



**Modelling Dynamic Financial Linkages, Spillover Effects
and Volatility Transmissions: Empirical Evidence from
China and International Financial Markets**

A thesis submitted in fulfilment of the requirements for
the degree of Doctor of Philosophy

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Declaration

I certify that except where due acknowledgement has been made, the work is that of the author alone; the work has not been submitted previously, in whole or in part, to qualify for any other academic award; the content of the thesis is the result of work which has been carried out since the official commencement date of the approved research program; any editorial work, paid or unpaid, carried out by a third party is acknowledged; and, ethics procedures and guidelines have been followed.

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Executive Summary

Over the last two decades, there has been a considerable change in the economic performance of China, making it the world's most powerful emerging market and the second largest economy in the world. China's stock market is now well developed and strongly influenced by global economic factors, regional financial development in Asia and local economic growth in China. Many crucial economic and financial reforms have been implemented, making the Chinese stock market more open to the world. Two well-established stock exchanges, based in Shanghai and Shenzhen are now operating with significant interdependence with other financial markets around the world.

The degree of market co-movements is an essential factor for determining the diversification opportunities across different financial markets. International stock market linkages have been extensively examined by empirical literature, suggesting that financial market integration is able to influence market co-movements. Given the increased market integration between China and other financial markets, this thesis investigates the dynamic financial linkages, spillover effects and volatility transmissions among different financial markets within China and between China and global markets, as strong interdependence among financial markets could lead to higher exposure to contagious effects when one market experiences a serious crash. Furthermore, this study also provides important practical implications for investors, portfolio managers and policy-makers based on the empirical findings.

The primary objective of this study is to investigate the nature and extent of market interdependence among the Chinese stock markets, the Chinese financial derivative markets and international stock markets. Various advanced econometrical models, including Vector Autoregression (VAR) models and Generalised Autoregressive Conditional Heteroscedasticity (GARCH) models, will be used to explore both return and volatility transmission mechanisms between different financial markets from China's perspective. In order to achieve the key objective, this study conducts four inter-related research undertakings as follows: 1. An examination of spillover effect between the Shanghai and Hong Kong stock markets while evaluating the impact of the recently introduced Shanghai-Hong Kong Stock Connect; 2. An investigation of financial linkages, information transmission and market co-movement in the Asia-Pacific region; 3. The work further considers dynamic relationships between the Chinese stock market and its index futures

market while evaluating the influence of Qualified Foreign Institutional Investors (QFII) scheme; and 4. An evaluation of dynamic spillovers among global oil price, equity and commodity markets in the Chinese region.

The purpose of the first empirical focus is to investigate the impact of Shanghai-Hong Kong Stock Connect by analysing the dynamic interdependence between the Shanghai and Hong Kong stock markets. High-frequency data are used to deeply examine the price movement and volatility behaviours of the two markets. The newly introduced Stock Connect initiative contributes to the increasing importance of the Chinese mainland stock market. Particularly, the increased conditional variances in both stock markets together with a weak and unstable cointegration relationship are observed following the introduction of Stock Connect. The observed strengthened volatility spillover effect from Shanghai to Hong Kong indicates a leading role of the former over the latter after this financial liberalisation reform. Overall, the empirical results suggest that the opening of Chinese mainland stock market could enhance the leading power, influence the risk level and improve the market efficiency of the Shanghai stock market. The success of the Shanghai-Hong Kong Stock Connect initiative provides valuable operational experience for the forthcoming Shenzhen-Hong Kong Stock Connect. In this way, the Chinese government should continue liberalising its financial markets to improve their market efficiency.

In the second empirical study, the price and volatility dynamics between China and major stock markets in the Asia-Pacific region around the Chinese stock market crash of 2015-2016 are analysed. Based on our estimation results of the Bayesian VAR and BEKK GARCH models, this study finds that price and volatility spillover behaviours are different during stable and stress periods. In particular, price spillovers from China to other regional markets are more significant during a bullish period, showing that ‘good news’ emanating from China has stronger impacts on its neighbours when China’s market increases. In the turbulent period, strong shock spillover effects from China to most Asia-Pacific stock markets and the enhanced volatility spillovers from China to the Asia-Pacific region are observed, implying an increasing degree of market interdependence across regional markets and the importance of China as a strategic financial centre in the region. The Asia-Pacific stock markets are also found to spill over their shocks to China during the crisis, showing that China is becoming more integrated with the regional financial markets.

The impact of the Qualified Foreign Institutional Investors (QFII) reforms on the dynamic relationship between the Chinese stock index futures and spot markets is further examined. 5 minutes high-frequency data together with various dynamic methods including VECM, GJR, BEKK and DCC GARCH models are employed to investigate the price discovery role and volatility spillover effect. This study finds a bi-directional asymmetric lead-lag relationship between the Chinese stock index futures and its underlying markets, indicating the futures market leads the spot market significantly, but there is a weak lead from the spot market to the futures market from the perspectives of both magnitude and lasting time. It is observed that the introduction of the QFII has enhanced the price discovery role of the futures market and increased the predictive power of the futures market. In addition, the Chinese stock index futures market is found to become less volatile (risky) and probably more efficient after the introduction of QFII. The enhanced volatility spillover effect from the futures market to the spot market is evident after the participation of foreign institutional investors in trading stock index futures contracts, suggesting an improvement in information transmission running from the futures to the spot market. The dynamic conditional correlation between the futures and spot markets decreases and becomes more volatile after the introduction of QFII, implying that the futures and spot markets become less correlated after the QFII.

Finally, the thesis provides a comprehensive analysis of dynamic spillover effects among the Chinese stock market, the Chinese commodity market and international oil market. Using a trivariate VAR-BEKK-GARCH model to estimate market volatility and its interactions, this study finds significant uni-directional return spillover effect from oil market to stock market, suggesting a strong dependence of the Chinese stock market on the oil market. The analysis results also indicate significant uni-directional return interaction from the Chinese stock market and global oil market to some key commodities in China. In particular, significant return contagions from the Chinese stock market to copper and aluminium futures and from oil market to silver, copper and aluminium markets are observed. The non-existence of return spillovers between gold and stock (oil) suggests the safe-haven role of the gold. In terms of the volatility spillovers, this study finds bi-directional shocks spillovers between oil and stock markets but uni-directional volatility spillovers from the oil market to the Chinese stock market. For commodities, the results show evidence of strong uni-directional shock and volatility spillovers from the stock market or oil market to some commodities. However, there are no spillover effects from all the commodity markets to

either the stock market or oil market, meaning there are potential diversification benefits from the Chinese commodity markets. Finally, important implications for portfolio management and hedge strategy are provided.

This research makes significant contributions to the empirical literature on the financial linkages and volatility transmissions by empirically examining the influence of several important Chinese financial liberalisation reforms and comprehensively analysing the dynamic interdependence between the Chinese stock market and its interrelated financial markets. Since understanding information transmission between financial markets is critical for both market participants and policy-makers, the results of this thesis will help to facilitate an enhanced understanding of information transmission mechanism and risk contagions. As volatility contagions greatly affect smooth functioning and economic viability of financial markets which are the major concerns of investors and policy-makers, therefore a better understanding of the drivers and origins of market volatility can assist them in the decision-making process.

Policy-makers may also use this information to introduce new financial instruments, propose prudent financial regulations and implement policy tools in a timely manner. In addition, important practical implications can also be drawn from this thesis. As the findings of this thesis indicate more integration between the Chinese stock market and other markets, these markets have become more interdependent and improved their efficiency in terms of market information transmission. In addition, the increased level of financial integration also underpins cross-borders capital flow and international investment which are key drivers of local economic growth and fosters international risk management for portfolio optimisation. Consequently, it is suggested that investors and policy-makers actively monitor market movement and the degree to which China's financial market is integrated. This will make it possible to predict future returns and volatility of other inter-related markets.

Chapter 1: Introduction

1.1 Introduction

China's economy has been successfully transformed to a more open market economy under 'socialism with Chinese characteristics' since the introduction of reforms in 1978. The success of China's economic reforms has significantly contributed to the establishment of financial markets, eased controls on capital movement and released restrictions on foreign investment. This study investigates the financial linkages and volatility transmissions regarding China, providing insights into the roles of China in return and volatility spillovers in developed and emerging markets. It should be noted that the recent market liberalisation reforms embraced by the country may have amplified the international transmission of volatility from and towards China. Even though research on the concept of contagion and volatility spillovers has been researched since the 1987 US October Crash, this study is timely due to the rising influence of China and its tighter financial and trade linkages with the Asia region and other emerging markets. It is therefore important to analyse volatility spillover impacts emanating from China due to its increased financial integration, especially during times of stress. Given that China is one of the fastest growing economies in the world, it is compelling to investigate the relative importance of different shocks from China and how they increase instability and volatility.

The economic liberalisation reforms that began in 1978 had a tremendous impact on China's economic growth and the whole of its society. After China joined the WTO in 2001, China has significantly increased its interaction with the rest of the world and become more integrated with regional economies. The rapid growth of the Chinese economy has a huge influence on the whole Asia-Pacific region. As China overtook Japan as the world's second-largest economy and replaced Germany as the world's largest exporter of goods in 2009, it started to play a more important role both regionally and globally. As a result, the centre of gravity of the regional and global economy is moving to China. As the world's second largest economy, and being the largest emerging market economy and also the largest exporter of goods, China is on its way to being the economic powerhouse of the Asia-Pacific region and is widely regarded as the principal engine of world economic growth (Das, 2012).

The Chinese financial market has also expanded tremendously after the establishment of two stock markets (Shanghai and Shenzhen Stock Exchanges). As a young financial market, but the largest emerging market, the Chinese stock market provides a good return and diversification benefits, while also attracting a large number of domestic as well as foreign investors. However, China's financial market is still imperfect, incomplete, not fully integrated globally and it has several unique characteristics, resulting in different market behaviours (Johansson, 2010). It is therefore important to know how Chinese domestic stock markets interact with the other markets due to increasing globalisation and financial liberalisation which contribute to the correlation and connectedness between financial markets. It is worth exploring the interaction between different stock markets within China, the spillover effect between China and other equity markets in Asia-Pacific and the dynamic behaviours of the stock market and derivative markets.

The understanding of the correlations and interactions among various stock markets is crucial for investors, regulatory bodies, and government, and thus it is an important part of financial risk management. For the past three decades, many significant events and financial crises have taken place, resulting in rising financial markets risk and volatility (for example, the US October Crash (19 October 1987), the Japanese Economic Bubble (1989), the Asian Financial Crisis (1997), the Russian Default Crisis (1998), the 9/11 attacks (2001), the Global Financial Crisis (2008) and the Chinese stock market crash (2015)). It is interesting that different financial markets around the world behave in such a manner where larger stock markets have spillover effects on the relatively smaller markets, especially during the crisis periods. The reasons why they are affected simultaneously despite the differences in economic fundamentals, market mechanisms and degree of mispricing can be attributed to some activities such as international trading, information transmission theory and globalisation.

Since the US October Crash in 1987, the research on the spillover effect becomes prominent and critical, due to its huge impact on other stock markets. The impact of financial liberalisation and globalisation has also caused international financial markets to become more interdependent and integrated. The spillover effect among developed countries has been widely researched (see for example, Eun and Shim, 1989; King and Wadhvani, 1990; Hamao et al., 1991; Theodossiou and Lee, 1993; Lin et al., 1994; Susmel and Engle, 1994). Most early studies could observe strong contagion effects from the US to others. As the

emerging markets developed, the research on the spillover effect is also extended to the emerging markets (see for example, Kim and Rogers, 1995; Hu et al., 1997; Bekaert and Harvey, 1997; Ng, 2000; Alaganar and Bhar, 2002; Baele, 2005). The empirical studies on emerging markets indicate that emerging markets have become more integrated with other of the world's markets. The impacts of the Asian Financial Crisis and the Global Financial Crisis on the spillover effect have also been examined with evidence showing that the financial crises significantly influence on market co-movement (Cheung et al., 2009; Yiu et al., 2010; Zheng and Zuo, 2013).

In terms of the spillover effect between China and other markets, some studies investigate this interesting and important issue but could not reach to a consensus. Some studies find evidence that the spillover effects originate from more advanced markets such as the US, Japan and Hong Kong and go to China's mainland stock market (Wang and Firth, 2004; Li, 2007; Huang et al., 2000). Some studies indicate that China is not well integrated with the rest of the world. For example, Lin et al. (2009) reveal that the Chinese A-Share market has never been correlated with the world market whereas the Chinese B Share market is found to be correlated with western markets at a low degree but with other Asian markets at a higher degree. As the Chinese stock market becomes more open, the increasing financial integration between China and global markets has been observed, and therefore some studies identify the influential power of China. Zhou et al. (2012) indicate that the volatility of the Chinese market is observed to have significantly positive impacts on other stock markets since 2005 with more prominent interactions among China, Hong Kong and Taiwan. Allen et al. (2013) find evidence of spillover volatility from the Chinese stock markets to its neighbours and trading partners such as Hong Kong, Australia, Japan, Singapore and the US.

Although there has been some research on spillover effect between China and other markets, there are still gaps in the literature on the drivers of economic interdependencies, especially from the emerging markets' perspective. Not many studies focus on the impact of significant events, such as economic slowdown, on the financial spillovers from China to its related financial markets. A significant example of financial liberalisation occurred on 17 November 2014 when the Shanghai and Hong Kong stock exchanges were connected via the new channel known as Shanghai-Hong Kong Stock Connect. This is now regarded as one of the most important financial reforms after Hong Kong returned to China in 1997. The impact of this event would result in a significant increase in the capital flow between Shanghai and

Hong Kong. This significant event also motivates the investigation of the spillover effect changes after the introduction of Shanghai-Hong Kong Stock Connect, and whether it impacts on the level of volatility in both markets. In this study, both Shanghai Stock Exchange Composite Index and Hong Kong Hang Seng Index will be used to investigate the effects of Shanghai-Hong Kong Stock Connect due to their importance and relevance.

