Chapter 5

Forecasting China's Stock Market Volatility using Macroeconomic and Financial Variables

This declaration concerns the article entitled:	
Forecasting China's Stock Market Volatility using Macroeconomic and Financial Variables	
Publication status (tick one) **Draft manuscript** ✔ **Submitted** ☐ **In review** ☐ **Accepted** ☐ **Published** ☐	
Publication details (reference)	
Copyright status (tick the appropriate statement) I hold the copyright for this material ✔ Copyright is retained by the publisher, but I have been given permission to replicate the material here ☐	
Candidate's contribution to the paper (provide details, and also indicate as a percentage)	The candidate contributed to / considerably contributed to / predominantly executed the… Formulation of ideas: 100% Design of methodology: 100% Experimental work: 100% Presentation of data in journal format: 100%
Statement from Candidate	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature.
Signed	Yuexian Tang — **Date** 30/08/2020

5.1 Introduction

The aim of this study is to determine whether macroeconomic and financial variables can be used to predict stock price volatility in the Chinese stock market. Over the previous twenty years, China's stock market has developed rapidly to the extent it is increasingly similar to the main Western markets. This development has been brought about through various reforms and the liberalization of transactions and stock ownership, as well as the allowing of derivative products and practices such as short selling. This has enabled the Chinese market to become increasingly efficient. If the market volatility can't be predicted through the main macroeconomic and financial variables, then it indicates that the market responds immediately to new information on these variables.

This study concentrates on market volatility as measuring and forecasting volatility is arguably among the most important pursuits in empirical asset pricing finance and risk management. For instance volatility is an important component in option pricing. There exists an extensive set of models that have been developed to evaluate the time variation of volatility and these advances have in a large part been motivated by the empirical observation that financial asset return volatility is time-varying with a persistent fashion, across assets, asset classes, time periods, and countries (See, for example, Bollerslev et al., 1988 and Harvey et al., 1994).

Many of these models have enjoyed substantial success in modeling and predicting stock price volatility. Although there is no consensus in the literature on the drives of the volatility. For example, Schwert (1989) posed the question regarding what were the principle drivers of secular variation in US stock return volatility? Although found only limited support for links between volatility and macroeconomic activity, subsequent papers have reported more encouraging evidence. The literature can be difficult to compare, as different studies examine different forecasting variables and apply different econometric approaches, although they tend to mostly use US data.

The main previous study in this area was by Paye (2012) for the US market. Using a linear estimation model, Paye (2012) argued that the lags of the stock volatility contained all the information that could be found in the macroeconomic and financial variables. This implies that there is no additional information that can be exploited by the forecasting models or methods to improve the forecasting accuracy. Most of the previous studies on stock price volatility and macroeconomic factors has commonly used realized volatility (Schwert, 1989; Paye, 2012). However using a GARCH type approach to the volatility produces different results, so the literature needs to take into account how the volatility series is produced. Using Chinese data, Chen et al. (2016a) compare the use of Chinese and US macroeconomic variables to forecast Chinese stock price volatility. They find that the US macroeconomic variables have a robust out-of-sample forecast performance which is better than the models with Chinese variables.

Further, as more data is becoming available, it has become popular to try to exploit as much as information contained in the data using machine learning techniques in both prediction and causal analysis issues (Athey and Imbens, 2017; Henrique et al., 2019). Machine learning techniques are able to attenuate the overfitting problem substantially which the traditional econometric estimators , like OLS, are prone to. Another superiority that machine learning techniques have over the most of the econometric models is no assumption about the probability distributions function of the errors terms in the model, which can lead to a more accurate prediction. The Support Vector Regression (SVR) is one of the most state-of-the-art machine leaning techniques, and are enjoying more popularity in the prediction associated with economic and financial problems. The one, most related with this study, is developed by Chen et al. (2010). They applied the SVR to predict the volatility of daily GBP exchange rates and the NYSE composite index on the basis of the GARCH framework and compared the forecasting performance of the SVR with the competing models, such as the GARCH model. They found that SVR-GARCH models significantly outperform the competing models in most situations in terms of one-period-ahead volatility forecasting.

Therefore, Inspired by Paye (2012) and using the SVR model and a larger set of data, this study aims to investigate the question: Does the macroeconomic and financial variables contain the useful information in predicting China's stock volatility after controlling the past stock price information? By answering this question, this study contributed to the literature in the following three aspects. First, it is one of the first to attempt to explain and predict stock price volatility in China, in particular with data after some of the main reforms were imposed on the market. Second, we use the support vector regression (SVR) approach to build Paye (2012) with a technique that can reduce the overfitting problem. Alongside this we also use a number of recent shrinkage techniques, such as LARS and Elastic-Net, so adding to the recent work of Stock and Watson (2012) as well as Bai and Ng (2008), who have developed several methods for shrinkage in the context of factor augmented autoregression models. Third, we use the GARCH-MIDAS methodology to produce the volatility series, as well as the more common realized volatility.

Following the introduction there is an assessment of the approach used in this study. We then describe the data and discuss the results. The final section concludes and offers some policy implications arising from the analysis.

5.2 Machine learning in Financial Literature

5.2.1 Neural Network Regression

Although parametric models are simple to implement and easy to explain, they make specific assumptions about the functional form of the data generation process and the distribution of error terms, which could cause that economic significance of macroeconomic and financial variables cannot be captured.

In contrast, non-parametric models provide much more flexibility in modeling the underlying data generation process. Instead of specifying a particular functional form and making a prior distributional assumption, the non-parametric model will search for the best fit over a large set of alternative functional forms. Thus, many nonlinear non-parametric models are developed and employed in economic and financial applications, among which the artificial neural network (ANNs) enjoys a wide popularity used[1]. ANNs are a class of generalized non-parametric models inspired by studies of the brain and nerve system. Compared with conventional models, the advantage of ANNs is that they can approximate any linear or nonlinear functions to an arbitrary degree of accuracy without any assumption on the data-generating process. For example, Qi (1999) employed neural network model to investigate the relationship between stock excess return and and a set of macroeconomic variables and found that the in-sample fit and out-of-sample forecasts perform better than the counterpart linear models. Using 61 accounting ratios for 2352 Canadian companies over the period 1976–1993,Olson and Mossman (2003) compared neural network forecasts of one-year-ahead Canadian stock returns with the forecasts obtained using ordinary least squares (OLS). They found that back propagation neural networks estimation outperformed the best regression alternatives and produced greater profitability using various trading rules.Kanas (2001) applied the trading volume and the dividend to estimate and predict monthly return from both DJ and FT indices through a linear model and a nonlinear ANNs model. Based on directional accuracy and forecast encompassing, they compared out-of-sample forecasts generated from the these two competing models and found that the ANNs forecasts are preferable to linear forecasts. This indicated that it is important to account for nonlinear relationship between stock returns and fundamentals.

5.2.2 Support Vector Regression

Despite many desirable features of ANNs, it is difficult to construct a good network for a particular application. ANNs are often criticized to suffer from underfitting and over-fitting problem. In addition, due to the relatively large number of parameters and nonlinearity inherent in these specifications, the objective function is unlikely to be globally convex and can have many local minima. Chatfield et al. (1993) questioned whether ANNs had been over sold as a miracle forecasting technique and a subsequent strand of literature documents that ANNs often under perform simple financial models, such as the random walk. For TBM daily stock returns, White (1988)found that the ANNs models wildly over-fit in sample, with no ability to forecast out of sample. For monthly New York Stock Exchange stock index returns, Chuah (1992) found that there was no market timing ability, and the forecast errors of the ANNs were not significantly different from those of the benchmark linear model. Racine (2001)replicated results using the same software, approach and data detailed by Qi (1999) and fund that, in fact, the switching portfolio based on the recursive neural-network

[1]Mittnik et al. (2015) applied componentwise gradient boosting techniques to identify financial and macroeconomic factors influencing volatility and to assess the specific nature of their influence.

forecasts generates lower accumulated wealth with higher risks than that based on linear regression.

To overcome the shortcomings of ANNs, this paper applied another nonlinear non-parametric tool: support vector machine (SVM). Grounded in the statistical learning theory or VC theory developed by Vapnik (2013), SVM is largely developed at AT&T Bell Laboratories by Vapnik and co-workers and has been widely applied in engineering, bioinformatics and decision sciences. The superiority of SVMs against ANNs lies in its several properties. The first is that the estimation of SVR is based on structure risk minimization principles (SMP). Using SMP, SVR aims to minimize the upper bound of the actual risk, which is achieved by minimizing the trading errors measured by a loss function and controlling the model complexity using norm term at the same time. Therefore, SVR is able to obtain a superior generalization performance. The second is that its optimizing functional is quadratic and linearly restricted, meaning that it only presents a single minimum without any local undesirable solutions. In addition, compared with the linear regression models, SVR does not assume any probability density function (pdf) over the return series and just adjusts the parameters relying on SMR, which means it is able to lead to better predictions than those obtained using least squares (ML) approach.

Based on the theoretical advantages of the SVM, Support vector regression (SVR) has been applied for regression and time series forecasting problems. For example, Chen et al. (2010) applied SVR to predict the volatility of daily GBP exchange rates and NYSE composite index on the basis of GARCH framework and compared the forecasting performance of SVR with the other models, namely, a simple moving average, standard GARCH, nonlinear EGARCH and traditional ANNs-GARCH models. Through two evaluation measures and robust Diebold–Mariano tests, they found that SVM-GARCH models significantly outperform the competing models in most situations of one-period-ahead volatility forecasting. Pérez-Cruz et al. (2003) used SVR to estimate the parameters of a GARCH model and applied this estimation to predict the conditional volatility of stock market returns. Both the empirical and simulation results showed that the estimation using SVR have a higher predicting ability than those obtained via standard GARCH model, which is due to that SVR does not need to assume the errors are normally distributed such that the maximum likelihood estimation can be implemented. However, although SVR has been shown to have a higher predicting ability in predicting stock returns and volatility, we have not found any study using macroeconomic or financial variables to predict stock return or volatility through SVR.