Most studies found evidence for the spillover effects going from the global and/or the regional financial centres to other countries. However, not much research has been done on China treating it as an important regional financial centre when investigating the spillover effect between it and the Asia-Pacific region. As China gradually becomes one of the most important regional financial centers in Asia-Pacific, it is expected to be more interactive with its neighbours, and therefore it motivates this study to explore spillover effect between China and Asia-Pacific markets. The recent Chinese stock market crash had a significant impact on not only China but also other stock markets throughout the world. This research fills the gap in the literature by comparing the spillover effect between China and other countries in the Asia-Pacific region during crash and non-crash stages to observe whether: firstly, this crisis did influence the information transmission mechanism process between Asia-Pacific stock markets and China; and secondly, the Chinese stock market increased its influence regionally.

While spillover effect between stock markets is an important area of research, due to the global transmission of information through multiple channels, how the stock market is affected locally by another market cannot be ignored. The stock index futures market is one of the most important local financial markets which are highly correlated with the stock market since the introduction of the first stock index futures (S&P 500 Index futures) in the US in 1982. The stock index futures market is observed to be more efficient due to lower transaction costs, fewer restrictions and leverage effect, playing an important price discovery role (Kawaller et al., 1987; Harris, 1989; Stoll and Whaley, 1990). In order to better understand how information flows between the index futures and spot markets, studies also investigate volatility transmissions between the two markets and indicate shocks from both markets can affect the volatility in the other market (Chan et al., 1991; Koutmos and Tucker, 1996).

The Chinese stock index futures market as a newly established stock index futures market has attracted increasing interests of researchers. Yang et al. (2012) conduct the first comprehensive analysis of price discovery role and volatility transmission regarding the

Chinese stock index futures market but could not find evidence of its price discovery function. Hou and Li (2013) perform a similar study and indicate strong evidence of price discovery of CSI 300 futures market one year after started operating. During the initial stages of the Chinese stock index futures market, the allowance of Qualified Foreign Institutional Investors (QFII) to trade on CSI 300 index futures has become one of the most important financial liberalisation reforms. Several studies indicate that these foreign institutional investors may be informed enough to have significant predictive power in the options and futures markets (Lee et al., 2013; Chang et al., 2009). This provides the motivation for this study to investigate the impact of QFII on the price discovery role of the Chinese stock index futures market and volatility transmission between futures and spot markets.

Commodity markets are also found to be interdependent with equity markets and have become more integrated with stock and bond markets in recent years (Delatte and Lopez, 2013; Creti et al., 2013; Silvennoinen and Thorp, 2013). Most empirical studies on the connection between commodities and stock markets focus on advanced markets such as the US and Europe. Little attention has been paid to Asian markets, especially China, and therefore the literature gap enables us to investigate the spillover effect among international oil market, China's stock and commodity markets. In doing so, a deeper analysis of interdependence structure between the three financial variables is provided.

1.2 Contribution and Significance of This Study

This study extends the limited finance literature on return and volatility spillover effects in China and emerging markets. It investigates the market interdependence and volatility transmissions between the Chinese stock market and other financial markets, including both domestic and international markets. The significance of this study arises from the importance of China due to its large economic scale and financial influence. To understand the behaviour of the Chinese stock market, this research has four different perspectives. The first two parts look at the spillover effect between China and other stock markets including Hong Kong and the major markets in the Asia-Pacific region. The last two sections examine the joint behaviour relationship between the Chinese stock market and several derivative markets including the stock index futures market and commodity market.

This study creates knowledge by providing a comprehensive analysis of how shocks can be transmitted between China and other financial markets, evaluating the impacts of several financial liberalisation reforms on information transmission, and comparing differences of market co-movement and volatility spillovers between the crash and non-crash periods. Contributing to the research on spillover effects, this thesis utilises sophisticated multivariate GARCH models together with other advanced financial and econometric tools such as cointegration and causality tests, portfolio construction and hedging strategy. They help to capture the first and second moments within China and cross-international stock markets.

First of all, this study looks at the market interrelationship between Mainland China and Hong Kong stock markets and examines the impact of Shanghai-Hong Kong Stock Connect. Shanghai-Hong Kong Stock Connect, as one of the most important financial liberalisation reforms for the Chinese stock market having a significant influence on both Shanghai and Hong Kong stock markets, will have a quantified effect on information transmissions. Therefore, this research conducts a comprehensive study to first explore its impact on both the Shanghai and Hong Kong stock markets. The empirical results from this thesis confirm that Shanghai-Hong Kong Stock Connect could increase the conditional variance in both markets and foster information transmission from Shanghai to Hong Kong, providing important policy implications.

Secondly, this study explores market co-movement and volatility spillover from the perspective of the Chinese stock market crash (2015-2016). While the Chinese economy has expanded rapidly, its financial interaction with the rest of the world together with its influential regional power has not been fully investigated. This thesis takes the 2015-2016 crash as an opportunity to analyse the spillover effect between China and the major markets in the Asia-Pacific region. This research contributes to the literature by firstly studying the influence of financial crisis originated from China on the spillover effect regarding China and its neighbours, enhancing the understanding of information transmission mechanism under a structural change. By comparing the estimation results between the crash and non-crash periods, this study sheds important light on different market interactions under bullish and bearish stages. The price and volatility spillovers are observed to be changing significantly when the Chinese stock market becomes bearish, with enhanced volatility contagions from China to the Asia-Pacific region, highlighting the regional financial influence of China.

Thirdly, permitting QFII to trade on CSI 300 futures market was an important event. This thesis has conducted timely and comprehensive research on the impacts of QFII on the joint behaviour relationship between Chinese stock index futures market and its spot market. It enables investors and regulators to understand the price discovery role and volatility transmission between CSI 300 futures and the spot market. In particular, the impacts of QFII on the price discovery function and volatility spillovers have been clearly documented. In addition, this study fills the literature gap by investigating the influence of QFII on the volatility of the CSI 300 futures market regarding the openness to foreign institutional investors on the local stock index futures market. It is observed that both price discovery role and volatility spillovers from the index futures market have been strengthened by QFII. Furthermore, the Chinese stock index futures market is found to be less volatile (risky) and probably more efficient after the introduction of QFII.

Fourthly, the last empirical study investigates the financial connections between oil, equity and commodity from the perspectives of return and volatility spillovers. It provides additional evidence for the dynamics among different financial markets during the post-Global Financial Crisis period. This study firstly incorporates three financial markets (China's stock market, China's commodity markets and international oil markets) under different categories to examine their interactions in the context of China. Methodologically, this study implements the trivariate BEKK GARCH model to capture more accurate dynamic volatilities for the three financial markets and provide important portfolio diversification implications. It is found that both return and volatility are uni-directional from the Chinese stock market or global oil market to some key commodities in China while shocks' spillovers between oil and stock markets are bi-directional.

The importance of China makes its financial market an alternative investment opportunity for other markets (both developing and developed), generating the diversification benefits. Research has shown that China and the advanced markets are not highly correlated due to market segmentation, encouraging international investment in China equity markets. However, as China gradually implements opening-up policies and financial liberalisation reforms, its financial market has become more interrelated to the rest of the world. In order to improve market openness, China's financial market is currently undergoing rapid changes with great transformations, and hence this research accesses the impacts from some key financial liberalisation reforms and market behaviours for different periods. The research

results have important policy implications for regulators and market participants who are suggested to set up appropriate policies and develop best strategies accordingly. China is currently restructuring its financial market and local under the “New Normal”, therefore policies and practices seek to promote more open economic, investment and trade environment for sustainable economic growth, benefiting China in the long-run under financial integration.

Our undertaking on the spillover effect among different stock markets can enhance the understanding of information transmission and the speed of market adjustment to new information. Generally, market co-movements reflect information transmission under the efficient markets hypothesis. Examining spillover effects can also help to understand the origins and drivers of volatility which are important for pricing securities, determining the cost of capital, implementing global hedging strategies, and making asset allocation decisions. Research on price discovery and volatility interdependence for futures market are helpful for understanding the efficiency of CSI 300 futures and the mechanism of information transmission between futures and spot markets. This research is very valuable for optimal global portfolios and provides important practical implications for international diversification, since the level of correlation between markets is a critical factor in determining potential diversification benefits. Furthermore, it is important for policy-makers to evaluate regulatory proposals, because the volatility spillover effect can be harmful to local economic performance and threaten the stability of local financial markets.

1.3 Research Questions

The main objective of this study is to investigate the extent and manner of market interdependence from the perspective of China and its interrelated financial markets. This thesis makes contributions to the literature by addressing the following research questions on financial linkages and volatility transmissions between China’s stock market and other financial markets:

1. Are there any impacts from Shanghai-Hong Kong Stock Connect on the long-term cointegration relationship and short-term causality between the Shanghai and Hong Kong stock markets?

2. Are there any impacts from Shanghai-Hong Kong Stock Connect on the volatility of Shanghai's stock market, the volatility of Hong Kong stock market and the spillover effects between the two markets?
3. What are the price spillover effects between China and 11 Asia-Pacific markets in bullish and bearish periods?
4. What are the volatility and shock spillover effects between China and 11 Asia-Pacific markets in bullish and bearish periods?
5. How do spillover effects between China and 11 Asia-Pacific markets change during bullish and bearish periods?
6. Are there any impacts from QFII on the long-term cointegration relationship and short-term causality between the Chinese stock index futures and spot market?
7. Are there any impacts from QFII on the price discovery role of the Chinese stock index futures market?
8. Are there any impacts from QFII on the volatility transmission and dynamic conditional correlations between the Chinese stock index futures and spot market?
9. What is the cointegration relationship among the global oil price, China's stock market and China's commodity market?
10. What are the return and volatility spillover effects among the global oil price, China's stock market and China's commodity market?
11. Are there any practical implications of portfolio management and hedge strategy arising from the results gathered in this study?

1.4 Thesis Structure

This thesis consists of 9 chapters and this current chapter introduces the topic, research background, contribution and significance of the thesis and research questions. Chapter 2 provides the background of China's economic growth and financial market development, especially the developments from 1978 onward, China's international trading status after

China's accession to the WTO, economic transformation under the 'new normal' context, stock market development, historical background of the Chinese index futures market and the development of commodity market are noted. This chapter also discusses the Chinese GDP growth, exports, foreign direct investment, financial liberalisation reforms, whilst showing evidence of what is actually happening in China. China as a socialist state under the people's democratic dictatorship has the world's largest population of 1.4 billion people, and therefore financial liberalisation may help to overcome some serious social issues, promoting the development of the so-called 'socialist market economy with Chinese characteristics'.

Chapter 3 reviews the literature regarding spillover effects. Here is an overall discussion on the theory related to spillover effect and market interdependence. Then it provides empirical evidence for both developed and developing stock markets with some comments on recent financial crises. After that, this chapter reviews studies seeking to understand the contagion effects between China and other markets. Furthermore, relationships between stock and its index futures markets are discussed with particular emphasis on price discovery role and volatility spillover effects. Finally, this chapter reviews theoretical and empirical research on the relationship between stock and commodity markets.

Chapter 4 describes the empirical methodology applied in this thesis. Unit root and cointegration test, Vector Autoregression (VAR), Vector Error Correction Model (VECM), and Generalised Autoregressive Conditional Heteroskedasticity (GARCH) family models are explained. Several multivariate GARCH models, such as BEKK, CCC and DCC GARCH specifications have been comprehensively reviewed due to their popularity in examining dynamic interactions between financial markets. All the above econometric methods are treated as sufficient tools that can help investigate financial integration and market interdependence.

Chapter 5 empirically tests the impact of Shanghai-Hong Kong Stock Connect. High-frequency data (one-minute interval) together with various dynamic methods such as cointegration test, Granger causality test, VAR, Impulse Response Analysis, GARCH models are employed to evaluate return and volatility spillover effects between Shanghai and Hong Kong. The findings explain whether the introduction of Shanghai-Hong Kong Stock Connect matters for stock market interactions between Shanghai and Hong Kong.

Chapter 6 investigates the price and volatility dynamics between China and major stock markets in the Asia-Pacific region around the Chinese stock market crash of 2015-2016. To examine the effects of this crash, the full sample has been divided into two sub-sample periods (bullish and bearish) in order to capture influence under structure break. In terms of methodology, the Bayesian VAR and BEKK GARCH models are used to analyse price and volatility spillovers.

Chapter 7 aims to provide a comprehensive analysis regarding the impact of the Qualified Foreign Institutional Investors (QFII) reforms on the dynamic relationship between the Chinese stock index futures and spot market. Both price discovery role and volatility spillover effect are examined by employing 5-minutes high-frequency data and VECM, GJR, BEKK and DCC GARCH models.

Chapter 8 focuses on the dynamic spillover effects among the Chinese stock market, Chinese commodity market and international oil market. Specifically, this study uses a trivariate VAR-BEKK-GARCH model to empirically estimate market volatility and their interactions, providing important implications on portfolio management and hedge strategies.

Chapter 9 is the conclusion chapter which summarises the findings of this thesis and provides important policy implications based on the analysis results. Finally, limitations of this study and future research areas are discussed.

Chapter 2: Overview of the Chinese Economy and its Financial Markets

2.1 Introduction

China is the world's largest emerging country and the second largest economy in the world with a successful development story. Since the establishment of the People's Republic of China in 1949, China moved from a low income to a middle-income class status. China becomes a continuous and rapidly growing economy in Asia after it opened its doors in 1978 and since then it has played a pivotal role in the regional and worldwide economy with its central geographical positioning in Asia. The successful economic reforms in China have made it become a major economic driver in the world. However, its success is not without challenges. Recently, the economic growth rate has dropped from the historical double-digit rate to around 7%, with key issues such as largely reliance on investment, high debt to GDP rate, more expensive labour costs, income inequality, corruption, unsustainable use of natural resources, and environmental degradation. China's financial market has developed rapidly with significant financial liberalisation reforms and it is now more integrated with the rest of the world. This chapter will provide an overview of China's economy and historical development of its local financial markets.