Therefore, considering the advantages of SVR and potential underlying nonlinear relationship between macroeconomic and financial variables and stock volatility, this paper applied SVR to examine the economic significance of macroeconomic and financial variables.

5.3 Methodology

5.3.1 Overfitting

In order to assess the forecasting ability of the macroeconomic and financial variables on stock volatility, the following two nested models are used (Paye (2012)):

$$y_t = \alpha' W_{t-1} + \varepsilon_t \tag{5.1}$$

$$y_t = \alpha' W_{t-1} + \beta' X_{t-1} + \varepsilon_t \tag{5.2}$$

Where W_{t-1} is a vector of predetermined variables such as a constant and the lags of y_t, X_{t-1} is a vector of predictors. The R squared and BIC or the out-sample forecasting performance can then be compared between these two nested models to determine the forecasting ability of the predictors under in-sample or out-of-sample forecasting analysis, respectively. However, a large number of predictors in the above regression will produce the well-known over-fitting problem and hence generate a spurious R squared and BIC or a poor out-of-sample forecasting performance (see Inoue and Kilian, 2005, 2006, Diebold, 2015). Bai and Ng (2008) also pointed out that although the estimated estimates $\hat{\alpha}$and $\hat{\beta}$ are $\sqrt{T}$consistent, the mean-squared forecast error is increasing in N.

One way of improving forecasts when a large number of predictors are selected is to use a diffusion index (DI) forecasting framework (Artis et al., 2005, Boivin and Ng, 2005, 2006, Kim and Swanson, 2014, Bai and Ng, 2002, 2006b,a, 2008 and Stock and Watson, 1999, 2002a,b, 2012). Another way is to use penalized regressions to firstly select the target variables from all the predictors and then assess the forecasting ability of these variable on the variable of interest (Bai and Ng (2008) and Kim and Swanson (2014)). In this paper, the DI forecasting method and penalized regression framework are used for robust comparison, we focus on using the Support Vector Regression (SVR) to address the question of interest in this paper, which is to determine if the SVR is superior to these linear parametric models and the other non-parametric models, such as the Artificial Neural Network (ANN).

5.3.2 Support Vector Regression (SVR)

This study uses the support vector machine learning regression approach, to overcome the 'overfitting' problem that can occur with linear regression methods. Although non-linear techniques have been used before in this context, such as neural networks (ANN), we have applied another nonlinear non-parametric tool: the support vector machine (SVM). Grounded in the statistical learning theory or VC theory developed by Vapnik (2013), it has been widely applied in engineering, bioinformatics and decision sciences. The technique has also recently been applied to predicting financial factors, such as financial distress Geng et al. (2015).

Given the data set ($\boldsymbol{x}_i \in \Re^d, y_i \in \Re$,for $i = 1, \ldots, n,$), where $\boldsymbol{x}_i$ is the input vector, y_i is the corresponding scalar output and the n is the number of the observations. The objective of SVR is to find a best function $f(x)$ to accurately approximate the unknown target function. For the nonlinear regression, it can be shown as follows:

$$f(\mathbf{x}_i) = \boldsymbol{w}^{\mathbf{T}} \boldsymbol{\phi}(\boldsymbol{x}_i) + b \tag{5.3}$$

Where b is a constant, $\boldsymbol{w}$ is a weight vector, $\boldsymbol{w} \in \Re^d$, $\boldsymbol{w}^{\mathbf{T}}$ denotes the transpose of $\boldsymbol{w}$, $\phi()$ denotes a mapping function which can map $\boldsymbol{x}_i$ in lower dimensional input space into a higher dimensional feature space ($\boldsymbol{x}_i \in \Re^d \rightarrow \phi(\boldsymbol{x}_i) \in \Re^H, d \leq H$). In SVR, the problem of nonlinear regression in the lower dimensional input space ($\Re^d$) is transformed into linear regression in the high dimensional feature space ($\Re^H$).

Denoting the deviation of estimated value $f(\boldsymbol{x}_i)$ from the observed value y_i as ξ_i, the relationship between $\boldsymbol{x}_i$ and y_i can be shown as follows:

$$y_i = f(\boldsymbol{x}_i) + \xi_i \tag{5.4}$$

In order to find such a regressor, the SVR is designed to minimize a loss function and also control the model's complexity simultaneously. A number of loss function such as ε-intensive loss (Vapnik, 2013), the Laplacain (Melacci and Belkin, 2011), Huber's robust loss (Huber, 1992; Cherkassky and Ma, 2004), Gaussian (Gao et al., 2002), Polynomial loss functions (Rosset et al., 2004) can be applied in SVR. The standard setting of loss function in SVR is a ε-intensive loss as proposed by Vapnik (2013):

$$L_\varepsilon(\boldsymbol{x}_i, y_i, f(\boldsymbol{x}_i)) = \begin{cases} \mid f(\boldsymbol{x}_i) - y_i \mid -\varepsilon & \text{if} \mid f(\boldsymbol{x}_i) - y \mid \geq \varepsilon \\ 0 & \text{otherwise} \end{cases} \tag{5.5}$$

The ε-intensive loss function implies that if the prediction errors are larger than ε, only the part larger than ε is penalized and the prediction errors with ε are not penalized. Apart from minimizing the prediction errors using the ε-intensive loss function, the SVR also controls for the model complexity by seeking a small $\boldsymbol{w}$, which can solve the over-fitting problem, which can produce good generalization properties in terms of improving the out-of-sample forecasting performance. By minimizing the loss and controlling for the model complexity, the SVR can be perceived as a constrained optimization problem:

$$\begin{aligned} &\min_{\boldsymbol{w}, b, \xi_i, \xi_i^*} \frac{1}{2} \parallel \boldsymbol{w} \parallel^2 + C \sum_{i=1}^{n} (\xi_i + \xi_i^*) \\ &\text{subject to} \begin{cases} y_i - \boldsymbol{w}^{\mathbf{T}} \boldsymbol{\phi}(\boldsymbol{x}_i) - b \leq \varepsilon + \xi_i \\ \boldsymbol{w}^{\mathbf{T}} \boldsymbol{\phi}(\boldsymbol{x}_i) + b - y_i \leq \varepsilon + \xi_i \\ \xi_i, \xi_i^* \geq 0 \end{cases}, \end{aligned} \tag{5.6}$$

Where the parameter C is the regularization constant applied for specifying the trade-off between the trading errors and model complexity. The larger C is, more penalization enforced on the trading errors.

One of the most important factors in building the default prediction model using the SVM is the selection of the kernel function. In this paper, the radial basis function (RBF) used as the kernel function of SVR for the nonlinear regression. According to Hsu et al. (2003), the reasons for using the RBF are as follows: First, the RBF is the most used default kernel function and is able to map the non-linear regressor of the input space into a linear regressor in higher dimensional feature space; Second, when examining the number of hyper parameters, the polynomial kernel has more hyper parameters than the RBF kernel; Third, the RBF has fewer numerical difficulties because the kernel values lie between zero and one, while the polynomial kernel values may go to infinity or zero when the degree is large. The RBF can be shown as follows :

$$\text{RBF: } \boldsymbol{k}(\boldsymbol{x}_i, \boldsymbol{x}_j) = \exp(- \parallel \boldsymbol{x}_i - \boldsymbol{x}_j \parallel^2 /(2\sigma^2)) \tag{5.7}$$

Where σ denotes the width of the RBF.

Once the kernel function is selected, it is necessary to decide three parameters: C, ε and σ. The penalization parameter C, threshold error ε and the kernel parameter σ play crucial roles in the performance of the SVR. Improper selection of these parameters can be counterproductive. Nevertheless, there is little general guidance to determine the parameter values of the SVR. Hsu et al. (2003) suggested a practical guideline for the SVM using a grid-search and cross-validation, and these guidelines are utilized in this study. This study performed a grid-search on C, ε and σ using the ten fold cross-validation approach. As Hsu et al. (2003) found, exponentially growing sequences of C, ε and σ is a practical method to identify good parameters. Hence, each parameter in this study is allowed to spans a sequence $(2^{-15}, 2^{-13}, 2^{-11}, \ldots, 2^{11}, 2^{13}, 2^{15})$. All the pairs of ($C$, ε,σ) in the grid are tested, and the one with the best cross-validation accuracy is selected.

5.3.3 Robust Regression Model

5.3.3.1 The Diffusion Index (DI) Forecasting

The diffusion index (DI) forecasting framework of Stock and Watson (2002a,b) has been widely used for to perform forecasts when a large number of predictors are used. Stock and Watson (2006) discuss in some detail the literature on the use of diffusion indices for forecasting. This methodology involves firstly estimating the principle components under a factor model:

$$X_{it} = \lambda_i' F_t + e_{it} \tag{5.8}$$

or in matrix form

$$X_t = \Lambda F_t + e_t \tag{5.9}$$

Where F_t is $r \times 1$vector of principle components, the estimate of $F_t$is denoted as $\hat{F}_t$. λ_i or Λ are the factor loadings associated with F_t.

Secondly, DI forecasting framework to an h period-ahead forecast is to estimate the forecasting equation using the data for $t = 1, \ldots, T - h$:

$$y^h_{t+h} = \alpha' W_t + \beta (L)' \hat{f}_t + \varepsilon_{t+h} \tag{5.10}$$

Where $\hat{f}_t \subset \hat{F}_t$, $\beta (L)$ are coefficients associated with $f_t$and p of its lags. As Bai and Ng (2008) indicated that if $\sqrt{T}/N \to 0$, then the generated regressor problem does not arise, which means the least squares estimates $\hat{\alpha}$and $\hat{\beta}$ are $\sqrt{T}$consistent and asymptotically normal.