2.2 The Economy of the People's Republic of China

The economic reforms together with several opening-up policies known as “Gai Ge Kai Fang” were introduced in the People's Republic of China in 1978, aiming to transform China from a planned economy to the socialist market economy with Chinese characteristics. Over the past four decades, this economic reform has proved to be very successful and exerts a considerable impact on the economic growth and social development in China. Consequently, China's economy has maintained considerable growth at an average of above 9.5% per annum¹. The remarkable economic growth in China has led China to become a major economic powerhouse and resulted in a huge increase in China's share of world production, increasing China's importance in the world economy. The rapid economic growth is strongly underpinned by the investment-driven growth model with both central and local government

¹ Calculation based on GDP growth (annual %) from the World Bank.

policies which mainly aim to foster manufacturing production, international business and infrastructure construction.

As the People's Republic of China officially joined the World Trade Organization (WTO) in 2001, China has significantly increased its interrelations and become more integrated with the rest of the world. Significant liberalisation reforms on many of its industries in foreign trade and foreign investment have been implemented in order to fulfil the WTO's requirement and several key issues have been addressed by the Chinese government since its entry into the WTO, reconstructing its local economy. For example, China is committed to reducing tariffs and removing all other non-tariff barriers (NTBs) on imported goods as required by the WTO. Lower tariffs would increase the level of imports, and therefore competition from foreign companies will speed up economic reform in many industries, such as agriculture, manufacture, banking and the service sectors. This will result in the local Chinese companies being expected to lower their prices, upgrade their products and improve their quality to benefit Chinese consumers. In terms of the banking system, foreign banks can now trade on the Chinese local currency market because there are no restrictions on foreign bank entry since 2006, providing a more competitive and efficient banking environment in China. China's accession to the WTO has increased China's economic growth, resulting in a more efficient economy which shifts it from a planned and closed economy to a more open and market-oriented economy.

For international trading, several strategies and open policies have been set up and implemented to promote exports. From the inception of its open-door reform, both local Chinese companies and foreign-invested firms produce a large proportion of their outputs for exports. Most of the export-related firms are located in the special economic zones, the open cities and Hainan Island. The exporting favourable investment strategies have produced some spectacular results with strong export and supported China's rapid economic expansion. Currently, electrical products, high tech products, clothing, textiles, footwear, furniture, and plastic products are the major export products with its main export destinations of the US, Hong Kong, Japan, Germany and the UK. However, the Global Financial Crisis dragged down China's exports of goods and services from US\$1.473 trillion in 2008 to US\$1.245 trillion in 2009. Nonetheless, the downturn did not last long with a dramatic increase to US\$2.524 trillion in 2014.

Since a significant part of the Chinese economy relies on international trade, the Global Financial Crisis also has a huge influence on the Chinese economy. China's economic growth rate has sharply decreased from 14.2% in 2007 to 9.6% in 2008, falling from the historical double-digit rate to under 10%, moderating downward till the current level of about 7%. Although the Chinese GDP growth rate decelerated after the GFC, China had not suffered a big recession and its economy has kept growing faster compared to most developed nations. The GFC hit Chinese exports, but swift policy action by the Chinese government has mitigated any damage done to the economy. Subsequently, the year-average growth remained above 9% in 2008, 2009 and 2010, only fractionally below the performance of the previous high growth decade (OECD, 2013). During the Global Financial Crisis, China's contribution to the world economy has helped the global economy to recover. By 2010, China became the main driver contributing 33% to the global growth compared with less than 0.1% contribution to the global growth in the late 1970s (OECD, 2010). Without the significant contribution of China's economy, the GFC would be more severe, deeper and longer. Despite the slowdown in China's GDP growth, China overtook Japan as the world's second-largest economy and replaced Germany as the world's largest exporter of goods in 2009 (Lin, 2013). China's surpassing of Japan and Germany makes its increasingly dominant role in the world economy.

The slowing down of the Chinese economic growth is also attributed to problems such as income inequality, environmental deterioration, energy constraints, corruptions with rent-seeking activities, inefficient financial markets and poor corporate governance. Yet, this slowdown is in some ways desirable and consistent with a gradual shift in China's growth model, addressing the vulnerabilities after the GFC. As a result, China starts to undertake a remarkable economic transformation from manufacturing to services, from investment to consumption, and from exports to domestic spending, shifting its economy to grow at a lower rate but still a sustainable one (World Bank, 2015). As President Xi Jinping stated, "China's economy has entered a 'new normal', but its economic fundamentals are unchanged." As China's economy steps into this "new normal" phase, the Chinese central government has decided to shift its focus from demand to supply, implementing the supply-side structural reform with a stronger focus on supply quality and economic rebalancing. More attention is being paid to quality and efficiency rather than speed.

Referring to the Foreign Direct Investment (FDI), FDI inflows have experienced considerable growth in the past four decades and China has become one of the largest home countries of foreign direct investment. FDI was prohibited before 1978 and restrictions were removed with the implementation of a new foreign investment law in 1979. In the early stages, the amount of FDI inflows was not substantial and FDI was restricted to the Special Economic Zones (SEZs) which were established and extended to fourteen coastal cities and Hainan Island with the foreign investors' administrative support and tax reduction benefits (Mah, 2010). A sharp increase in FDI only occurred after Deng Xiaoping's famous Southern Trip in 1992 when China reaffirmed the policies of openness and market-oriented reforms. Since then, FDI has made a positive and significant contribution to Chinese local economic growth, playing an important role in economic development, filling the investment gap in China, creating a favourable environment for future sustainable growth and bringing in new international business practices (Yao, 2006). The total FDI inflow increased from US\$4.366 billion in 1991 to US\$11.156 billion in 1992, then rising to US\$44.237 billion in 1997, US\$171.535 billion in 2008 and US\$290.928 billion in 2013². However, as shown in Table 2.1, FDI inflow started to fall from 2013 and decrease to US\$170.557 billion in 2016 with a decline of more than one-third of its highest level, reflecting the recent downturn in the Chinese economy.

In terms of the GDP co-movement, it is notable that a dramatic increase in the correlations between China and the most advanced emerging countries, such as some Asian countries, Brazil and Russia, but excluding India and the Philippines (Borin et al., 2013). However, the correlation of growth rates between emerging and developed economies has remained at a low level, compared with the correlations among Asia's emerging economies, Brazil and Russia. China is a member of APEC, dominating the Asia-Pacific region as their key trading partner. For example, China has become Australian largest trading partner since 2009. For this reason, China is on its way to becoming the economic centre of the Asia-Pacific region (Das, 2012).

² Data source: the World Bank.

Table 2. 1: Key Economic Indicators of China

Billion US\$

	FDI	GDP	Mkt Cap	Export
1990	3.49	360.86	N/A	50.61
1991	4.37	383.37	N/A	58.57
1992	11.16	426.92	N/A	68.85
1993	27.52	444.73	N/A	79.89
1994	33.79	564.32	N/A	108.83
1995	35.85	734.55	N/A	135.42
1996	40.18	863.75	N/A	161.07
1997	44.24	961.60	N/A	178.26
1998	43.75	1029.04	N/A	193.07
1999	38.75	1094.00	N/A	204.36
2000	42.10	1211.35	N/A	257.24
2001	47.05	1339.40	N/A	279.11
2002	53.07	1470.55	N/A	338.08
2003	57.90	1660.29	512.98	461.13
2004	68.12	1955.35	447.72	621.34
2005	104.11	2285.97	401.85	788.94
2006	124.08	2752.13	1145.46	1023.11
2007	156.25	3552.18	4478.87	1276.95
2008	171.53	4598.21	1778.78	1472.54
2009	131.06	5109.95	3573.15	1244.69
2010	243.70	6100.62	4027.84	1602.48
2011	280.07	7572.55	3412.11	2006.30
2012	241.21	8560.55	3697.38	2175.08
2013	290.93	9607.22	3949.14	2354.25
2014	268.10	10482.37	6004.95	2524.16
2015	242.49	11064.67	8188.02	2431.26
2016	170.56	11199.15	7320.74	2199.97

Note: FDI, GDP, Mkt Cap and Export represent Foreign Direct Investment (net inflows), Gross Domestic Product, Market capitalisation of listed domestic companies and Exports of goods and services, respectively. Data source: The World Bank.

2.3 The Historical Development of the Chinese Stock Markets

The establishment of two stock markets was one of the most important milestone events in the early 1990s. The 3rd plenary session of the 11th Central Committee of the CPC in 1978 decided to implement key reforms with the opening up policy - “Gai Ge Kai Fang” - paving the way for the emergence of the Chinese capital markets. Following the guidance of Deng Xiaoping’s Theory and the development of the socialist market economy, the Shanghai Stock Exchange (SSE) was established on 26th November 1990 and launched the Shanghai Composite Index on 15th July 1991, while the Shenzhen Stock Exchange (SZSE) was established on 1st December 1990 and launched the Shenzhen Composite Index on 4th April 1991 (SSE, 2014; SZSE, 2014). The stock markets were established to create a platform for the partial privatisation of the state-owned enterprises in China with 8 listed stocks and 25 members in Shanghai and 6 listed stocks and 15 members in Shenzhen at the end of 1991 (CSRC, 2008). Since 1991, the Chinese stock markets in Shanghai and Shenzhen have expanded rapidly in both total market capitalisation and the number of firms listed. At the end of 2016, the number of listed companies rose to 1182 in Shanghai and 1870 in Shenzhen. The total market capitalisation had reached about RMB 28.5 trillion in Shanghai with the total turnover of RMB 283.9 trillion. It is approximately RMB 22.3 trillion for the Shenzhen Stock Exchange with the total value traded of RMB 93.4 trillion (SZSE, 2016; SSE, 2017).

The Shanghai Stock Exchange Composite Index (SSEC) is the most important benchmark index representing the majority of the largest listed enterprises in China. Figure 2.1 illustrates the index movement of SSEC from 2006 to 2016. We can see that the index experienced a dramatic increase from around 1000 points in 2006 to an all-time high of 6124 points in 2007 which was more than tripled the value of the previous year. After reaching the peak of 6,124 points, the stock market ‘bubble’ started to burst and the Shanghai Stock Exchange Composite Index crashed to 1664 points at its lowest points one year later. Although it recovered to more than 3300 points in 2009, the Shanghai stock market fluctuated between 2000 and 3000 points until the end of 2014, becoming highly volatile in the post-Global Financial Crisis period. Then the Shanghai index started another cycle with a sharp surge to a peak of 5178 points in June 2015 with a truly bullish market. This is likely due to the huge capital inflow through the newly introduced Shanghai-Hong Kong Stock Connect.

However, the Chinese stock market experienced the second most serious crash since the GFC due to a sharp slowdown in its economic growth and unexpected devaluation of the Chinese currency (RMB). The index went down to 2850 in August 2015 with almost half of the value lost over the next 2 months from its peak in June and then it recovered to around 3600 points in December 2015. Because of the newly introduced circuit breaker mechanism in 2016, another huge plunge happened in January with nearly 30% down for the first month in 2016. This dragged the stock index to around 2600 points. From 2016, Shanghai's stock market experienced a long-term recovery with slightly upward fluctuations at around 3000 points.

Figure 2. 1: Market Movement of Shanghai Stock Exchange Composite Index



Following the creation of the two stock exchanges in China, China's State Council established the formal legal system for regulating the capital markets. In October 1992, the China Securities Regulatory Commission (CSRC) and State Council Securities Commission (SCSC) were established to monitor the Chinese capital markets and issue a series of laws, rules and regulations, establishing a centralised and uniform supervisory framework which aims to improve its regulatory and supervision systems. This is an important milestone as it propelled the securities markets into a new stage of development. In December 1992, "the Circular on Further Strengthening of the Macro-management Over the Securities Market" was issued to emphasise the government's oversight role on the securities market. Since the inception of CSRC, a number of laws, rules and regulations for the capital markets have been

implemented, including the following: “The Provisional Regulation on the Issuing and Trading of Shares”, “The Implementation Rules on Information Disclosures of Companies Issuing Public Shares”, “The Provisional Measures on Prohibiting Fraudulent Conducts Relating to Securities and the Circular on Prohibiting Securities Market Manipulation” (CSRC, 2008).

However, there were still problems with overlapping regulators and regulations in the regulation system and frequently contradictory policies from the two governing bodies. After realising these issues, China implemented several reforms in its regulatory system to gradually solve the above problems. As a result, China separated the operations and supervisions of its financial industry by consolidating the supervisory functions of SCSC and People’s Bank of China (PBC) into the CSRC in 1998. After then, both Shanghai and Shenzhen stock exchanges operated under the regulations of the new CSRC (merged with SCSC).

In order to strengthen corporate governance, protect investors’ rights and formalise the legal status of China’s capital markets, the Company Law was implemented in July 1994 and the Securities Law was promulgated in 1999, facilitating the further development of China’s capital markets. With the introduction of new legislation, great progress has been made in the construction of the legal system governing the local securities market. The introduction of the Company Law was a significant milestone for China’s contemporary legal regulation system, since it was the first time that the National People’s Congress used the legislation to stipulate requirements on the securities market in China. It laid the foundations for the further development of China’s securities market.

The introduction and implementation of the Securities Law in 1999 also created a new stage in the legislative governance of China’s securities market and made a significant contribution to the stable development of the securities market over the long-term. The Securities Law 1999, as the fundamental law for China’s securities market, coming into force on 1st July 1999 established basic principles for the securities market, formalising and strengthening the legal status of its capital markets with specific regulations and rules. After the formal establishment of the legal regulation system, the development of China’s securities market moved rapidly with more advanced legislative governance. On 27 October 2005, the National People's Congress revised and adopted a comprehensive revision of the Company Law and Securities Law which would come into effect on 1 January 2006. Based on the

newly promulgated legal system, the reform on split-share structures began in 2005 and was completed at the end of 2007, laying a solid foundation for the future healthy development and efficient operation of the Chinese stock market.

The split share structure, a peculiar characteristic of China's capital market, started to obstruct and restrict the healthy development of China's capital market and listed companies, so it was necessary for Chinese authorities to further implement reforms on the split share structure. Therefore, on 29 April 2005, under the approval of the State Council, CSRC issued a notice related to split share structure reform (SSSR), officially launching the split-share structure reform which is the most influential institutional change for the capital market. Before SSSR, the shares of Chinese listed companies were artificially divided into tradable shares which could be exchanged freely on the stock market and non-tradable shares which are forbidden to be exchanged freely and publicly under split share structure. This can cause a conflict of interest between different shareholders, poor corporate governance and performance, excessive use of equity financing and ineffective capital market pricing mechanisms (Tseng, 2012).

The majority of non-tradable shares are state-owned shares which have the same voting and legal rights as their tradable counterparts, becoming problematic for minority shareholders since the split structure fails to motivate government agents to maximise the firm performance and market value of the listed company (He et al., 2017). The implementation of SSSR has led to the conversion of non-tradable shares to tradable shares by paying negotiated compensation to the shareholders of tradable shares, aligning the interests of the government and investors, mitigating Chinese listed companies' structural problems, leading to significant improvements in corporate governance and reducing potential agency problems. After SSSR, trading activity and liquidity in the secondary stock markets have considerably increased and the transparency of financial markets has been improved with substantial changes in China's firms' capital structure (Guo et al., 2016).

China liberalised its capital market but one unique characteristic of the Chinese stock market is the segmentation into A and B Share markets. This in effect means that completely segmented trading between two distinct investors' classes: foreign investors and domestic investors. Initially, only Chinese domestic investors were allowed to trade shares listed on both stock exchanges and denominated in the Chinese currency --- RMB. However, the Chinese securities authorities liberalised its local stock market by removing restrictions on

the acquisition of Chinese companies' shares by foreign investors. As a result, local Chinese companies were permitted to issue a special class of shares - B shares (denominated in RMB but traded in US dollar in SSE or HK dollar in SZSE). The purchase and sale of Chinese B shares are limited to foreign investors with several restrictions. For example, individual foreign investors are only allowed to hold up to 25% of a company's B shares with a maximum of 49% in total foreign ownership (through the B share issues) (Chakravarty et al., 1998). The first "B" shares - Shanghai Vacuum - were issued on 20 January 1992 and commenced trading on the Shanghai Stock Exchange on 21 February 1992. By the end of 1992, each exchange had nine "B" share listings with the initial offerings of US\$640 million in Shanghai and US\$170 million in Shenzhen (Nottle, 1993).

However, the Chinese B share market has generally been traded at substantial discounts with lighter trading volumes, smaller market capitalisation and lower liquidity compared with its corresponding A-share market, even though both A-shares and B-shares of the same company have identical voting and ownership rights. In order to foster the growth of the Chinese B share market, the Chinese Securities Regulatory Commission (CSRC) released the ownership restrictions on B shares on 19 February 2001, allowing the Chinese domestic investors to open B share accounts and trade B shares legally. The removal of the ownership restrictions had led to a significant increase in share prices and reduction in discounts caused by local Chinese investors' actively trading when the markets reopened on 28 February 2001. As a result, there has been a huge domestic capital inflow into the B-share market, reflected by a dramatic increase in its trading volume and the number of newly opened B share trading accounts (Tong and Yu, 2012).

In order to open China's capital market to the world, the Chinese government introduced the Qualified Foreign Institutional Investor (QFII) scheme in 2002, allowing the largest overseas institutions to trade A shares and debt securities under a quantitative quota system. This financial initiative scheme is a pilot scheme, aiming to relax foreign exchange controls over the country's capital account in a limited way and to leverage the investment and management skills of successful foreign financial institutions to raise the standards of the Chinese market (Tam et al., 2010). As foreign investors were only allowed to invest through the markets of B Share, H share³ and N share⁴ before the introduction of QFII, thus it opened up the domestic securities markets to overseas institutions for the first time with expectation

³ Shares of PRC companies traded on the Hong Kong Stock Exchange

⁴ Chinese companies listed on the NYSE, NASDAQ, or the American Stock Exchange

to bring greater market stability, longer-term investment notions and a more rational investment approach but reduce short-term speculative behaviour. In late 2011, the RMB Qualified Foreign Institutional Investor (RQFII) scheme, an extended version of QFII was established to allow foreign investors who hold the RQFII quota to invest directly in Mainland China's equity and bond markets using offshore RMB, further lifting existing restrictions on currency settlement and loosening investor eligibility requirements. Since the inception of QFII and RQFII, these two financial initiative schemes have evolved rapidly, attracting a wide range of international investment institutions, including sizable investment banks, wealth management funds and insurance companies. As of 31 July 2017, 284 foreign institutions have been granted QFII licenses with the total quota of US\$93.3 billion while 185 foreign institutions having been granted with RQFII licenses. The total quota is RMB548.2 billion⁵.

QFII's 'twin brother', the Qualified Domestic Institutional Investors scheme (QDII) was announced by CSRC on 13 April 2006, providing limited opportunities for domestic investors to access foreign markets. There are several restrictions on capital and foreign currencies which cannot be moved completely freely in and out of China. In particular, the QDII scheme empowers Chinese domestic investors to entrust Chinese financial institutions to invest in financial products overseas. Due to China's tight control on its capital market, the QDII is the rare legal avenue for domestic investors to invest abroad, creating more profitable and diversification opportunities for Chinese investors.

More recently, CSRC and the Securities and Futures Commission (SFC) in Hong Kong jointly announced the official launch of Shanghai-Hong Kong Stock Connect which took effect on 17 November 2014, creating mutual trading access between Shanghai and Hong Kong. The scheme established a direct link between the two stock exchanges, allowing Hong Kong investors to buy and sell shares listed on the Shanghai Stock Exchange through their local brokers and vice versa. Shanghai-Hong Kong Stock Connect has been treated as a milestone moment for China's capital market development, because it has further opened the door to investors, liberalised its capital market and promoted the internationalisation of China's currency (RMB). As noted by Huo and Ahmed (2017), this landmark financial liberalisation reform provides a feasible, controllable and expandable channel for mutual markets access, relaxes market restrictions and reshapes financial structures, enabling

⁵ Data source: State Administration of Foreign Exchange (SAFE), China and Shanghai Stock Exchange

intensive interactions between the two markets. It also creates an opportunity and a new channel for both domestic and international investors to diversify their investment portfolio. Based on the successful experiment of Shanghai-Hong Kong Stock Connect, CSRC implemented another similar scheme, Shenzhen-Hong Kong Stock Connect on 5 December 2016, two years after the launch of the Shanghai-Hong Kong Stock Connect. These two pilot schemes create a unique collaboration between the Hong Kong, and Mainland China's stock exchanges, making possible capital flow between northbound and southbound and allowing investors to trade shares via their home exchanges.

2.4 Development of the Index Futures Market and Commodity Market in China

CSI 300 index future is the first stock market index future in Chinese capital market, laying the foundation for further introduction of the CSI500 index futures and SSE 50 stock index futures. The underlying asset for the CSI 300 index future is the CSI 300 index which was introduced by China Securities Index Co. Ltd on 8 April 2005. It is a capitalisation-weighted stock market index designed to replicate the performance of the most representative 300 stocks traded on the Shanghai and Shenzhen stock exchanges, representing about 60% of capitalisation in the two Mainland China's stock markets. The introduction of the CSI 300 index aims to reflect the price fluctuation and performance of the top listed companies in the Chinese stock market. Based on the CSI 300 index, CSI 300 index futures contracts were introduced on 16 April 2010 by the China Financial Futures Exchange (CFFEX). The introduction of CSI 300 index futures contracts was a landmark event in the development of Chinese financial markets, bringing a unique opportunity for Chinese investors to short sell and hedge risks.

Compared with the mainstream stock index futures market, the CSI 300 futures trading is relatively restricted to the domestic retail and institutional with several tough conditions for opening an account. In order to open an account, individual investors must have more than RMB500,000 in their margin account, understand the basics of index futures trading and have trading experience in mock trading. Concerning institutional investors' eligibility, they must have not less than RMB1,000,000 in their net asset with RMB500,000 plus available in their margin account. In addition, both individual and institutional investors have to pass the relevant test with no bad credit record. Despite strict investors' eligibility requirement and trading restrictions, the CSI 300 futures contracts still attract much attention

from domestic investors initially and are one of the most actively traded financial instruments in China. As a new financial instrument which is still carefully monitored by CSRC, the average daily trading turnover of CSI 300 futures contracts hit RMB230.8 billion over the first three months after its introduction but with very low open interests, suggesting strong speculative behaviours in this market trading (Yang et al., 2012). To further liberalise the stock index futures market in China, CSRC promulgated “The Guidelines on the Participation of Qualified Foreign Institutional Investors in Stock Index Futures Trading” on 4 May 2011, enabling the foreign institutional investors to access CSI 300 futures trading (CSRC, 2011). More detailed information concerning the CSI 300 index futures contract regarding trading hours, margin requirement and settlement is summarised in Table 7.2 in Chapter 7.

In terms of the Chinese commodity market, the first commodities market (Zhengzhou Grain Wholesale Market, now as Zhengzhou Commodity Exchange) opened on 12 October 1990 for commodity spot transactions with the first grain forward contract signed in March 1991. Futures trading began in May 1993, as the first pilot unit in China’s commodity market under regulations of CSRC. In October 1992, the first standardised futures contract - “Standard Contract for Special Grade Aluminum Futures” - was introduced in the Shenzhen Metal Exchange, achieving the transition from forward contracts to futures transaction. However, the commodity futures market started chaotically at its initial stage with more than 40 commodity futures exchanges and more than 300 futures brokerage companies at the end of 1993 (CSRC, 2008). Some of them had poor management, speculative trading, underground deals and fraud transactions. Once realising those issues regarding disordered market behaviours, the Chinese government introduced several new restrictions to govern the futures markets, resulting in a sharp decline in commodity futures exchanges and products.

Despite several actions taken by CSRC, there were still fraud behaviours with some severe speculative activities (e.g. the 327 event of T-bond futures in 1995 and the Tianjin red bean futures event in 1997). Therefore the CSRC has implemented a range of more stringent rectifications on the futures market to suppress excessive speculation and effectively enhance its hedging and price discovery functions (Zhao, 2015). With more strict restrictions, improved regulatory system, supportive government policies and efficient risk control, China’s commodities futures markets have developed rapidly, although the number of futures exchanges has sharply decreased to four (Dalian Commodity Exchange, Zhengzhou Commodity Exchange, China Financial Futures Exchange and Shanghai Futures Exchange). In 2017, Shanghai Futures Exchange, Dalian Commodity Exchange and Zhengzhou

Commodity Exchange were ranked, respectively, as the 9th, 10th and 13th largest futures exchanges in the world in terms of trading volumes.⁶

2.5 Conclusion

Regional and global financial integration is significantly influenced by China's economic and financial development. Since opening-up policies in 1978, China's unique reform-based economic development explains the country's continuously high GDP growth rate. Over the past several decades, both FDI inflows and exports of China have experienced a dramatic increase, making significant contributions to international trading and investment. Despite significant impacts from the Global Financial Crisis, China has still kept its GDP growth to higher than most developed countries' and become the main driver of the global economy, substantially contributing to the economic recovery from the GFC. The recent slowdown in China's economic growth has led to the focus shifting from demand to supply. As a result, China has attempted to restructure and rebalance its economy to achieve a "new normal" stage of slower but more sustainable development, paying more attention to the quality and efficiency of economic growth. Against the background of financial liberalisation and globalisation, China's capital market has also experienced rapid development. With the establishment of Shanghai and Shenzhen stock exchanges, China's capital market has made considerable progress in its expansion, making the investment environment more attractive for both domestic and overseas investors. Several significant regulatory and liberalisation reforms, such as QFII, QDII and stock connect initiatives, have taken place and built a more open and sound investment environment both locally and internationally. Meanwhile, China has also established its financial derivative market, including several commodity and futures exchanges. The introduction of CSI 300 stock index futures has brought a unique opportunity to short sell and hedge risks in China, becoming an important milestone in its capital market development. With China's ongoing financial liberalisation reforms, the country has great potential to build a world-class international financial centre with improved efficiency and more diversified opportunities.

⁶ Data source: Futures Industry Association website, <https://fia.org/articles/infographic-2017-volume-highlights>

Chapter 3: Literature Review

3.1 Introduction

This chapter provides a comprehensive review of the literature on spillover effects among different financial markets. In the last few decades, the increasing importance of globalisation and financial liberalisation has become a popular topic for academia in both finance and economics. The US stock market crash in October 1987 boosted much research on market interdependencies across different financial markets. Most studies focus on volatility transmission between stock markets and several interesting questions related to market co-movement have been raised in the literature, for example: (i) how interdependent are the international stock markets? (ii) has financial integration led to faster information transmissions among different financial markets? (iii) what are the causes of volatility transmissions? (iv) to what extent can a financial crisis be transmitted to other markets? and (v) which market might suffer more as a result of a financial crisis? These issues are crucial for policy-makers from the financial stability perspective and investors also find it is important to recognise the potential risks and diversification benefits and furthermore make investment decisions. An extensive body of literature provides strong evidence that the spillover effects not only exist between mature stock markets but also between developed and emerging markets (King and Wadhvani, 1990; Syriopoulos et al., 2015).

This chapter is organised as follows: section 3.2 provides a comprehensive discussion on recent literature about spillover effects between stock markets. Then section 3.3 discusses recent studies on relationships between stock and index futures markets. This is followed by section 3.4 which presents both theoretical and empirical evidence on the relationships between stock and commodity markets (including the oil market and other commodity markets). Finally, section 3.5 provides a conclusion and a summing up of the main themes discussed in this chapter.