With regard to the choice of r, Bai and Ng (2002) provide a solution to the problem of choosing the number of factors. They establish convergence rates for factor estimates under the consistent estimation of the number of factors, r, and propose panel criteria to consistently estimate the number of factors. Namely, Bai and Ng (2002) define selection criteria of the form $PC\,(r) = V(r, \hat{F}) + rh\,(N, T)$, where $h\,(\cdot)$ is a penalty function. In this paper, the following version is used (for discussion, see Bai and Ng, 2002 and Ayi Armah and Swanson, 2010):

$$SIC\,(r) = V(r, \hat{F}) + r\hat{\sigma}^2 \left(\frac{(N + T - r) \ln (NT)}{NT} \right) \tag{5.11}$$

A consistent estimate of the true number of factors is $\hat{r} = argmin_{0 \le r \le r_{max}} SIC\,(r)$. In this paper, we use this criteria to determine the number of the principal components. After determining the number of principle components, the SIC information criteria is used to determine the lags of the principle components included in the forecasting regression.

5.3.3.2 Least Squares with Penalized Regressions

As there are potentially a large number of macroeconomic and financial variables that could determine stock price volatility, we have used a number of approaches to shrink this to a more manageable number of the most significant variables. One way of dropping the most uninformative regressors is to use penalized regressions. One method we have used, The LASSO (least absolute shrinkage and selection operator) regression, was introduced by Tibshirani (1996) and it uses both continuous shrinkage and automatic variable selection simultaneously by imposing the L1penalty function on the regression coefficients such that the coefficients of unimportant variables are shrunk to zeros. Many comparisons have been made between the LASSO regression and ridge regression, with the conclusion that neither of them could uniformly dominate the other in out-of-sample forecasting exercises (De Mol et al. (2008), Fu, 1998, Tibshirani, 1996).

Although the LASSO estimator is an improvement over the ridge estimator, LASSO also has its limitations. Empirically, it seems that when there is a high correlation in the predictors, LASSO is dominated by the ridge. Conceptually there are two problems as highlighted by Zou and Hastie (2005). First, if the number of regressors p are more than the number of the observations n , LASSO selects at most n variables. Second, if there is a group of variables with high pairwise coefficients, LASSO tends to select only one variable from the group and does not care which one. These concerns suggest that a convex combination of ridge and LASSO estimation might be desirable. The result is the 'elastic net' (EN) estimator of Zou and Hastie (2005). The idea behind the elastic net is to stretch the fishing net that retains all the 'big fish'. Like LASSO, the EN simultaneously shrinks the estimates and performs model selection to ensure only the most relevant variables are selected.

It can be shown that the EN shrinkage estimation proposed by Zou and Hastie (2005) can be regarded as a linear combination of a LASSO regression and ridge regression. As previously mentioned, neither of these methods could uniformly dominate the other in out-of-sample forecasting exercises, so it seems reasonable to combine these two approaches adaptively. Using the ridge regression alone does not remove any predictors, but shrinks all the predictors. By combining it with the LASSO regression, however, we could select a subset of variables using this flexible shrinkage estimation approach. The two shrinkage intensities applied here, are determined by the cross-validation method.

In addition we have also used the Least Angle Regression (LARS) approach, which is a well-known forward stage wise regression, that is more cautious than many other forward selection regressions as it takes smaller steps towards the final model (Efron et al. (2004), Bai and Ng (2008)). According to Efron et al. (2004), forward stage wise regressions are in fact special cases of LARS. LARS can also be regarded as an algorithm to solve LASSO and Elastic Net (Efron et al. (2004)), this study apply the LARS algorithm Elastic Net rather than the coordinated descent algorithm (Wu et al. (2008)) because LARS is able to give us a ranking of the predictors when the presence of other predictors are taken into account. Therefore, we have two penalized regression models, which are denoted as EN and LARS. Next, these two techniques will be intruduced briefly as follows:

1. Elastic Net

Efron et al. (2004) showed that, the lasso objective function can be written into following matrix notation:

$$\boldsymbol{\beta}^{\boldsymbol{T}}(\boldsymbol{X}^{\boldsymbol{T}}\boldsymbol{X})\boldsymbol{\beta} - 2\boldsymbol{y}^{\boldsymbol{T}}\boldsymbol{X}\boldsymbol{\beta} + \lambda|\boldsymbol{\beta}|_1 \tag{5.12}$$

where $\boldsymbol{y} = (y_2, ..., y_{T_0})^{\boldsymbol{T}}$, $\boldsymbol{\beta} = (\beta_1, \beta_2, \dots \beta_J)^{\boldsymbol{T}}$ is a vector of regression coefficients, $\boldsymbol{X}$is the corresponding design matrix, with the tth row given by $(x_{t-1,1}, x_{t-1,2}, \dots, x_{t-1,J})$, $|\beta|_1$ is the L1 norm of vector, λ is the tuning parameter.

Since $\boldsymbol{J}$ is very large in economic forecasting, $\widehat{\boldsymbol{\Sigma}} = \boldsymbol{X}^{\boldsymbol{T}}\boldsymbol{X}$ is the sample covariance matrix of $\boldsymbol{J}$ time series, which is a estimator of the population covariance matrix $\boldsymbol{\Sigma}$. However, it is well known that $\widehat{\boldsymbol{\Sigma}}$ is far from the optimal estimator when $\boldsymbol{J}$ is very large. For example, Kan and Zhou (2007) pointed that it is not appropriate to use $\widehat{\mathbf{\Sigma}}$ as the estimator of $\mathbf{\Sigma}$ when large number of asset prices or economic time series are considered.

Instead of using $\widehat{\mathbf{\Sigma}}$ as the estimator of $\mathbf{\Sigma}$, the large covariance matrix is suggested to be estimated using a shrinkage estimator. For example, in portfolio management, Ledoit and Wolf (2003, 2004) proposed a shrinkage covariance estimator as follows:

$$\widehat{\mathbf{\Sigma}}_s = (1-\gamma)\widehat{\mathbf{\Sigma}} + \gamma\widehat{\mathbf{\Sigma}}_{target} \tag{5.13}$$

where $\widehat{\mathbf{\Sigma}}$ is the sample covariance matrix, $\widehat{\mathbf{\Sigma}}_{target}$ is a shrinkage target, and $0 < \gamma < 1$ is the shrinkage intensity. $\widehat{\mathbf{\Sigma}}_{target}$ could be either an identity matrix $\boldsymbol{I}$, or the covariance matrix implied by a factor model. In particular, by taking into the benefits of the shrinkage estimator, the coefficients can be estimated based on the following objective function:

$$\hat{\boldsymbol{\beta}}_{enet} = \underset{\boldsymbol{\beta}}{argmin} \boldsymbol{\beta}^{\boldsymbol{T}}((1-\gamma)\widehat{\mathbf{\Sigma}} + \gamma\widehat{\mathbf{\Sigma}}_{target})\boldsymbol{\beta} - 2\boldsymbol{y}^{\boldsymbol{T}}\boldsymbol{X}\boldsymbol{\beta} + \lambda|\boldsymbol{\beta}|_1 \tag{5.14}$$

where $\widehat{\mathbf{\Sigma}}_{target}$ is this paper is an identity matrix. This is corresponds to the elastic net shrinkage estimation proposed by Efron et al. (2004).

It can be shown that elastic net regression can be regarded as a linear combination of LASSO regression ($\gamma = 0$) and ridge regression ($\gamma = 1$). Since the comparisons between LASSO regression and ridge regression concluded that neither of them could uniformly dominate the other in the terms of the performance out-of-sample forecasting (De Mol et al., 2008, Fu, 1998, Tibshirani, 1996), it seems reasonable to combine these two approaches adaptively.

2. LARS

Apart from the above penalized regression, a wildly-used variable selection method is the forward regression. Briefly, suppose $\hat{\mu}_k$is the current estimates of y with k predictors, let $c\left(\hat{\mu}_k\right)$ be the vector of current correlations between covariates X and the current residual vector $y - \hat{\mu}$:

$$\hat{c} = c\left(\hat{\mu}\right) = X'\left(y - \hat{\mu}\right). \tag{5.15}$$

There exists a j such that $|\hat{c}_j|$ is maximized:

$$j = argmax|\hat{c}_j|. \tag{5.16}$$

$\hat{c}_j$is the correlation between the covariate x_j (or X_j: j-th column in covariates matrix X) and the current residual vector. Then the current estimate is updated in the direction of the greatest current correlation:

$$\hat{\mu} \to \hat{\mu} + \hat{\gamma} sign\left(\hat{c}_j\right) X_j. \tag{5.17}$$

When $\hat{\gamma} = |\hat{c}_j|$, then the updating rule is: $\hat{\mu} \to \hat{\mu} + |\hat{c}_j| sign\left(\hat{c}_j\right) X_j$, it is the well-known forward selection regression. Forward selection regressions tend to be too aggressive in the sense of eliminating too many predictors correlated with the ones included (Efron et al., 2004, Bai and Ng, 2008). When $\hat{\gamma}$is a small constant, say ε, then the updating rule is: $\hat{\mu} \to \hat{\mu} + \varepsilon \cdot sign\left(\hat{c}_j\right) X_j$, it is the well-known forward stagewise regression, which is more cautious than forward selection regressions as it takes smaller steps towards the final model (Efron et al., 2004, Bai and Ng, 2008). According to Efron et al. (2004), it showed that forward stagewise regressions is in fact special cases of what is known as LARS, or least angle regressions[2]. According to Efron et al. (2004), define K as the set of indices corresponding to variables with the largest absolute correlations:

$$K = \left\{ j : |\hat{c}_j| = |\hat{C}| \right\}, \hat{C} = \underset{j}{max} |\hat{c}_j|, \tag{5.18}$$

and define the active matrix corresponding to Kas:

$$X_K = \left(s_j x_j\right)_{j \in K}. \tag{5.19}$$

In LARS, the updating rule can be written as follows:

$$\hat{\mu}^{new} = \hat{\mu} + \hat{\gamma}\mu_K \tag{5.20}$$

5.3.4 Evaluation of Forecasting Performance

5.3.5 Out-of-sample R squared statistic

To convey the economic significance of differences in forecast performance, I followCampbell and Thompson (2007), Welch and Goyal (2008), and Rapach et al. (2010) and consider the out-of-sample R squared statistic, defined as:

$$R^2_{OOS} = 1 - \frac{\hat{\sigma}^2}{\hat{\sigma}^2_0} \tag{5.21}$$

where $\hat{\sigma}^2$ represents the out-of-sample MSPE for the model of interest and $\hat{\sigma}^2_0$ represents the out-of-sample MSPE based on the historical average. A measure of the economic significance of forecast improvement relative to the univariate benchmark is expressed as a percentage:

$$\Delta R^2_{OOS} = \left(1 - \frac{\hat{\sigma}^2_2}{\hat{\sigma}^2_0}\right) - \left(1 - \frac{\hat{\sigma}^2_1}{\hat{\sigma}^2_0}\right) = \frac{\hat{\sigma}^2_1 - \hat{\sigma}^2_2}{\hat{\sigma}^2_0} \tag{5.22}$$