3.2 Spillover Effects between Stock Markets

3.2.1 The Theory of Spillover effect and Market Interdependence

When a financial crisis besets a country, asset prices usually experience a sharp decrease and market volatility increases dramatically. However, a financial crisis can be easily transmitted from one market to another, leading to the loss of public confidence and negative momentum that reaches other countries and their financial systems. The primary information transmission channels are market prices and volatility. Financial liberalisation and globalisation also improve the possibilities for national markets to react rapidly to new information from international markets and increase the co-movement of international markets.

Information transmission theory can be used to explain the volatility spillovers, because Ross (1989) indicates that volatility is related to the rate of information flow to the markets. King and Wadhvani (1990) believe that the spillover effect is caused by incomplete information. Without full information, market participants are uncertain about the impact of a financial crisis in one country on another country's fundamentals. For example, if there is no relationship between two countries' fundamentals but investors wrongfully assume the existence of the interdependence or market participants falsely interpret a country-specific shock as a common shock for other markets, the specific shock originating from one country would nevertheless be transmitted to another in the case of incomplete information. Consequently, a crisis in one country could lead to an inefficient review and inaccurate assessment of other countries' fundamentals, causing investors to sell assets, call in loans or stop lending despite the unchanged fundamentals in those markets.

Goldstein (1998) provides a different theory called the "wake-up call" hypothesis to explain the spillovers. The "wake-up call" hypothesis shows that a crisis in one country can possibly be treated as a 'wake-up call' for investors to take a closer look at the fundamentals of similar countries. When market participants detect problems or risks they did not see before, the spillover or contagion occurs. The "wake-up call" hypothesis encourages investors to be aware of existing problems and further conduct a more accurate assessment of fundamentals. This time, the contagion is the result of an efficient correction.

Pretorius (2002) provides a theoretical framework for the stock market interdependence. The author indicates that there are three categories of interpretations on

market co-movement, namely, contagion effect, economic integration and stock market characteristics. The contagion effect captures markets co-movement not caused by economic fundamentals and two key factors (informational and institutional related) serve to explain this phenomenon. Specifically speaking, if investors believe that other investors will sell a class of assets, they sell the same assets. A significant sell-off by a sufficient number of investors could possibly lead to a stock market engaging in 'herd behaviour' and further cause a widespread decline in that stock market. As well, a large-scale redemption of open-ended mutual funds will also cause strong selling off the funds' assets and further result in a contagion effect without justifying changes in fundamentals (Wolf, 1998). In terms of the economic integration category, strong international trading ties will probably lead to a higher degree of markets co-movement. The stronger the bilateral trade relationship, the more interdependent their economies and stock markets are expected to be. Besides, following the cash flow model, factors such as interest rates, GDP growth and inflation rates which can influence discount rate or dividends growth rate, are able to influence stock prices. Therefore, the key macroeconomic variables also impact on the market performance and hence further market correlations. Apart from important macroeconomic variables, several characteristics of stock market such as market volatility, market size and industrial similarity also make potential contributions to regional and world market correlations.

Moser (2003) tries to explain cross-country propagation of shocks not caused by economic fundamentals. He identifies three leading activities that result in spillover effect, namely international trade, counterparty defaults and portfolio rebalancing. International trade is considered to be a major channel of shock or volatility propagation. A crisis in one country which is often related with economic recession or currency devaluation can negatively affect trading partners' exports, because of a reduction in demand and weak price competitiveness. The trade propagation mechanisms become obvious when trade relationships are closer. Also, the mechanisms do not only work through bilateral trade links, but also through indirect trade links and therefore the third markets may be affected. Counterparty defaults can also lead to shock or volatility propagation. The banks' high exposure to troubled debtors is very likely to cause a crisis in the banking system. If the major banks suffer huge losses from defaults on foreign loans, the effects would be easily transmitted across boundaries. Portfolio rebalancing due to liquidity constraint and capital constraint is another explanation of the spillover effect. The liquidity constraint may force investors to sell assets in order to raise liquidity. Meeting margin calls or other collateral

requirements, or fulfilling investor redemptions for the mutual funds are the main reasons for investors unwinding their positions. When market liquidity sharply declines because of a big loss or huge withdrawal from an important market participant, the liquidity needs may arise. In terms of capital constraint, banks are induced by their capital requirements to adjust the capital ratios. Consequently, they cut back foreign loans or shift into low-risk assets such as government securities to improve their capital-asset ratio.

Claessens and Forbes (2004) point out several reasons why contagion can occur. First of all, a common shock such as a significant change in commodity prices, a major economic shift in developed countries, or a huge reduction in the world's economic growth could possibly trigger a financial crisis, leading to significant market co-movements. Secondly, direct or indirect trade linkages can cause contagion. Once there is a crisis in one country, it is likely to reduce its income, lead to a corresponding reduction in demand for imports and further results in its currency devaluation. Devaluation of a country's currency could boost its competitiveness temporarily, but then its trade competitors are at a competitive disadvantage and therefore adversely affected. In this way, a crisis could possibly be spread to its trading partners through the trade channel. Thirdly, financial linkages also contribute to contagion effects. Foreign direct investment and other capital flows could become the transmission channel when the market integration is high.

3.2.2 Empirical Evidence of Spillover Effect among the Developed Stock Markets

The US October Crash in 1987 inspired much research on the spillover effect. Early studies which mainly focused on developed countries, for example, the US, the UK, and Japan are able to show significant evidence of interdependence between these mature markets. Using a vector autoregression (VAR) system, Eun and Shim (1989) find that shocks from the US are rapidly transmitted to nine largest stock markets but no adverse spillovers exist, suggesting that the US market is the most influential in the world. Their results also indicate that the intra-regional correlations tend to be higher than the inter-regional correlations due to the differences in time zone and economic integration. King and Wadhvani (1990) provide both a theoretical framework and empirical evidence showing that an increase in market volatility could possibly lead to stronger contagion effect. They argue that mistakes in one market may

be transmitted to another market, explaining the uniform fall in global markets during the US October stock market crash in 1987.

Utilizing the GARCH-M model and decomposing the daily stock market returns into close-to-open and open-to-close, Hamao et al. (1990) report asymmetric volatility spillovers in the US, the UK and Japan. Specifically, they find relative strong spillover effects from the US and the UK to the Japanese market but weak spillovers from Japan to the US and the UK, indicating that Japan is the most sensitive market. In terms of return spillover, they find that exhibits a positive return spillover effect from New York (London) to Tokyo (New York). Extending the research of Hamao et al. (1990), Theodossiou and Lee (1993) add Canadian and German stock markets to their study and find weak mean spillovers from the US to the UK, Canada and Germany and from Japan to Germany. Significant volatility spillovers are detected from the US to the other four stock markets, from the UK to Canada, from Germany to Japan. Their results indicate that Germany's stock market is the least integrated market and the conditional volatility in the UK and Canadian markets is mainly influenced by the US. However, they cannot find conditional volatility wields a significant effect on the expected return.

Using the intraday data and signal extraction model, Lin et al. (1994) find that in general Tokyo (New York) daytime returns are significantly correlated with New York (Tokyo) overnight returns, providing evidence that information contained in one market during its trading time has a global impact on the other market. Susmel and Engle (1994) use high-frequency hourly data to investigate the spillover effects between the US and the UK. They find no mean spillover during the non-overlapping period but weak bi-directional volatility spillover effects between the two markets which are only for short duration and mainly occur around New York opening period. Extending the GARCH framework to allow for asymmetric effects, Bae and Karolyi (1994) find that the positive and negative shocks have different impacts on domestic markets, suggesting that bad news from both domestic and foreign markets tend to exert bigger impacts on subsequent volatility than good news. Their results suggest that the normal GARCH model understates the magnitude and persistence of shocks that can be transmitted to the other market compared with several asymmetric GARCH models. This leads to the necessity to consider asymmetric effects in volatility spillover effects.

Koutmos and Booth (1995) also investigate asymmetric volatility transmissions across the US, Japan and the UK stock markets using a multivariate EGARCH model. Their results indicate strong evidence of asymmetric volatility spillovers which means that volatility spillovers are more pronounced for bad news. They also find that the links among the above three markets increase after the US October 1987 Crash, suggesting that these three major international stock markets become more interdependent. Employing a bivariate GARCH model to examine the short-run dynamics of returns and volatility between Canada and the US, Karolyi (1995) discovers that the shocks in one market are rapidly transmitted to another market. However, the cross-market spillovers in return and volatility between the US and Canada have changed over time and the influence of shocks from New York on the Canadian stock returns has diminished during the late 1980s. In addition, the author reports evidence of the difference between the impact of innovations from the US on a portfolio of inter-listed stocks and that on non-inter-listed stocks, suggesting that the different investment environments are important to understand the dynamic interdependence between stock markets. Focusing on Scandinavian stock markets, Booth et al. (1997) employ an extended multivariate EGARCH and find significant but weak asymmetric price and volatility spillovers among the Danish, Norwegian, Swedish, and Finnish stock markets.

In summary, the empirical studies conducted in the early 1990s have several key points: Firstly, the volatility of stock markets has a time-varying characteristic. Secondly, the price changes in major stock markets seem to be highly correlated when volatility becomes high. Thirdly, at the time of the US October Crash in 1987, correlations in volatility and prices are found to be causal from the United States to other markets. Fourthly, spillover effects of return and volatility are found between major markets. Fifthly and finally, asymmetric effects are reported in several studies, implying that good news and bad news tend to affect the other market's volatility differently.⁷

3.2.3 Empirical Evidence of Spillover Effect Related to the Emerging Markets

The emerging markets become an important part of the global economy due to financial liberalisation and globalisation, so both researchers and investors become increasingly interested in the relationship between developed and emerging markets. A substantial part of

⁷ For more detail, please refer to Gagnon and Karolyi (2006)

the empirical literature focuses on the spillovers from developed markets to emerging markets. For example, John Wei et al. (1995) find evidence of the price changes and volatility spillover effects between developed and emerging markets and report several interesting findings. First, the stock market in Japan has less influence on the Taiwanese and Hong Kong markets than that in the US. Second, the Taiwanese stock market is more sensitive to the price and volatility behaviour of the two mature markets compared with the market in Hong Kong. Kim and Rogers (1995) also confirm significant spillovers of return and volatility from the major stock markets (Japan and the US) to the South Korean stock market. Their results indicate that financial liberalisation enhances the return and volatility spillovers in terms of close-to-open returns, suggesting that information from foreign stock markets has played a more important role for the local market's opening prices after the South Korean stock market is fully liberalised.

Bekaert and Harvey (1997) explore the relative importance of world and local factors in explaining the return and volatility of several emerging markets. They indicate that the impact from the world factors is relatively small before the US October Crash in 1987 but increases significantly after the crash. Their empirical results also reveal that the capital market liberalisations significantly drive up the correlation between emerging and advanced markets but reduce volatility in most emerging markets. Examining the return and volatility spillover effects from the US and Japan to four Asian markets (Taiwan, Singapore, Hong Kong, and Thailand), Liu and Pan (1997) report an unstable return and volatility spillover effects during the sample period. They point out that the spillover effects have increased significantly after the US October Crash in 1987. In addition, it seems that the US stock market tends to become more influential than the Japanese market over the four Asian markets in terms of return and volatility transmission. Hu et al. (1997) utilise a causality-invariance test to examine the volatility spillover effects, concluding that markets of the South China Growth Triangular region (Hong Kong, Taiwan, Shanghai and Shenzhen) are contemporaneously correlated with the return volatility of the US market. Besides, the Shanghai and Shenzhen stock markets are more correlated with the stock markets in the US and Japan than Hong Kong and Taiwan. Their results show that global factors are more important for less opened markets (e.g. Shanghai and Shenzhen) and geographic relationships do not necessarily cause strong volatility interactions between stock markets. Ghosh et al. (1999) estimate an error correction model to investigate the degree of market integration of Asia-Pacific markets with the US and Japan. Their empirical evidence suggests that some

stock markets (Indonesia, the Philippines and Singapore) are found to be integrated with the Japanese stock market whereas some other equity markets (Hong Kong, India, South Korea and Malaysia) share long-run interdependence with the US market. However, there is no evidence of a long-term cointegration relationship between stock markets in Taiwan (Thailand) and the US or Japan.

Ng (2000) constructs another volatility spillover model considering three sources of shocks - a local idiosyncratic shock, a regional (Japan) shock and a world (US) shock - to analyse the relative importance of the largest stock markets on several Pacific-Basin stock markets. The results reveal that both regional and world factors are important to explain market volatility in the Pacific-Basin region with greater influence being exerted by the US. Several important liberalisation reforms together with exchange rates, sizes of trade and country fund premium are found to influence the relative importance of the world and regional factors. However, the volatility spillovers from the US and Japan are generally small (less than 10%), suggesting that the Pacific-Basin stock markets are driven by some specific local information. Lamba and Otchere (2001) investigate the dynamic relationships between South Africa and some major developed markets and find evidence of a long-run equilibrium between the South African market and major Western markets. Their results demonstrate that the US, Canada and Australia have the most significant influence on South Africa, while Japan has only minimal influence. The end of apartheid in the early 1990s has enhanced the long-run relationship between South Africa and major developed markets, enabling the country to become more economically and financially integrated with the rest of the world.

Masih and Masih (2001) use the vector error correction models (VECM) to explore the dynamic causal linkages among the world's nine major stock markets. Their study provides significant evidence of strong interdependencies between the OECD and emerging Asian markets and the leadership of the US and the UK markets in both the short- and long-term. They also report the leading position of Japan's stock market has been strengthened based on levels VAR and post-shock impulse response analysis, suggesting that Japan becomes an additional force that drives international stock market co-movements. Johnson and Soenen (2002) examine the level of integration of 12 Asia-Pacific stock markets with Japan and find strong evidence that the equity markets in Australia, New Zealand, Hong Kong, Singapore, Malaysia and China are highly integrated with the Japanese stock market.

Several macroeconomic variables such as import and export, FDI, inflation rates, real interest rates, and GDP growth are found to influence the degree of market integration significantly.

Employing a different volatility spillover methodology from Ng (2000), Miyakoshi (2003) reports that only the US (not Japanese) stock market is found to have a significant influence on the returns of seven Asian market whereas the volatility of the Asian market is influenced more by the Japanese market than by the US. The results also confirm the existence of an adverse influence of volatility from the Asian stock markets to the Japanese stock market. Focusing on spillover effects between second board markets and controlling the effects from the New York Stock Exchange, Lee et al. (2004) report significant evidence that the lagged returns and volatility from the NASDAQ market have substantial spillovers to the Asian second board markets, despite the existence of the contemporaneous and lagged returns and volatility spillovers from the local main board markets to the corresponding second board markets. Baele (2005) uses a regime switching model to quantify the extent of volatility spillover effects from the US (global effects) and aggregate European (EU) stock markets to thirteen local stock markets in Europe. Furthermore, Baele reports substantial evidence of increased shock spillovers from the US and aggregate European markets. Moreover, the study indicates a more pronounced rise for EU spillovers due to strong trade integration, fast stock market development and low inflation rates and a significant contagion effect from the US to several Western European markets during the highly volatile period.

Gallo and Otranto (2008) proposed a new Markov Switching model to examine the volatility transmission and find that Hong Kong has long-term spillovers to South Korea and Thailand, interdependence with Malaysia and co-movement with Singapore, implying Hong Kong stock market dominates the region. Yu and Hassan (2008) employ an EGARCH-M model with GED distribution to examine the financial integration of stock markets in the Middle East and North African (MENA) region. Their empirical results indicate that the US stock market plays an important role in forecasting the volatility of the most MENA stock markets, although own-volatility spillovers are generally higher than cross-volatility spillovers. Due to the fast progressed financial liberalisation in the MENA region, the enhanced long-run equilibrium is observed between non-GCC countries and the US stock market. Singh et al. (2010) study the information transmission among across North American, European and Asian stock markets and conclude that most Asian stock markets are influenced by lagged returns of the US and European markets. However, after considering the

same day effect, they find a different result, showing evidence of return spillovers from the US to Japan and South Korea. In addition, the Singaporean, Taiwanese and Malaysian markets are influenced by same day returns of Japan and South Korea. Their empirical results indicate that the Japanese, Singapore and Hong Kong markets are the most important markets in Asia whereas the UK and German markets are more influential than other European markets, although the US retains its dominant role in the world.

Lee (2013) develops a range-based bivariate Weibull Conditional Autoregressive Range (BWCARR) model to study volatility spillover effects. The study indicates the existence of spillovers among the US, Japan, Mainland China, Hong Kong and Taiwan stock markets and confirms the global spillover effects from the US and regional spillover effects from Japan to the Taiwanese market. Syriopoulos et al. (2015) estimate the time-varying dynamic correlations and investigate volatility spillover effects between the US and the BRICS (Brazil, Russia, India, China and South Africa) equity markets. Their empirical analysis based on the VAR-GARCH framework identifies strong return and volatility spillovers between the US and BRICS countries. Moreover, the US industrial sector is found to exert predominant impacts on the market returns of Brazil, Russia, India and South Africa while the US financial sector is able to impact only the returns of Russia and South Africa. For shocks and volatilities, there is a significant impact whereby the shocks of the US industrial sector are observed to affect stock markets in India, Russia and Brazil. Conversely, volatility in the US industrial sector has significant impacts on industrial sector volatility in all BRICS markets with the exception of China. In addition, Brazil and India are found to be most affected by the shocks and volatility emanating from the US financial sector.

In summary, empirical evidence has confirmed the existence of volatility transmissions among the US, Japanese and major emerging stock markets. Market interdependence among global stock markets has increased since the US October Crash in 1987. Return and volatility spillovers seem to be time-varying and the degree of integration between the emerging markets and mature markets has increased generally. The US stock market, as the world factor and the Japanese stock market, as the regional factor, play different roles in information transmissions. These are as follows: financial market liberalisation, deregulation in financial markets and institutions, and free international capital movements. Furthermore, advances in electronic communication have enhanced international

market interdependence and seriously compromised the benefits of international diversification.

3.2.4 Empirical Evidence of Spillover Effect with the Impacts of Financial Crises

During 1997, Asia's stock markets experienced substantial financial distresses and crisis, which spread rapidly from one country to another. The crisis not only caused stock markets to crash but also led to a dramatic loss of confidence for investors, posing a threat to the economic growth of the region and the world. Subsequently, the contagion mechanism during the emerging market crisis, especially the Asian Financial Crisis in 1997 which is attributable to a variety of factors, motivated many researchers to examine spillover effects and financial contagion in Asian emerging markets. Yang et al. (2003) investigate the impact of the Asian Financial Crisis on stock market integration through comparative analyses and indicate that both long-run cointegration relationships and short-run causal linkages among the US, the Japanese and 10 Asian markets are intensified during the crisis. It suggests these stock markets have been more integrated after the Asian Financial Crisis. Interestingly, the US stock market is found to influence the Asian markets in all three sample periods, but the stock market in Japan has little influence on the other Asian markets except during the financial crisis.

Wang and Firth (2004) provide a comprehensive analysis of returns and volatilities transmission across four emerging stock markets in the Greater China area and three developed markets. Their study indicates that at least one of the 3 advanced markets' daytime returns have predictive power on Greater China's markets, showing that the spillover effects are generally uni-directional from developed markets to the emerging Chinese markets. The bi-directional return and volatility spillovers are found after the Asian Financial Crisis, suggesting that information from Asian markets start to become important. Overall, the results reveal that Greater China's equity markets are more integrated with the rest of the world. Phylaktis and Ravazzolo (2005) apply the multivariate cointegration model in both the autoregressive (AR) and moving average (MA) forms to explore the dynamic financial linkages among the stock markets of the US, Japan and several Pacific-Basin countries for the period 1980–1998. They report no evidence that the stock markets are linked together for either the 1980s or 1990s, suggesting that relaxation of foreign currency restrictions cannot

enhance market interdependence. However, an increase in financial linkages for open and semi-open markets is observed in the second sub-period, indicating that the relaxation of foreign ownership restrictions seems to have strengthened market interrelations. In addition, they find the Asian Financial Crisis has no substantial impact on the degree of market interdependence based on the recursive analysis. Also, the US and Japanese stock markets do not have a unique influence on the Pacific-Basin stock markets with a small role played by the US but a more significant one by Japan.

Employing a dynamic conditional-correlation model to nine Asian stock markets, Chiang et al. (2007) find supportive evidence of a contagion effect during the Asian Financial Crisis and identify two different phases for the crisis (contagion phase and herding phase). They also find that the dynamic correlation coefficients are very sensitive to changes in sovereign credit ratings, indicating that international sovereign credit-rating agents are important in shaping the structure of dynamic correlations in the Asian markets. Using a bivariate EGARCH model to investigate the degree of financial integration among the BRIC (Brazil, Russia, India and China) countries, Bhar and Nikolova (2009) contend that India has the highest level of integration amongst the BRIC countries, followed by Brazil, Russia and China. A negative conditional correlation between India and Asia-Pacific region is observed, implying that India is not highly affected by the Asian Financial Crisis. Weak conditional correlations of China with the region and the rest of the world are reported, showing that the Asian Financial Crisis has little impact on the Chinese stock markets because it is not fully opened given that the country has conducted a gradual liberalisation process.

Chuang et al. (2007) use a well-established VAR GARCH (BEKK) to study volatility transmissions among Japan, Hong Kong, Singapore, South Korea, Taiwan and Thailand. They point out that the Japanese market is the most influential in exporting volatility to the other markets in East Asia region but with little influence from East Asian markets. Their estimation results also confirm the clustering, stationary and long persistence characteristics of volatility and show evidence of increased volatility for East Asian markets during the Asian Financial Crisis. Engle et al. (2012) utilise a newly established asymmetric multiplicative error model (MEM) to estimate the interactions of stock market volatility in 8 East Asian countries before, during, and after the Asian Financial Crisis. They find significant evidence of interdependence among all stock markets under consideration and increased volatility transmission during the Asian Financial Crisis in October 1997, but few

or no effects during the 9/11 terrorist attacks. Their results also indicate that Hong Kong transmits greater risks to the others, playing a major role as a net creator of volatility.

Beirne et al. (2013) examine volatility spillovers between mature and 41 emerging stock markets. Their tests results indicate evidence of changes in the transmission mechanism during turbulent episodes (the Asian Financial Crisis in 1997 and Global Financial Crisis in 2007) and suggest that mature market volatility affects conditional variances in many emerging markets during the crisis period. The increased conditional correlations between emerging and mature markets are observed during turbulence periods.

The subprime mortgage market crisis originating in the US began in 2007 and developed rapidly into a Global Financial Crisis (GFC) with an international banking system crash triggered by the bankruptcy of Lehman Brothers (the fourth largest investment bank) in 2008. Because the financial system crisis spreads so far and quickly, stock markets worldwide experience a disastrous collapse in their asset prices and become highly volatile. The Global Financial Crisis seems to trigger a prolonged worldwide fear of spillovers and causes substantial changes in the interrelations among international stock markets. This has motivated academic researchers to investigate its unique influence on the interdependence between global financial markets. For example, using various econometric models to investigate the influence of GFC on the interactions among international stock markets, Cheung et al. (2009) document pervasive spillover effects from the US to the stock markets in the UK, Hong Kong, Japan, Australia, Russia and China. Their results indicate enhanced linkages between the US and other markets for both short-term and long-term relationships during the crisis period. The TED spread, serving as a leading fear indicator is observed to adjust to new information rapidly during the crisis and shocks from both the US market and the TED spread have significantly increased impacts on other global markets during the crisis.

Yilmaz (2010) use a newly established spillover index method based on the VAR model to investigate return and volatility spillovers across ten stock markets in the East Asia region and find that the behaviours of volatility and return spillovers are very different during the crisis and non-crisis periods. Particularly, stock markets in East Asia have become more interdependent since the mid-1990s, although the return spillovers have declined from the peak after the Asian crisis. However, return spillovers between East Asian stock markets reach their highest level during the GFC in 2008. Yiu et al. (2010) utilise the an asymmetric Dynamic Conditional Correlation (DCC) model to examine the dynamics between the US

stock market and each of the eleven Asian markets during the turbulent periods. They document evidence of contagion from the US to the Asian markets in the period from late of 2007 (GFC) but no such evidence of contagion during the Asian Financial Crisis period. Aloui et al. (2011) use copula functions to study the extreme interdependencies and spillover effects across different stock markets around the 2007–2009 global financial crisis and show evidence of extreme co-movement for all pairs of BRIC countries both in the left (bearish markets) and right tails (bullish markets). They also indicate that the dependence on the US is higher and more persistent for Brazil and Russia compared to China and India.

Samarakoon (2011) constructs a novel shock model framework to estimate the impact of shocks during the crisis and non-crisis periods, providing important empirical evidence of market interdependence and contagion effects between the US and emerging markets during the Global Financial Crisis. With important regional variations, bi-directional and asymmetric interdependence together with contagious effects is found between the US and emerging stock markets. In particular, the interdependence is driven more by the US shocks while the contagion is driven more by emerging market shocks, showing that the widespread and large decline in emerging markets during the GFC is mainly attributed by normal interdependence rather than contagion. Looking at a different emerging market crisis in the 1990s and the recent US subprime crisis, Kenourgios and Padhi (2012) find evidence of contagion between stock markets during the Russian default, the Asian crises and the subprime crisis, but little evidence for the Argentine turmoil. Based on an asymmetric GARCH model with dynamic conditional correlation framework, their analysis indicates that emerging markets are very vulnerable to external shocks because of the existence of asymmetric contagious effects during Russian default and subprime crisis. The Asian Financial Crisis is found to have strong intra-regional characteristics while the Argentine crisis seems to have isolated nature.

Zheng and Zuo (2013) propose a Markov switching causality method to capture the instability of volatility transmissions over turbulent periods and show evidence of spillover effects among the US, the UK, Germany, Japan and Hong Kong. They report that bilateral volatility spillover effects are more evident during turbulent episodes, especially for the Asian Financial Crisis and subprime mortgage crisis (GFC) periods. The US stock market is found to serve as a major risk source globally with the closest relationship to the UK stock market, whereas the German stock market does not seem to have a significant influence on Asian markets. In addition, Japan is found to be interconnected with other markets during the

Asian Financial Crisis and the Global Financial Crisis, but much less interrelated with others during European sovereign debt crisis and Hong Kong is treated as a net generator of volatility with an important role in international stock markets. Chiang et al. (2013) use ARJI model to study the spillover effects of between the US and BRICV (Brazil, Russia, India, China and Vietnam) countries stock markets. Their estimation results suggest that the US has obvious spillover effects of returns and volatility on BRICV markets with the greatest effects on Russian and Vietnam when the subprime crisis occurs, demonstrating the powerful leadership of US as the largest global financial centre. Among BRICV countries, India is found to be the most efficient market with the lowest risk, and therefore investors are suggested to allocate more funds in Indian markets in order to gain diversification benefits.

Focusing on BRICS (Brazil, Russia, India, China and South Africa) countries and the US, Dimitriou et al. (2013) investigate the contagion effects of GFC in a multivariate DCC-FIAPARCH (Dynamic Conditional Correlation-Fractionally Integrated Asymmetric Power ARCH) model. They find no evidence of a contagion effect for most BRICS during the early stages of the GFC, but confirm a contagion effect that the linkages between the US and BRICS markets emerged after the Lehman Brothers collapse, indicating a change on investors' risk appetite. However, increased correlations between all BRICS and the US are observed from early 2009 (post-crisis period), suggesting that their dependence is larger in bullish period than that in the bearish period. As shown in their findings, BRICS countries' common trade and financial characteristics do not contribute to the pattern of contagion, providing important implications for policymakers and investors. Dungey and Gajurel (2014) adopt a latent factor model to examine the stock market contagion from the US to both developed and emerging markets during the turbulent period. Their analysis results indicate strong evidence of contagion effects in both mature and emerging stock markets, suggesting the significant explaining power of the crisis on market volatility. However, less contagion is observed for the financial industry, implying that contagion is not significantly correlated to global integration.