5.3.6 Giacomini and White (2006) test

The question of interests in this paper is that whether the macro economic and financial variables can improve the out-of-sample forecasting performance . To answer this question, a large number of forecasting tests focus on evaluating the out-of-sample forecasting ability of competing forecasts can be applied (Diebold

[2]LASSO is also a special cases of LARS (see details in Efron et al., 2004 and Bai and Ng, 2008).

and Mariano, 1995, West, 1996, McCracken, 2000, Clark and McCracken, 2001, Giacomini and White, 2006,Clark and West, 2007). Compared with the other forecasting tests, Giacomini and White (2006) have several exclusive appealing properties. For example, Giacomini and White (2006) can be applied for both nesed and non-nested models, whereas the West (1996) is not applicable for the nested models. Clark and West (2007) can only be applied for the linear nested models based on least square technique (Paye, 2012). In addition, Giacomini and White (2006) test is applicable for general estimation procedures including Bayesian and semi- and non-parametric estimation which are excluded from the Diebold and Mariano (1995), West (1996) and Clark and West (2007) framework. In this paper, we have both linear parametric nested models based on least squared technique and non-parametric SVR models. Therefore, we will use Giacomini and White (2006) test framework to assess the significance of predictive ability of macroeconomic and financial variables. Based on Giacomini and White (2006), we introduce the test as follows:

Given two alternative forecasting models $f_t\left(\beta_1\right)$and $g_t\left(\beta_2\right)$ where β_1 and β_2 are the population parameters, The objective is to compare the accuracy of these two models for the τ steps ahead variables $Y_{t+\tau}$ using a loss function $L\left(\cdot\right)$ under some set of information Φ_t available at time t. The null hypothesis of Giacomini and White (2006)) test states that the two alternative models have equal forecasting ability:

$$H_0 : E\left(L_{t+\tau}\left(Y_{t+\tau}, f_t\left(\hat{\beta}_{1t}\right)\right) - L_{t+\tau}\left(Y_{t+\tau}, g_t\left(\hat{\beta}_{2t}\right)\right) \mid \Phi_t\right) = 0. \tag{5.23}$$

The loss function used in the test depends on estimates $\hat{\beta}_{1t}$ and $\hat{\beta}_{2t}$, rather than on population parameters estimates $\beta_{1t}$and β_{2t}. The focus on the parameter estimation ennable the GW test to access the superiority of the forecasting method rather than the forecasting models which are the focus of West, 1996 and Clark and West (2007). Forecasting method is a broad concept which contain not only a set of model specification but also the procedures used to estimate forecasts. These procedures inlcude the estimation methods, the estimation window, and so forth. It is useful to express the null in terms of parameter estimates because it allows us to capture the impact of estimation uncertainty on relative forecast performance. For example, by comparing expected estimated mean squared forecast errors (MSE), rather than their population counterparts, we accommodate the possibility of a bias–variance trade-off such that forecasts from a small, misspecified model (biased with low variance) are as accurate as forecasts from a large, correctly specified model (unbiased with high variance). Because of its focus on the forecasting model rather than the forecasting method, the DMW approach cannot accommodate such a trade-off. This emphasizes the distinction between evaluation of a forecasting method, which is a practical matter, and evaluation of a forecasting model,which may be appropriate for obtaining economic insight, but is less informative for prediction purposes. Therefore, using the GW test, we can also compare the forecasting ability of different models using different forecasting methods. For example, we can compare the forecasting performance between linear parametric models and the non-parametric SVR models. In addition, we can also compare the forecasting ability of different linear parametric models such as the PCA, LARS and LARSEN. Using MSE as the loss function, the null hypothesis above can be adopted into the following format:

$$H_0 = E\left(\hat{\delta}_1^2 - \hat{\delta}_2^2 \mid \Phi_t\right) \tag{5.24}$$

where δ_1^2 and δ_2^2 represent the MSE of the two competing models, respectively. Taking $\Phi_t = \{\emptyset, \Omega\}$, conditional test become unconditional test of equal predictive ability. The Giacomini and White (2006) test then can takes the form:

$$GW = \frac{\hat{\delta}_1^2 - \hat{\delta}_2^2}{\hat{\delta}_P / \sqrt{P}} \tag{5.25}$$

where $\hat{\delta}_p$ is a heteroskedasticity and autocorrelation consistent (HAC) estimator of the asymptotic variance $\delta_p^2\left[\sqrt{p}\left(\hat{\delta}_1^2 - \hat{\delta}_2^2\right)\right]$. This unconditional test statistic is equivalent to the test statistic proposed by (Diebold and Mariano, 1995), and the asymptotic results in Giacomini and White (2006) provide a rigorous justification for this test when forecast parameters are estimated.

5.4 Data and Results

The data analysis parts including 5.4.1 and 5.4.2 is similar to 4.4.1 and 4.4.2 in Chapter 4. However, I put them here to keep the completence of this chapter.

5.4.1 Long-term Volatility Estimated from GARCH-MIDAS Models

This paper used the daily Shanghai A-share index from 28th December 2004 to 28th December 2018[3] to estimate the GARCH-MIDAS model with a fixed window RV and a rolling window RV, respectively. The long-term volatility from the model with the smallest SIC is used as the dependent variable in the subsequent forecasting equation. For each GARCH-MIDAS model, the beta lag structure will be firstly determined. According to Engle et al. (2013), the optimal ω1 is always 1 such that the weights decrease monotonically in the GARCH-MIDAS models with RV. Next, the optimal number of lags used in the long-term volatility specification will be determined according to the SIC criteria; Then, each model above will be estimated with the optimal number of lags.

According to Figure 4.1a, Figure4.1b and Table 4.1, the GARCH-MIDAS with a fixed span and rolling window RV produce the smallest BIC at the

[3]The stock return series starts from the 4th January 2005 which is the beginning of trading days to 28th December 2018. The long-term volatility is calculated from GARCH-MIDAS model using daily stock return series, so the the daily Shanghai A-share index from 28th December 2004 to 28th December 2018 is collected.

seventh and sixth lags by allowing the maximum number of lags to be 24, respectively. It should be noted that taking lags in model estimates leads to a loss of observations, as a result, both the short-term and long-term volatility obtained from the GARCH-MIDAS with a Fixed Span RV and Rolling Window RV start from 01/08/2005[4].

According to Table 4.2, most of the parameter estimates in these two models are significant at the 1% significance level. It can be seen that the covariance stationarity condition ($\alpha + \beta < 1$) is satisfied in the GARCH components of both the GARCH-MIDAS fixed span RV and rolling window RV. According to Figure 4.2a and 4.2b, there is a monotonically decreasing trend in the weighting schemes, implying that the recent information contained in the realized volatility is more important than the older information by allowing more weights. The parameter θ, which is of the most interest, determines how realized volatility affects long-term volatility. The significance of θ suggests that the information contained in both the fixed span and rolling window realized volatility has a significant effect on the long-term volatility. It can be seen from both Figure 4.3a and 4.3b that the long-term volatilities from the GARCH-MIDAS models are smoother than the realized volatilities, which is in line with the argument of Engle et al. (2013) that the GARCH-MIDAS model can be used to filter realized volatility in order to produce a smooth long-term volatility.

In this study, the long-term volatility from the GARCH-MIDAS model with a rolling window is used since the BIC of this model is smaller than that of the GARCH-MIDAS model with a fixed window RV. It should be mentioned that the GARCH-MIDAS with a rolling window RV model produced the lowest frequency daily volatilities. Therefore, as with Engle et al. (2008), a measure of the low-frequency volatility used in this paper can be defined as the average of the daily low-frequency volatilities over a long-term horizon—namely, one month.

5.4.2 Data Description

Table 4.3 lists the description of the data series, their source, transformations and any variable abbreviations. The first column presents the original variables which are collected based on the economic theory, previous empirical research and the Chinese economic and financial characteristics. Considering the data availability and increased development and openness experienced by China's stock market in recent years, the monthly data starts from December of 2004 to December of 2018, ensuring that the growth rate or return of these series can start from January of 2005, However, we lose 12 observations when calculating the volatility of the macroeconomic variables according to Equation (4.1). Therefore, the final dataset is from December of 2006 to December of 2018.

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[4]In this paper, monthly rolling window RV is used in GARCH-MIDAS with Rolling Window RV model. As a result, the first month data will be abandoned and hence the data actually starts from 01/02/2005. Therefore, the long-term volatility from GARCH-MIDAS with rolling window RV starts from 01/08/2005 considering the optimal number of lags is six.

The second column listed different sources of the data, namely, China's stock Market and Accounting Research (CSMAR) database, the RESSET database, the CEIC database, and Datastream. Among them, CSMAR and RESSET are widely used Chinese databases (Fan et al., 2007; Lo et al., 2010; Lyon et al., 2013; Li et al., 2015; Firth et al., 2016) and CEIC is a widely used Asian database (Chen et al., 2016b and Fernald et al., 2014). Apart from these databases, the US Federal fund rate is collected from the official website of the Federal Fund Board; the CBOE Market Volatility Index is collected form the official website of the Chicago Board Options Exchange (CBOE); China's Policy Uncertainty Index is collected from the website of Economic Policy Uncertainty.