Mollah et al. (2016) provide evidence of contagion in developed and emerging markets during the global and Eurozone crises, showing that contagion spread from the US to the rest of the world during both crises. In particular, the stock markets in Latin America are equally affected during both crises. In contrast, the Asian emerging markets are partially affected by the Global Financial Crisis (GFC) but unaffected by the Eurozone crisis (EZC)

while the African and Middle Eastern markets are partially affected by the EZC but unaffected by the GFC. Additionally, their results indicate that the bank risk transfer between the US and others is the key channel for cross-country information transmission. Adopting a DCC-GARCH framework to study contagion between the US and ten international stock markets, Hemche et al. (2016) report evidence of increased dynamic correlations between the US and the majority of stock markets. Their findings confirm the contagion effects between the US and France, Italy the UK or Mexico during the crisis because of the observed substantial higher correlations whereas only interdependencies between the US and China, Japan, Morocco, Tunisia or Egypt are observed.

Overall, researchers have observed that both the Asian Financial Crisis and the Global Financial Crisis spread rapidly throughout the world, and did much damage to international stock markets. These events create considerable systematic risks due to direct or indirect linkages with the global financial system. In particular, the dynamic correlations across international stock markets are observed to be time-varying. Most studies have identified an increase in stock market correlations during both the Asian Financial Crisis and the Global Financial Crisis, providing important evidence of the contagion effect and strong market co-movement during the turmoil periods. The US stock market has the leadership role for other markets due to its position as the centre of global finance.

3.2.5 Empirical Evidence of Spillover Effect Related to China

The fast development of the Chinese economy and its stock market has drawn attention to both researchers and investors. There is a unique characteristic in the Chinese stock market which can be classified into two main categories --- A-share market and B-share market. Firstly, the A-share market is only restricted to the Chinese domestic investors whereas the B-share market is only for foreign investors. Emphasising on the relationships between the Chinese A-share and B-share markets, Chui and Kwok (1998) point out that the information flow is mainly from B-share market to A-share market because the returns of B-share market are found to lead the returns of A-share market, implying that foreign investors have better or earlier information than China's domestic market participants. Brooks and Ragunathan (2003) extend the previous study and find significant cross-market influence for both A share and B share in terms of market return based on the VAR model. However, they cannot find

evidence of volatility spillover between the Chinese A Share and B share markets according to their GARCH estimation results.

In the late 1990s, researchers started focusing on the Greater China stock markets because of their close economic and geographical relationship. For example, the study by Hu et al. (1997) is one of the first to examine market interactions between the Chinese and other stock markets. Their analysis results show evidence of contemporaneous correlations between the volatility of the US market and the South China Growth Triangular markets (Hong Kong, Taiwan, Shanghai and Shenzhen). The stock markets in Mainland China (Shanghai and Shenzhen) are found to be more correlated with the developed stock markets, confirming that the global factors are more important for less opened markets. Focusing on four stock markets in the Greater China area, Yeh and Lee (2000) confirm the asymmetric effects for stock markets in this area using a GJR GARCH model. Interestingly, the stock markets in Mainland China are found to respond more to good news compared to bad news while bad news is found to have more impacts on the Taiwan and Hong Kong stock markets. Their vector autoregression (VAR) analysis results confirm the regional leading role of Hong Kong on the other stock markets in the Greater China area.

Wang and Firth (2004) study the returns and volatility spillover effects across four emerging stock markets in the Greater China area and three developed markets (the US, the UK and Japan). The daytime returns of the three advanced markets are observed to have predictive power on each market in the Greater China area, which is consistent with the view that information flow is generally uni-directional from more developed markets to the Chinese market. However, in the wake of the Asian Financial Crisis, there exist bi-directional return and volatility spillovers, suggesting that Asian markets start to become influential. Their findings demonstrate that the equity markets in the Greater China region have become partially interrelated with developed markets. Cheng and Glascock (2005) indicate that the three markets in the Greater China Economic Area (GCEA) are not cointegrated with each other and not cointegrated with either the US or Japanese stock market. This implies that they do not move together or share a common linear equilibrium in the long run. However, weak nonlinear relationships do exist between these markets. According to the innovation analysis, the US market is found to have a larger influence than on the GCEA markets compared to Japan, suggesting the US is the main market driver. Hong Kong, as a developed market is observed to act as the dominant market in the Greater China Economic Area.

Employing an asymmetric multivariate BEKK GARCH model to exam the market interdependence among stock markets in Mainland China, Hong Kong and the US, Li (2007) report evidence of small magnitude uni-directional volatility spillovers from Hong Kong to Shanghai and Shenzhen, indicating weak integration of the Chinese stock exchanges with the regional developed market. However, there is no evidence of a direct linkage between the stock markets in Mainland China and the US. In addition, the estimation results demonstrate that the linkages between Hong Kong and Mainland China seem to depend on the relations between Hong Kong and the US, showing that Hong Kong serves as a go-between role in information transmission. In terms of volatility spillover, the uni-directional volatility spillover effects from Hong Kong to Mainland China and the bi-directional shock spillovers between Shanghai and Shenzhen stock exchanges are observed. Finally, the asymmetric effects of volatility behaviours are confirmed for all the stock markets under considerations, suggesting that the sign of shocks can also influence the market volatility. Following the asymmetric DCC GARCH model to estimate the correlations between each of the four markets in Mainland China and nine international markets, Lin et al. (2009) indicate that correlations between Shanghai and Shenzhen stock markets have significantly increased. In contrast, A Share indices are observed not be correlated with world markets while B Share indices only exhibit a low degree of correlation with Western markets (0–5%) and a slightly higher degree of correlation with other Asian markets (10–20%) despite foreign investors' access to B share markets.

Johansson and Ljungwall (2009) study the market interrelations among China, Hong Kong and Taiwan based on a multivariate EGARCH model. Their preliminary tests results indicate no evidence of a long-run cointegration relationship among these three markets. However, significant mean spillover effects from Taiwan to China and Hong Kong and strong volatility spillover effect from Hong Kong to Taiwan and from Taiwan to Mainland China are observed, implying these three stock markets are more integrated. Wang and Wang (2010) provide new findings on the market interactions between stock markets in Greater China and the US (the world market) or Japan (the regional market) based on multivariate GJR GARCH with BEKK specification. Their analysis results indicate evidence of stronger volatility spillovers between the Greater China markets and two developed markets (the US and Japan) compared with price spillovers. In particular, the volatility spillovers between the Greater China markets and two developed markets are bi-directional at an almost equal degree whereas the price spillovers are very weak. The extent of influence by the developed

market has decreased following the order of Hong Kong, Taiwan, Shenzhen and Shanghai, suggesting that the greater openness of the stock market is associated with the influence of the advanced market.

Li (2012) explores China's regional and global linkages using a 4 variables asymmetric BEKK GARCH framework. There are bi-directional spillovers between China and the US and uni-directional spillovers from China to South Korea and Japan. Based on the sub-period analysis, financial liberalisation and institutional reforms in China are found to foster the spillover effects from China to international stock markets to increase. According to the analysis results on the time-varying conditional correlations method, the implementations of several major liberalisation reforms have contributed to the increased interdependence between China and the regional markets. Zhou et al. (2012) use a spillover index method based on variance decomposition in the VAR framework to study the volatility spillover between China and other markets. They find that the Chinese stock market was hardly affected by world markets in terms of volatility spillover from 1996 to 2009. Particularly, other markets had little influence on China before 2005 while the Chinese stock market started to show a significant and positive volatility spillover effect on other markets after 2005, indicating the enhanced influence of the Chinese stock market in recent years. The volatility interactions among the Chinese, Hong Kong, and Taiwanese stock markets are found to be more prominent than those among the Chinese, Western, and other Asian ones, suggesting strong markets integration within the Greater China region. More distinctive volatility spillovers among the Chinese, Japanese, and Indian markets are observed compared with those among the Chinese, the US, and the UK markets, showing that the interrelations among Asian markets have become more obvious in recent years. However, the US stock market is still characterised as having strong volatility impacts on others during the Global Financial Crisis, confirming its dominant role in the global financial system.

Nishimura et al. (2015) propose a China-related stock index which includes several Japanese listed companies with major operations in China. They explore the return and volatility spillovers between China and Japan and find that the China-related stock index reacts to changes in the Chinese stock market (Shanghai) more strongly than does Tokyo's overall market index, indicating that China has a huge influence on the Japanese stock market through the channel of these China-related companies in Japan. However, they find no evidence of volatility transmission between the two markets, implying that the main channel

for information transmission from China to Japan is the market returns. Majdoub and Ben Sassi (2017) investigate volatility spillovers between Islamic indices in China and several Asian Islamic countries using a bivariate VARMA-BEKK-AGARCH model. They find significant evidence of positive return spillovers from China to India and Malaysia but negative return spillovers from China to South Korea, Thailand and Indonesia. In terms of shock spillover effects, negative spillovers are observed from China to the South Korean and Thailand Islamic stock markets while only positive spillover effects from Thailand to China are statistically significant. For long-term volatility spillovers, the Chinese Islamic stock index is found to influence the Islamic stock markets in Malaysia and Thailand. However, no long-term volatility spillover effects exist between the Chinese Islamic and Indonesian, Indian and South Korean Islamic stock markets.

Overall, the research on spillover effect between China and other markets provide mixed results, revealing the complex dynamics between China and international stock markets. However, the research focusing on the Chinese stock market is limited compared with that on developed markets and other emerging markets, and therefore it is necessary to conduct further academic investigations on financial linkages between China and other markets. We can see that most studies are able to find evidence of spillover effects from the developed countries to China but little evidence is found for the reverse case, suggesting that the Chinese stock market is inefficient. Several articles indicate strong market interdependence among stock markets in the Greater China area, implying strong regional financial integration. Some studies find the US stock market exerts much influence on China, implying that the US is still acting as the dominant global financial centre to spillover its volatility. Japan and Hong Kong, as the important regional markets are also found to interact with the Chinese stock market actively. Therefore, research evidence reveals that the regional financial centers start to exert their influential spillover power on their neighboring markets, despite the fact that the US is still the most important spillover exporter.

3.3 Relations between Stock and its Index Futures Markets

3.3.1 Price Discovery Role of the Futures Markets

The stock index futures market acts as an important and active market in the global financial system. It is very important for market participants and policy-makers because it has a price

discovery role, enhances information transmission procedures, improves financial market efficiency, provides arbitrage opportunities and helps to hedge against risks. Since the introduction of the first stock index futures (S&P 500 Index futures) in the US in 1982, this derivative market has become one of the most important risk management tools in the financial markets (CME, 2014). There are several advantages of trading on the index futures contracts. For example, it can reduce the cost of trading, provide more liquidity, increase the number of information transmission channels and foster the transfer of spot market's risks, making this financial derivative instrument to become more important. Due to the importance of the index futures market, a large number of studies have examined the joint behaviour between the spot and futures markets, learning how information flows between the two markets and shedding light on the efficiency of the two markets.

Theoretically, the lead-lag relationship between the spot and futures markets should not exist in a perfectly efficient market, as the information will arrive at the spot and futures markets simultaneously if the market is perfectly efficient. However, due to many other factors which contribute to the markets' inefficiency, it is not possible for the information to arrive simultaneously, and thus a lead-lag relationship exists between the two markets in the real world. Consequently, futures markets are usually observed to incorporate information more efficiently than spot markets due to several advantages of future markets such as low transaction cost, the absence of short selling restriction, inherent leverage and greater liquidity, functioning as price discovery role. Price discovery role of futures markets is commonly defined as the use of futures prices to determine expectations of cash (spot) market prices and either short run or long run relations could be identified between the two markets (Yang et al., 2012).

Early research on this topic producing evidence of price discovery of futures market mainly focuses on developed markets such as the US, the UK and some European countries. There are a substantial number of studies indicating evidence that the stock index futures market has played a price discovery role and contributed to the spot market's efficiency. Looking at the US index futures market, Kawaller et al. (1987) provide an empirical analysis of the relationship between S&P500 spot and futures markets using high-frequency minute to minute data. The estimation results based on three stage least squares regression suggest that the S&P500 futures market can lead its spot market by 20 to 45 minutes while the lead from cash prices to futures prices hardly exceeds 1 minute. Focusing on the ten-day period during

the US October Crash in 1987, Harris (1989) identifies the long lagged relationship between the market index and its futures index, showing evidence that the S&P500 futures market leads the spot market. The large futures-spot basis during the crash seems to be mainly contributed by market disintegration due to their capacity and regulatory disruptions, despite the fact that the nonsynchronous trading is able to explain part of this.

Stoll and Whaley (1990) investigate the return behaviours of stock index and its futures markets in the US and report evidence that the returns of S&P500 and Major Market Index futures tend to lead their underlying markets by about 5 minutes on average. In addition, the two futures returns are found to lead the returns of actively traded stocks like IBM. The lagged stock index returns are also observed to have a mild positive predictive impact on current returns of futures markets, yet this effect tends to shrink as the futures contracts mature. Chan (1992) find asymmetric lead-lag relationships between the futures market of the S&P500 and MMI futures and their underlying market, indicating that the index futures markets have predominant lead-lag relations on their cash index; however, the feedback from the cash to the futures markets is weak. This asymmetric lead-lag relationship is also confirmed in all component stocks in the indices. The author also points out that the nonsynchronous trading issue cannot be used to explain the lead-lag phenomenon completely, and furthermore the futures market is the main source of market-wide information. This is because it has higher lead-lag impacts on its underlying market when more stocks move together.