The third column listed the transformed variables, Δln denotes the first difference of the logarithm of the variables transforming the series into the growth rate or return, lv represents the level of the series; Δlv denotes the first difference of the series; lv (Δlv) means that the level of the series contains a unit root and thus the series is differenced into the stationary process. It can be seen from the Table 4.3, the Philips-Perron (PP) test suggests that the Shibor, the long-term government bond rate and the spread between China's benchmark rate and federal fund rate all contain one unit root, and thus these three series are differenced (Bai and Ng, 2008). Apart from these three series, the others are all stationary. Equation (4.1) is estimated to produce the volatility of the series.

The last column listed the variable denotations. In addition, since PMI is only available since January of 2005, the PMI value in December of 2004 is imputed using the average of 12 months PMI in 2005. China's three month interbank offered rate from December 2004 to September of 2006 is used because of the fact that Shibor only starts from October of 2006. Because the tradings using hot money is too frequent to be monitored, there is no well-defined, direct method for estimating the amount of hot money flowing into a country during a period of time. Following Martin and Morrison (2008), we calculate the amount of hot money inflows as follows: (the change in foreign exchange reserves) minus (the trade and service balance) minus (foreign direct investment). In the analysis, the HM is the hot money inflow measured in billions of dollars in the preceding month. DF is the difference between the Chinese one-year lending rate which is regarded as the benchmark rate and the three month federal fund rate.

5.4.3 Results

To begin with we determine whether the macroeconomic and financial variables have predictive power for stock volatility after controlling for the lags of stock volatility itself. We have used both in-sample analysis and a one-step-ahead out-of sample forecasting framework to address this question. In both in-sample and out-of- sample analysis, we have constructed a benchmark model only containing the lags of the dependent variables and the models including the same number of lags of the dependent variables and some macroeconomic and financial variables, so that a number of nested models are implemented. In this paper, we not only consider the linear parametric models but also the non-parametric models. Specifically with parametric nested models, it is common to apply AR models as a benchmark, therefore, an AR(3) model (LLV_AR/LRV_AR) is used as the benchmark, where the number of lags were determined based on the BIC information criteria.

The competing model includes additional macroeconomic and financial variables selected using the DI, LARS and Elastic-Net (EN) approaches respectively. Based on the linear parametric nested models, we have constructed non-parametric models including the SVR(3) model as a benchmark (LLV_BSVR/LRV_BSVR) and the other SVR models including all the macroeconomic and financial variables (LLV_NSVR/LLV_NSVR). In the in-sample analysis, we compare the BIC of the benchmark models and the competing models along with the R-squared statistic in the SVR models[5] to assess the predictability of the macroeconomic and financial variables. Under the out-of-sample forecasting framework, we implement both recursive and rolling windows with one-step-ahead out-of-sample-forecast strategies for each model proposed in this paper to predict the one-step-ahead stock price volatility. Next, several forecasting criteria are applied to examine the predictive ability of the macroeconomic and financial variables. Specifically, the MSEs of the two competing model.

Table 5.1: Model Description

Regression Model	Depedent Variable	Predictors
Benchmark Model		
LLV_BSVR/LRV_BSVR	LLV/LRV	Three lags of LLV/LRV
Competing Model		
LLV_NSVR/LRV_NSVR	LLV/LRV	All the variables
Robust Regression Models		
Benchmark Model		
LLV_AR/LRV_AR	LLV/LRV	Three lags of LLV/LRV
Competing Model		
LLV_DI/LRV_DI	LLV/LRV	
LLV_EN/LRV_EN	LLV/LRV	Predictors selected by Elastic-Net
LLV_LARS/LLRV_LARS	LLV/LRV	Predictors selected by LARS

BSVR denotes the SVR benchmark model . NSVR denotes the non-linear SVR model using RBF kernel. EN denotes the Elastic-Net. AR denotes the Autoregression model. DI denotes the Diffusion Index forecasting model. The meaning of the model abbreviation, taking LLV_BSVR as example, can be explained as follows: the log long-term stock volatility is regressed on the its first three lags using SVR. The models with LRV are robust estimation techniques.

5.4.3.1 In-Sample Analysis

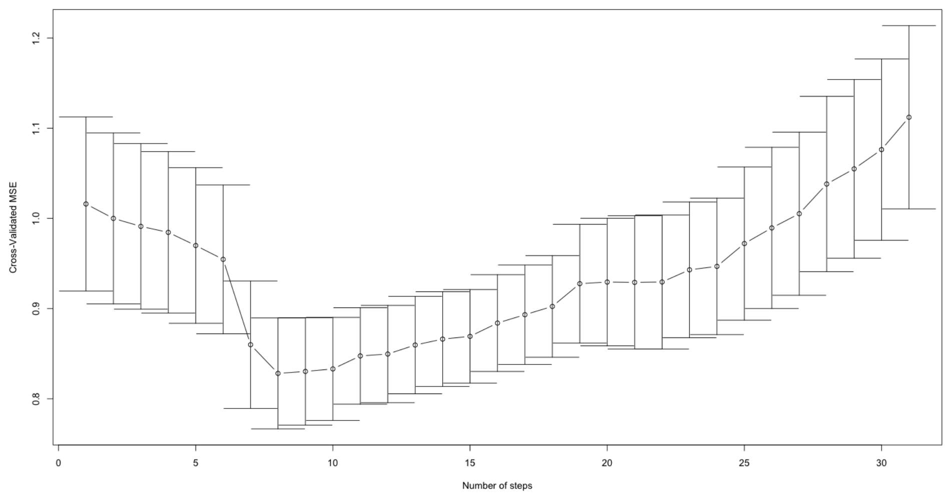
Regarding the in-sample analysis, Figure 5.1 shows the plots of the cross validation errors pathways and variables selection pathways in the penalized models.

[5] According to Diebold (2015), SIC is used to compare the models. Because there is no SIC statistic in SVR model, so we can only use R squares in SVR models.

Table 5.2 lists the selected variables in each model. It is evident that the volatility of the PMI is most correlated with the stock volatility in each case. The second most powerful effect is the volatility of investor sentiment. In addition M2, STR and PS are also shown to have an important correlation with stock volatility. To assess the forecasting ability of the macroeconomic variables, the benchmark models (LLV_SVR and LLV_AR) are compared with the competing models (the SVR model with all variables and penalized models with both the lags of volatility and the macroeconomic variables). Table 5.3 and 5.5 shows the results of the in-sample estimation and the competing models including the PMIV model outperform the benchmark models in all cases. It implies that the macroeconomic variable can predict stock volatility. In addition, it is also evident that the models using volatility from the GARCH-MIDAS method outperform the models using realized volatility. This is consistent with the arguments of Engle et al. (2013).

Figure 5.1: CV and Variables Path

(a) LLV_LARS_CV



(b) LRV_LARS_CV

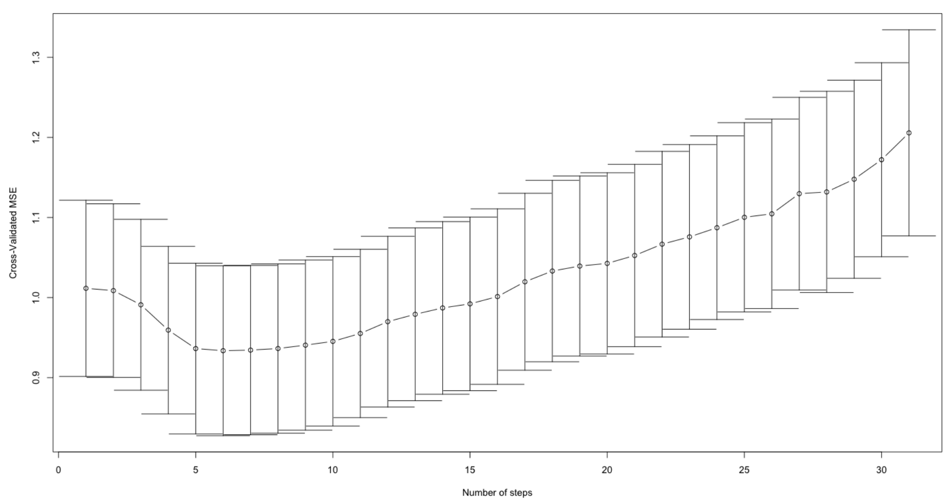
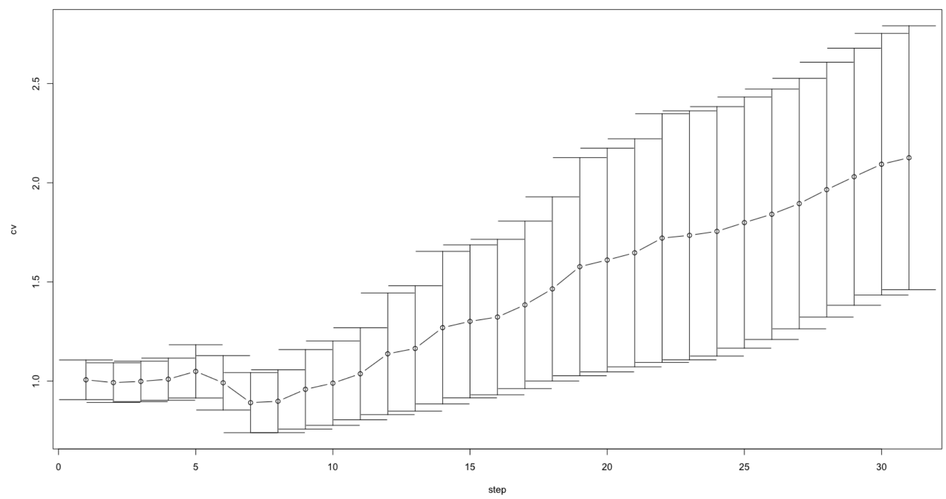


Figure 5.1: CV and Variables Path

(c) LLV_EN_CV



(d) LRV_EN_CV

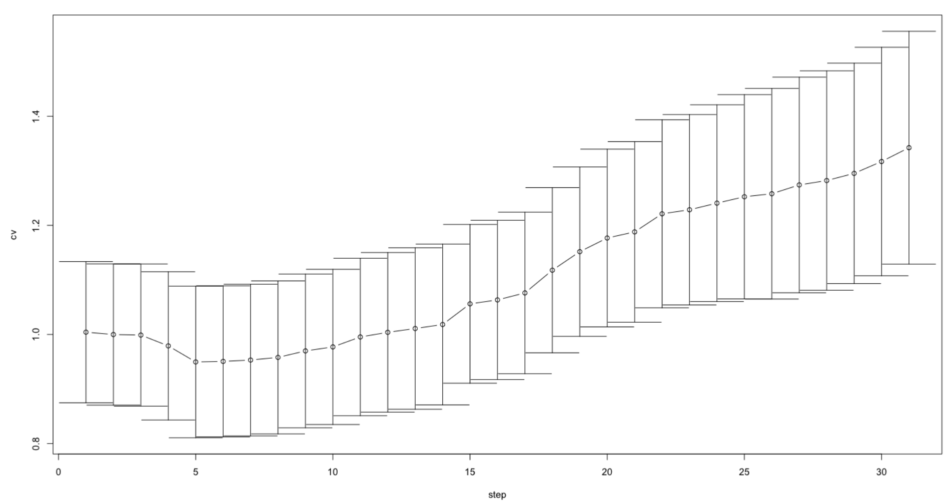
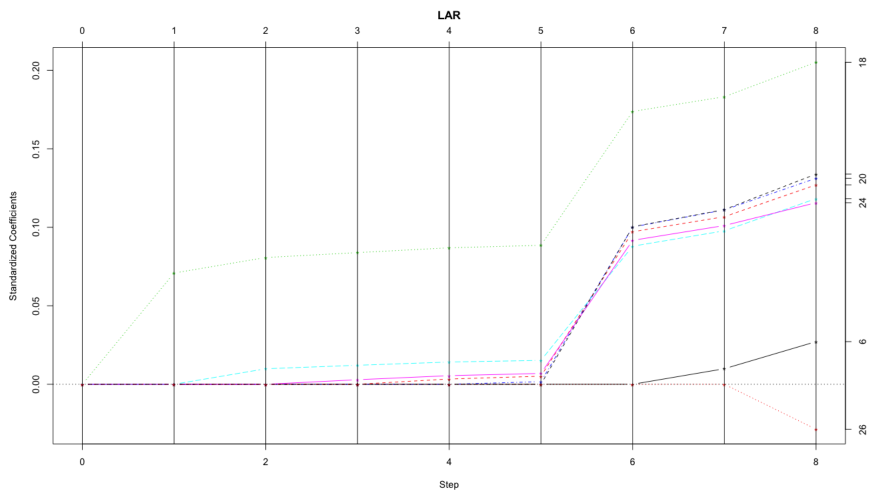


Figure 5.1: CV and Variables Path

(e) LLV_LARS_VARS



(f) LRV_LARS_VARS

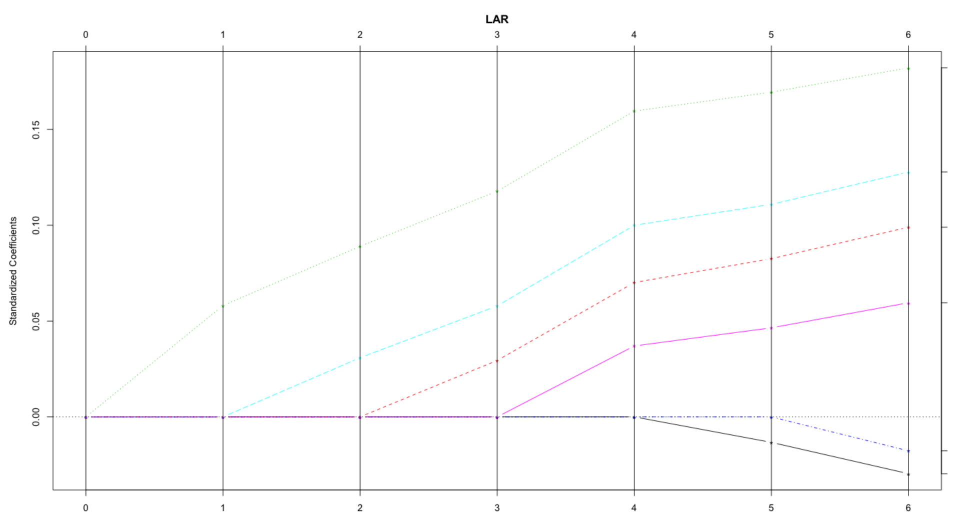
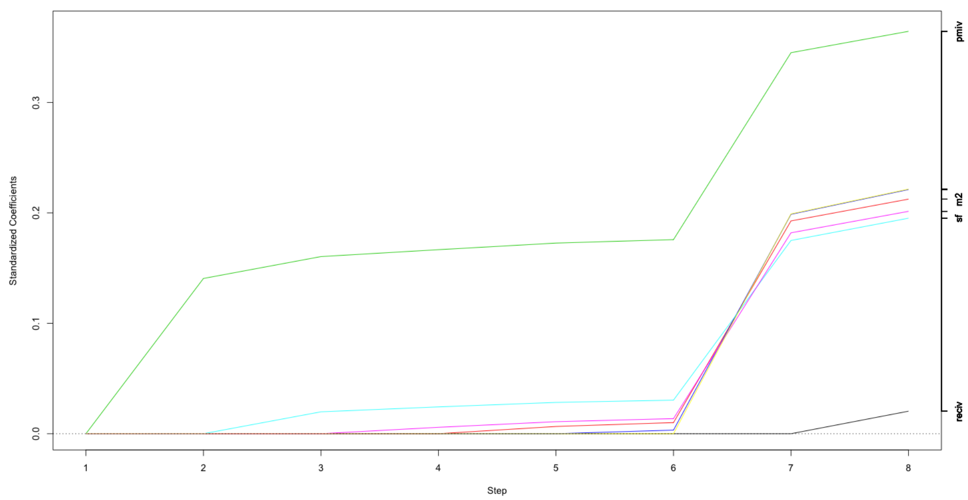


Figure 5.1: CV and Variables Path

(g) LLV_EN_VARS



(h) LRV_EN_VARS

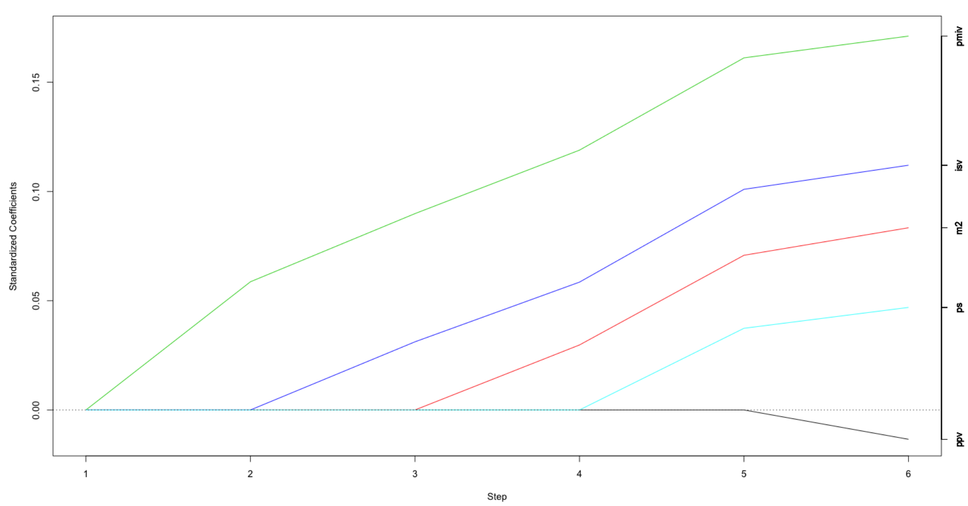


Table 5.2: Variable Selection

LLV_LARS	PMIV	ISV	STR	M2	PE	RECIV	PS	RP
LLV_EN	PMIV	ISV	STR	M2	PE	RECIV	PS	
LRV_LARS	PMIV	ISV	M2	PS	RPV	IS		
LRV_EN	PMIV	ISV	M2	PS	RPV			

The description of Variable abbreviation can be found in Table A.3

5.4.3.2 Out-of-Sample Analysis

In this study, the data sample includes 153 observations from April 2006 to December 2018 and has been divided into an estimation sample including 81 observations from April of 2006 to the December of 2012 and a forecasting sample including 72 observations from the January of 2013 to the December of 2018. For variable selection, as Engle et al. (2008) did, we do not restrict the optimal predictors to be same in each step of forecasting when using LARS and LARSEN to select the macroeconomic and financial variables. Instead, the predictors are selected at each step and the forecasting equation is re-estimated after new factors are estimated. In recursive estimation strategy, the first estimation is obtained using the sample from April of 2006 to the December of 2012,

Then, the forecasting model is re-estimated using a new estimation sample by including the observation at the next date into the previous one. The process goes as this until the last estimation is reached. In the rolling window estimation, the only difference is that the new estimation window is constructed by dropping the first observation of the previous estimation sample and adding new observation at next date into the precious estimation sample. After selecting the variables, the competing forecasting models against the benchmark model can be constructed by including these selected models. Therefore, for each variable selection method, we have 72 competing models because the variables selected in each estimation step are different.

The one-step-ahead forecast values can be obtained by feeding the new observations of the in- dependent variables at the next date into these 72 forecasting models. For example, in both the rolling and recursive window forecast, the first forecast at date January of 2013 is obtained based the forecasting model estimated using observation from April of 2006 to the December of 2012. The last forecast values at date December of 2018 in the recursive and rolling window forecasts are obtained based on the forecasting models using the observations from to April of 2006 to November of 2018 and March of 2012 to November of 2018, respectively. For the linear benchmark model and the SVR nested models, there is no need to select the macroeconomic and financial variables. Therefore, the forecasting models are firstly estimated using the observation in the estimation sample and the forecast can be obtained based on the estimated forecasting models. Then the forecasting models are re-estimated using new estimation sample and new forecast can be obtained based on the new estimated forecasting model.

Table 5.4 and 5.6 list the MSEs using the proposed models under the rolling window one-step-ahead out-of-sample forecasting framework. It can be seen that the LLV_BSVR model outperforms the LLV_NSVR model in terms of the MSE. To assess the statistical significance of this test, the GW tests are implemented and the results show that there is no significant difference between the performance of the benchmark SVR(3) mode and SVR model containing all the macroeconomic and financial variables.

The GW test is suggesting that the additional information contained in these macroeconomic and financial variables cannot produce a significant effect on the predictability of stock volatility and even produces a worse forecasting performance than the benchmark models. This might be due to the fact that the additional information contained in these macroeconomic and financial variables contains little power in predicting stock volatility, but also produces some noise leading to an even poorer forecasting performance. For the robust techniques, it can be seen that LLV_AR model has the smallest MSE among all these models and in addition, both MSE and GW test statistics suggest that LLV_AR model even outperforms the alternative models incorporating additional macroeconomic and financial information.

Using a recursive window one-step-ahead out-of-sample forecasting framework, the results are slightly different to those under the rolling window equivalent. Based on the MSEs shown in Table 5.4, LLV_BSVR model is slightly higher than that of the LLV_NSVR model (-0.0001). These results are consistent with the results of the GW test suggesting that the difference in the forecasting performance between LLV_BSVR model and LLV_NSVR model is significant. For the robust techniques, it can be seen that the LLV_LARS model (0.0085) outperforms LLV_AR model (0.0088). Although the MSEs based on LLV_DI (0.0114) and LLV_EN (0.0090) are slightly higher than the MSE of LLV_AR model. Therefore, all these statistics under the SVR models and linear parametric models in both rolling and recursive window forecasting frameworks suggest that macroeconomic and financial variables have no forecasting power of stock volatility after controlling for the lags of stock volatility.

In order to check the robustness of the results above, we repeat the process using LRV as the dependent variable volatility. The most distinct difference between the LRV method and using GARCH-MIDAS is that latter has a much lower MSE in each proposed model than the RV method. This is consistent with the argument of Engle et al. (2013) that the volatility generated using GARCH-MIDAS is much smoother than the realized volatility. Therefore, compared with RV, there is less noise using GARCH-MIDAS, and consequently, the forecasting accuracy of the stock volatility is improved substantially. Therefore, this suggests that it is better to use the GARCH-MIDAS method to measure stock volatility when forecasting stock volatility.

Table 5.3: LLV In-sample Results

Model	R squared/BIC
SVR	
Benchmark Model	
LLV_BSVR	0.7411
Competing Model	
LLV_NSVR	0.8231
Robust Regression Models	
Benchmark Model	
LLV_AR	-10703.37
Competing Model	
LLV_DI	-10711.42
LLV_EN	-10730.25
LLV_LARS	-10730.25

For robust regresson models, BIC is appled to compared the competing model and the benchmark model. For SVR models, R squared is used for comparison between the competing model and benchmark model because BIC is not avaliable in SVR model. The preference on BIC is according to the argument of Inoue and Kilian (2005, 2006) and Diebold (2015).

Table 5.4: LLV Out-of-sample Results

Model	MSE		ΔR^2_{OOS}		GW	
	Rolling	Recursive	Rolling	Recursive	Rolling	Recursive
SVR						
Benchmark Model						
LLV_BSVR	0.0090	0.00878				
Competing Model						
LLV_NSVR	0.0103	0.00884	-0.0022	-0.0001	0.98(-) [0.613]	0.15(-) [0.929]
Robust Regression Models						
Benchmark Model						
LLV_AR	0.0089	0.0088				
Competing Model						
LLV_DI	0.0112	0.0114	-0.0040	-0.0040	3.39(-) [0.184]	3.66(-) [0.160]
LLV_EN	0.0097	0.0090	-0.0014	-0.0003	2.73(-) [0.255]	0.21(-) [0.901]
LLV_LARS	0.0090	0.0085	-0.00002	0.0004	0.02(-) [0.988]	0.71(+) [0.702]

MSE denotes mean squared error; ΔR^2_{OOS} denotes the defference out-of-sample R squared between benchmark and competing model (Goyal and Welch (2008)); GW denotes GW test (Giacomini and White (2006)). In GW columns, the first value is GW test statistic; The sign in the prentheses shows whether the competing model outperforms the benchmark model, (+) means the competing model outperforms the benchmark model and (-) means the benchmark model outperforms the competing model; P value is in the braket and shows whether the competing model significantly outperform the benchmark model.
.

Table 5.5: LRV In-sample Results

Model	R sqaured/BIC
SVR	
Benchmark Model	
LRV_BSVR	0.5413
Competing Model	
LRV_NSVR	0.7235
Robust Regression Models	
Benchmark Model	
LRV_AR	-10308.7
Competing Model	
LRV_DI	-10324.32
LRV_EN	-10377.51
LRV_LARS	-10377.51

For robust regresson models, BIC is appled to compared the competing model and the benchmark model. For SVR models, R squared is used for comparison between the competing model and benchmark model because BIC is not avaliable in SVR model. The preference on BIC is according to the argument of Inoue and Kilian (2005, 2006) and Diebold (2015).

Table 5.6: LRV Out-of-sample Results

Model	MSE		ΔR^2_{OOS}		GW	
	Rolling	Recursive	Rolling	Recursive	Rolling	Recursive
SVR						
Benchmark Model						
LRV_BSVR	0.4995	0.5038				
Competing Model						
LRV_NSVR	0.5252	0.5423	-0.0204	-0.0257	2.82(-) [0.244]	0.98(-) [0.612]
Robust Regression Models						
Benchmark Model						
LRV_AR	0.4898	0.4977				
Competing Model						
LRV_DI	0.4898	0.4993	0.00003	-0.0011	0.70(-) [0.704]	0.69(-) [0.709]
LRV_EN	0.4941	0.4996	-0.0034	-0.0013	0.60(-) [0.742]	0.04(-) [0.981]
LRV_LARS	0.4823	0.4777	0.0059	0.0134	0.54(+) [0.765]	0.83(+) [0.660]

MSE denotes mean squared error; ΔR^2_{OOS} denotes the defference out-of-sample R squared between benchmark and competing model (Goyal and Welch (2008)); GW denotes GW test (Giacomini and White (2006)). In GW columns, the first value is GW test statistic; The sign in the prentheses shows whether the competing model outperforms the benchmark model, (+) means the competing model outperforms the benchmark model and (-) means the benchmark model outperforms the competing model; P value is in the braket and shows whether the competing model significantly outperform the benchmark model.
.

5.5 Conclusion

The question of interest is whether the macro economic and financial variables have predictive power for stock volatility after controlling the lags of stock volatility itself. Both the in-sample analysis and one-step-ahead out-of sample forecasting framework were applied to address this question. In both in-sample and out-of- sample analysis, we constructed a benchmark model only containing the lags of dependent variables and the models including the same number of lags of dependent variables and some macroeconomic and financial variables. In other words, a number of nested models are implemented. In this paper, we not only consider the linear parametric models but also the non-parametric models. Specifically, in the linear parametric nested models, it is common to apply AR models as a benchmark, therefore, an AR(3) model is used as the benchmark where the number of lags are determined depending on the SIC information criteria. The competing models were constructed by including additional macro economic and financial variables selected using PCA, LARS and LARSEN, respectively. Inspired by the construction of the linear parametric nested models, we constructed the non-parametric models including SVR(3) as a benchmark and the other SVR models including all the macroeconomic and financial variables. In the in-sample analysis, we compared the SIC of the benchmark models and the competing models in the parametric models and compare the R squared in SVR models to assess the predictability of the macroeconomic variables. Under the out-of-sample forecasting framework, we implemented both recursive and rolling window one-step-ahead out-sample-forecast strategies for each model proposed in this paper to predict the one-step-ahead stock volatility.

Next, several forecasting criteria were applied to examine the predictive ability of the macroeconomic and financial variables. Specifically, the MSEs of two competing models were first compared. Then, ΔR^2_{OOS} (Paye, 2012) was compared among the competing models. Because neither MSE nor ΔR^2_{OOS} can provide any statistically significant evidence, the GW test was applied to examine whether the difference in forecasting performance of these competing models is statistically significant. Lastly, we used the realized volatility as the dependent variables in order to assess the robustness of the results. When the realized volatility was applied as the dependent variable, the SIC information criteria suggested that only one lag of the realized volatility should be included in the benchmark model. Therefore, the AR(1) model and SVR(1) model are used as benchmark models in linear parametric and non-parametric models system, respectively.

Using the data and models, the in-sample results showed that macroeconomic and financial variables have the ability in predicting China's stock volatility. However, considering that a large number of literature criticized the in-sample analysis, we rely more on the out-of-sample results. Under the out-of-sample forecasting framework, both rolling window and recursive window one-step-ahead out-of-sample forecasting are implemented to get the forecasts of the stock volatility. Then three different prediction criteria, namely MSE, ΔR^2_{OOS} and GW test, are used to assess the predictive power of the macroeconomic and financial variables. The results showed that there is no evidence showing that the macroeconomic and financial variables have ability in predicting Chinese stock volatility after controlling the lags of stock volatility itself, which is consistent with the finding of Paye (2012). Paye (2012) argued that the lags of the stock volatility have captured the information contained in the macroeconomic financial variables such that no additional information can be exploited by the forecasting models or methods to improve the forecasting accuracy. Another interesting finding is that using the stock volatility obtained from the GARCH-MIDAS model can produce a better forecasting performance than using realized volatility which is commonly used in the literature (Schwert, 1989; Paye, 2012). It should be mentioned that the results are robust because of the fact that both the linear parametric and non-parametric models, both the rolling window and recursive window forecasting strategy, both the commonly used measurement of volatility RV and the volatility based on the fancy GARCH-MIDAS method and three different forecasting accuracy criteria were applied to investigate the question of interest in this paper.

However, this study has a number of limitations. First, it would be better to apply more data when using machine learning techniques. However, the data used in this study is relatively limited due to the data availability in China, though the data has become more available in recent fifteen years than before. Second, this study only made the one-step-ahead forecasting, which is the most widely used in the literature about forecasting, however, the multiple-steps-ahead forecasting could be implemented in the future studies to provide more robust analysis. Third, this study only considered the US stock market as the international variables. However, the Japan's stock market could be accounted for in the future studies.

Chapter 6

Conclusion

6.1 Conclusion

Chinese stock markets have experienced unprecedented development over the last thirty years, especially over the last fifteen years, during which a series of significant reforms and initiatives have been implemented regarding e.g., market privatization, market openness, financial instruments abundance and enhancement and the establishment of the risk management system. As a result of the development, the Chinese stock market has grown to be the second largest stock markets in the world and thus are playing a pivotal role in China's economy and international finance and economy. For example, MSCI quadrupled the amount of the China A-shares in its major benchmarks to 20% in 2019. China's stock markets have served as major investment markets for both the domestic and international investors, who have been especially welcomed by the financial institutions.

However, it is clear as well that China's stock markets are still undeveloped compared with the developed stock markets such as the US stock market although this significant development has been achieved over recent years. There is still a long way to go with both various opportunities and risks waiting for China's stock markets to proceed to reach the maturity level.

Given the complicated and interesting properties of China's stock markets, there have has been a relatively limited level of literature focusing on studying the Chinese stock markets from a wide range of topics. However, some basic questions in finance regarding the market efficiency, financial risk modeling and forecasting have not as yet been well researched. This issue is naturally raised by the complications inherent in China's stock markets, for example, it is difficult to capture the fast changing behavior of the Chinese stock prices caused by obscure and interactive shocks. In addition, the wide availability of the econometric models and increasing amount of data produce more difficulties for the researchers. As a result, a consensus, by far, has not yet been reached on these basic questions. This thesis, therefore, aims to provide more concrete evidence to these questions.

Specifically, this thesis has firstly aimed to examine the efficiency of China's stock market given the distinguished development over the last fifteen years. Using a variety of tests including both the traditional techniques and advanced recently developed techniques on the nonlinearity and nonstationarity of China's stock returns, this thesis found that the Chinese stock market displayed nonlinearity while this nonlinearity is characterized by the smooth structural breaks rather than the sharp structural breaks as has happened in the developed stock markets. This encouraging finding distinguished this study from the majority of studies investigating the efficiency of Chinese stock markets which focus on the sharp structural breaks as the cause of the nonlinearity.

Accordingly, the panel unit root test, which allows for the smooth structural breaks as well as that the cross-dependence between the shocks in the panel is considered using the information contained in the macro variables as common factors, is used in this thesis and have more power to investigate the efficiency of the stock markets. They indicated that China's stock markets are weak-form efficient. This finding mainly contributed to not only shedding a light on the efficiency of the Chinese stock market, but also provides more confidence to the policy makers, who, therefore, can continue to develop and open the stock markets, and the investors, who can have more confidence when investing in China's stock markets.

Then, this thesis investigates the drivers of China's stock markets risks measured by stock return volatility. This thesis considered a comprehensive set of potential drives including the international factors, especially the US stock markets, macroeconomic and financial variables, and variables related to the development, openness and privatization of China's stock markets which has distinguished this study from many existing research investigating the drivers of China's stock volatility.

In addition to the data, this thesis also applied the LASSO regression, a well-known and widely used variable selection technique, and the recently developed creative significance tests based on the LASSO regression to not only select the important drivers the importance of which can be achieved using LARs algorithm, but also to produce the statistical significance of these selected drives. This is the first study that produced the statistical inference for the selected variables, helping to get a better understanding on the drivers of China's stock volatility. More importantly, The findings found that the VIX index, a variable measuring the fear of the US stock markets, have the most significant impact on the Chinese stock volatility, which reflects the fact that China and the US are increasingly integrated with each other over the last thirty years, especially since China joined into the WTO at late 2001.

Further, this thesis applied the Bayesian time-varying structural VAR model to investigate the dynamic impact of the US stock market represented by the VIX index over time. Interestingly, the results showed that China's stock volatility is affected most heavily during the Jinping Xi and Donald Trump presidency compared with the Jinping Xi and Barack Obama presidency and Jintao Hu and Barack Obama presidency. This implied that the China-US trade war has had an significant effect on China's stock market. In addition, another finding has shown that the variables related with the openness and development of the Chinese stock markets played an important role as well in driving China's stock volatility.

Since some variables have been shown to play an important role in driving China's stock volatility, it should be useful to incorporate the information contained in the potential drivers into the volatility prediction models. This takes the thesis into the last objective aiming to investigate whether the accuracy of China's volatility prediction can be improved by including the information contained in the potential drivers conditional on the past information captured by the lags of the volatility.

Using a variety of forecasting models including the traditional predictive regression models, the factor model and the machine learning models such as the penalized regression models and Support Vector regression model under both the in-sample and out-of-sample forecasting frameworks, this thesis found that the information contained in the potential drivers is not useful in predicting China's stock volatility although the drivers have significant effects in explaining the changes of China's stock volatility. This indicated that the information contained in the drivers has been already captured by the lags of the volatility, which implied that China's stock markets are weak-form efficient, consistent with the conclusion of the third chapter of this thesis.

This findings are strongly supported by the application of the powerful machine learning techniques which will be applied in many areas in the economy and finance due to its superiority over the majority of existing Econometric models in term of dealing with big data and overfitting problem.

In summary, using recent Chinese data in the last fifteen years during which China's stock market experienced comprehensive changes and a variety of both econometric models and machine learning techniques, this thesis studies the basic questions in finance regarding the market efficiency and volatility modeling and prediction. The results show that China's stock market is weak-form efficient, and the information contained in some macroeconomic and financial variables plays a significant role in driving China's stock volatility but isn't useful in predicting China's stock volatility, which in turn suggests that China's stock market is weak-form efficient.

6.2 Policy Suggestions

These results suggest that a series of reforms and initiatives primarily regarding the openness, trading, privatization, liberalization and legalization which are mentioned in Chapter 2 have indeed promoted the efficiency of China's stock markets. However, in recent years, the Chinese stock market has suffered numerous shocks. The most recent is known as the 2015–16 Chinese stock market turbulence. As explained in Chapter 4, the instability of China's stock market is attributed to both the external and internal factors. Therefore, in order to achieve the long-term stability and efficiency, this thesis suggests the following policy directions. First, it is necessary to enhance the quality of listed companies and their investment value. Particularly, since China is experiencing a structural transition form a industrial oriented economy to a tech-oriented economy, more high-tech innovative firms with a good quality should be allowed to be listed in the stock market through IPO. Meanwhile, to maintain and even promote the level of industrialization, the state-owned reforms regarding the ownership structure should be further strengthened to increase the vitality of blue chip stocks. Second, the long-term capital should be increased into the stock market. the pension system reforms would provide a stable long-term capital sources for the stock market. Meanwhile, allowing more foreign institutional investors to invest in China's stock market can also achieve the long-term capital and promote value investment. Third, the supervisory system should be strengthened, which, on the one hand, can increase the creditability of the listed companies, on the other hand, can attenuate the market manipulation activities. This can protect the legitimate rights and interests of investors, especially small and medium investors, to increase their confidence in China's stock markets.

6.3 Limitations and Future Studies

However, this thesis has several limitations: First, Chapter 3 only used the unit root tests to investigate the weak-form efficiency of China's stock markets, it would be more robust to include the results from other techniques (e.g., Bai et al., 2016; Carpenter et al., 2020). In addition, the macroeconomic variables used as common factors to deal with the cross-sectional dependence in the panel unit root test are based on the suggestions by, which might not suitable for China's stock market.Second, Chapter 4 applied GARCH-MIDAS model to produce the stock volatility, and then regress dependent variable on a set of macroeconomic and financial variables. A robust analysis would include the regression of realized volatility on those independent variables should be implemented. In addition, the data used in this thesis only account the US and Hong Kong stock markets as the international factors in driving China's stock volatility, other foreign stock markets should be considered, e.g., the Japan's stock markets. Moreover, since the data about China's economy and finance is too limited compared with that for the US, the power of significance tests based on the machine learning techniques (LASSO and LARS) applied in Chapter 4 possibly cannot be fully exploited. Third, in Chapter 5, the data availability is a key limitation for using machine learning techniques (SVR, LASSO, LARS and Elastic-Net).

According to these limitations, the future studies can apply the other techniques to study the efficiency of China's stock market and can apply some machine learning techniques to select the most relevant macrovariables as the common factors in the panel unit root test (Pesaran et al., 2013 and Lee et al., 2016a). In addition, this thesis suggested that China's stock market has achieved the level of weak-form efficiency, but since China's stock market is growing quickly, future studies may want to revist this analysis with updated data and techniques. Machine learning techniques have began to attract economists' attention in both prediction and causal analysis, as more and more data becomes available in the future, these techniques will enjoy a overwhelming advantage in dealing with the overfitting problem in prediction and heterogeneity problem in economics and social science (see, Athey and Imbens, 2017; Henrique et al., 2019). Current economic and financial empirical literature currently still uses econometric models to carry out analysis, future studies can apply machine learning techniques as alternatives to compare with the econometric models when the data is not largely available. If data is large, it is necessary to focus more on machine learning techniques to deal with the research problems. Future studies are also recommended to focus more on China's stock market. Compared with the volume of China's economy which has become the second largest one, China's stock market has much to be developed to match with the economic development. This thesis has already put an emphasis on the development and openness of China's stock market, the future studies can investigate the effects of future development and openness of China's stock market on the market efficiency, capital allocation, risk diversification, and the market internationalization.

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