Emphasising the price causality between spot and futures markets for indices of S&P500 and Financial Times-Stock Exchange 100 (FT-SE 100), Wahab and Lashgari (1993) find that the spot and futures markets are cointegrated, thus confirming the appropriateness of applying the error correction model. The lead-lag relationship exists between the spot and futures markets with a more pronounced lead from spot to futures and the futures prices are found to respond to the disequilibrium more significantly than does the cash market. Fleming et al. (1996) provide strong evidence to support their trading cost hypothesis. They indicate the market involved with lower trading cost responds more quickly to new information, and subsequently the S&P 500 index futures are found to lead its cash index. Tse (1999) uses minute by minute data to investigate the price discovery role of the Dow Jones Industrial Average (DJIA) index based on a vector error correction model (VECM), and indicates

pronounced price discovery role of DJIA futures, implying the efficiency of the index futures market.

Several analyses have focused on non-US index futures markets. For example, Martikainen and Puttonen (1994) empirically examine information flow related to the Finnish financial market. Their results reveal that the worldwide index is found to influence the Finnish stock index futures market which is also observed to have significant impacts on that country's stock market. The price discovery role of the Finnish stock index futures market seems to be attributed by the restrictions of short selling. Abhyankar (1995) use a structural break test to divide the sample period into three sub-periods to investigate the contemporaneous relationship between FT-SE futures and spot markets in London. Findings indicate strong evidence that the futures market could lead the cash market during all three sub-periods. However, the cash market is only observed to have weak predictive power for futures market after the Big Bang (the second period).

Turkington and Walsh (1999) study the causal relations between the All Ordinaries Index (AOI) and its stock index futures (SPI) in Australia and find that the two markets are cointegrated. Strong bi-directional causality between SPI futures and AOI spot markets is observed based on bivariate Error Correction Model. However, the Australian futures market seems to respond more to the shocks from its underlying market compared with vice versa. Frino et al. (2000) investigate the impact of macroeconomic information release on the lead-lag relations between futures and spot markets in the case of Australian stock index futures contracts. Their empirical results indicate that both macroeconomic and stock-specific information are able to influence the lead-lag relationship between the two markets. Specifically, the macroeconomic information is observed to significantly enhance the lead from the futures while the stock-specific information slightly strengthens the lead from the underlying stock market. Supported here is the hypothesis that investors with better market-wide information prefer to trade index futures contracts but investors with better stock-specific information are more likely to trade individual shares.

Extending the univariate model to a bivariate error correction EGARCH model to incorporate the long-term relationship into both return and volatility, the study by Zhong et al. (2004) indicates a cointegration relation between the Mexican futures and spot markets and shows evidence of price discovery function of Mexico futures market. Kavussanos et al. (2008) explore the lead-lag relationship between the cash and futures markets in Greece.

They confirm the existence of a bi-directional relationship between cash and futures for indices of FTSE/ATHEX-20 and FTSE/ATHEX Mid-40 with a stronger lead from the futures returns, suggesting that new information propagates to the futures market earlier than the cash market. Choy and Zhang (2010) emphasise the price discovery process of Hong Kong index futures market and suggest that the regular Hang Seng index futures contract plays a dominant and leading role in price discovery. The reason for this is its low transaction cost, supporting the trading cost hypothesis. However, the mini-futures contracts and cash index are observed to play minor roles. Similarly, Tao and Song (2010) indicate that the Hang Seng Index Futures (HSIF) market has the largest information share (about 71.0%) while its underlying market only has a 12.2% share. Interestingly, the Mini Hang Seng Index futures market is observed to contribute about 16.8% to price discovery, which is a disproportionately high share because of their relatively low trading volume.

Some studies also examine the influence of investors' structure on the lead-lag relations between futures and cash markets. Focusing on different investor groups, Bohl et al. (2011) investigate the relations between causal spot-futures linkages and investor structures in the case of the Polish WIG20 index futures market. Their analysis indicates that that price discovery role of the futures is related to the investor structure in the futures market. In particular, no price discovery role is observed under the dominance of uninformed individual investors whereas a stronger interaction between the two markets occurs when institutional investors are main market participants, showing that the change in the composition of investor from individual to institutional investors can lead to an increased price discovery contribution of the futures market. Lee et al. (2013) analyse the informational role of trading activity in Taiwan Stock Exchange Capitalisation Weighted Stock Index futures and find evidence that the futures market leads the spot market. In terms of trading activities, the net open buy of foreign institutional traders is found to have predictive power for both the futures and cash markets. Their results indicate that the foreign institutional investors seem to have better information and prefer to trade in the futures market. Also focusing on Taiwan index futures market, Wang et al. (2013) investigate the price discovery role of both regular and mini-index futures in Taiwan markets and demonstrate that the mini-index futures contribute more to the price discovery process compared to the regular index futures. The price discovery role of Taiwan mini index futures is influenced by its relative liquidity and changes in liquidity between the mini and regular index futures. Unlike previous studies, Judge and Reancharoen (2014) look at the price discovery process in Thailand futures and stock markets.

They indicate that the spot (SET50) index leads SET50 index futures, which is inconsistent with the general opinion that futures markets usually have a pronounced prices discovery function.

To sum up, the price discovery role of the stock index futures market is confirmed by most empirical studies. Some papers indicate evidence of a bi-directional asymmetric lead-lag relationship between the futures and spot market, suggesting the existence of a strong lead from the futures market to the spot market but a weak lead from the spot market to the futures. The observed asymmetric effect implies that the informed traders may prefer to trade in the futures market rather than to trade in the spot market. In addition, most empirical studies can confirm the existence of the cointegration (long-term) relationship between the futures and spot markets, implying that these two markets move together. Several pieces of empirical evidence suggest that the investors' structure also has a significant influence on the lead-lag relations between the two markets.

3.3.2 Volatility Spillover between the Futures and Spot Markets

Apart from the information which is contained in prices, volatility as an important source of information that plays a critical role in information transmission, and therefore understanding volatility spillover between the futures and spot markets is also very crucial for market participants. Since the volatility of the cash and futures markets has a time-varying feature in a related way and represents another way to measure information flow, thus only focusing on price level lead-lag relations may result in inclusive and incomplete evidence on how information flows to the two highly related markets. As a result, examining the relationship between volatility in cash and futures markets can help to understand the pattern of information flows between the two markets and further help the portfolio and hedge fund managers to manage risks. Besides, the volatility spillover is related to the risk spillover effect between the two markets, so it is necessary for the policy-makers to have a better knowledge on the risk spillovers in order to assess the markets' stability. Several studies have investigated the lead-lag relations in the volatility of market returns between cash and stock index futures markets because of the theoretical linkages between volatility and information flow.

However, the volatility spillover effects between the stock index futures and its underlying cash markets are not clear given the level of disagreement in the literature. Some research papers indicate there is no consistent evidence for a lead-lag relationship between the two markets. For example, Kawaller et al. (1990) use intraday data and Granger test to study the relationship between the volatilities of S&P 500 futures and cash markets. They report evidence that both futures and cash markets' volatilities have increased directly with higher futures trading volume, implying that greater futures trading activities seem to lead to higher market volatilities. However, a systematic and robust lead-lag relationship between the two markets is not observed, since the lead and lags in volatility are sensitive to sample periods, indicating there is no consistent pattern for volatility spillovers between the two markets. Focusing on the volatile period during the US October Crash in 1987, Arshanapalli and Doukas (1994) confirm the ARCH effects in both S&P 500 futures and cash markets. Their ARCH-feature test results indicate the volatility process in the two markets is different, suggesting independence of their second moments (volatility). Similarly, Abhyankar (1995) could not find a consistent pattern in the lead-lag relation between the volatilities of the FT-SE 100 index futures and cash returns for all the periods of good news, bad news, high trading volume and low trading volume.

Several studies report significant evidence of bi-directional volatility spillovers between stock index futures and its underlying cash markets. For example, Chan et al. (1991) find strong evidence of cross-market bi-directional intraday volatility spillovers between the S&P500 futures and spot markets, suggesting that new information in each market is an important predictor of the future volatility in the other markets. Their results suggesting critical informational role of both futures and spot markets are inconsistent with the general opinion that information flows to the futures market. Tse (1999) investigates the volatility spillover effects between the DJIA futures and spot markets based on a bivariate EGARCH and reports evidence of a significant bi-directional volatility spillover effect between the two markets. However, the volatility spillovers from the futures to spot market are found to be stronger compared with vice versa. Kang et al. (2013) use three high-frequency intraday data sets (10 minutes, 30 minutes, and 1 hour intervals) to empirically examine the relationship between the South Korean futures and spot markets. Their analysis reveals strong evidence of a significant bi-directional volatility spillover between KOSPI200 futures and spot markets, indicating simultaneous reflection of the new information in both futures and spot markets.

There are some studies which can only find the volatility spillover from futures market to spot market. For example, Koutmos and Tucker (1996) find innovations originating in the S&P500 futures markets can increase volatility of the stock market in an asymmetric way, implying that bad news increases volatility in both futures and spot markets more than does good news. However, shocks from the stock market seem not to influence the volatility of the futures market. Zhong et al. (2004) employ a modified error correction EGARCH model to show that the deviation from the long-term cointegration equilibrium is able to propagate volatility in both Mexican futures and spot markets. They further suggest that the futures trading can intensify the volatility of its underlying cash market. Kavussanos et al. (2008) find uni-directional volatility spillover from FTSE/ATHEX-20 and FTSE/ATHEX Mid-40 futures markets to the corresponding spot markets.

The general conclusion of previous studies is that the investigation for volatility spillovers between the futures and spot markets demonstrates variable results over different sample periods and stock index futures contracts. Generally speaking, the volatility spillover effect from the futures to spot market is observed in most countries. However, the volatility spillover from the spot to futures market varies for different markets, depending possibly on the markets' efficiency, restrictions imposed on the markets, transaction costs charged in each of the markets, etc.

3.3.3 Studies Related to the Chinese Stock Index Futures Market

The Chinese stock market began operating in the early 1990s with the establishment of two stock exchanges - Shanghai and Shenzhen – and since then has grown rapidly in the last three decades. In order to measure the overall market performance of the Chinese A shares, the CSI 300 index, a capitalisation-weighted index representing the performance of the top 300 stocks traded in both the Shanghai and Shenzhen stock exchanges was launched on 8th April 2005. Based on the CSI 300 index, the CSI 300 index futures contracts were created on 16th April 2010 by the China Financial Futures Exchange. Following the introduction of the CSI 300 index futures, several studies focus on the impact of CSI 300 futures on the underlying spot market. For example, using a panel data approach, Chen et al. (2013) observe that the introduction of the Chinese index futures market significantly decreases the volatility of its underlying stock market, showing that the Chinese index futures market, as an effective risk

management tool, has improved information efficiency in the Chinese stock market. Hou and Li (2014) employ both univariate and bivariate GARCH family frameworks to study the impacts of the CSI 300 index futures on its spot market and discover that the CSI 300 stock index futures could intensify and attract positive feedback trading in its spot market. Although the volatility of the Chinese stock market is observed to decrease after the introduction of CSI 300 index futures contracts, strong positive feedback trading in the Chinese stock market seems to destabilise the underlying spot market and further downgrade information efficiency. The estimation results reported by Bohl et al. (2015) suggest that the introduction of the Chinese index futures decreases the volatility of not only its underlying CSI 300 spot index but also the A50 index in Singapore and HSCEI index in Hong Kong.

Apart from examining the impacts of the Chinese stock index futures market, few studies focus on price discovery role and volatility spillover effect between Chinese stock index futures and spot markets. Since several strict entry requirements and high barriers exist for investors to enter the index futures market, institutional investors who are the most informed are expected to dominate the index futures market and other investors. So the Chinese stock index futures market is expected to have a price discovery process regarding its spot market. However, Yang et al. (2012) believe that the Chinese stock index futures market does not function well in its price discovery role at its initial stage. This observation is explained by the implemented higher barriers to entry to the futures market which practically exclude many informed traders and lead to the absence of the price discovery function in the CSI 300 index futures market. However, Hou and Li (2013) provide a contrary conclusion when using similar high-frequency data to explore price discovery in the CSI 300 futures market roughly one year after its introduction. They observe that the CSI 300 futures market has its price discovery role 1 year after its introduction. Xu and Wan (2015) find evidence that the futures market in China makes more contributions to the price discovery process. Moreover, institutional investors' trading is found to improve the price discovery role of the futures market positively whereas individual investors' trading is observed to influence the price efficiency in the futures market negatively.

In terms of volatility spillover effect, the research of Yang et al. (2012) indicate strong evidence of a bi-directional dependence between the intraday volatility of the futures and spot markets, showing that volatility can be easily transmitted between each other. Zhou et al. (2014) confirm there is a strong bi-directional volatility spillover effect between CSI 300

futures and spot markets by using realised volatility to proxy for market risk. Cao et al. (2014) analyse the cross-correlation between the index futures and spot market in China and report evidence of the existence of multifractality in the cross-correlation and a bi-directional causal relationship between the two markets with stronger impacts from the futures market. Covering a long period from 2010 to 2015, Miao et al. (2017) document evidence of the dominant role of the stock index futures in China in the price discovery process. However, the volatility transmission is observed to be bi-directional with asymmetrical feedback effects, showing that the shocks from the stock market dominate information transmission.

For the Chinese stock index futures market, most studies are able to identify the significant impacts on its underlying spot market. In terms of price discovery function, only a few articles investigate this issue but they do provide controversy results (Yang et al., 2012; Hou and Li, 2013; Xu and Wan, 2015). A few academic papers discover the existence of a bi-directional volatility transmission between the CSI 300 futures and spot markets. However, research on the price discovery and volatility transmission on CSI 300 futures market is still limited and subject to different time intervals, various research methods with divergent empirical results. It is noted that permitting Qualified Foreign Institutional Investors (QFII) to trade on CSI 300 futures market was an important and significant event during the market development. For this reason, further research is needed to study the impacts of QFII on this important financial derivative market in China with unique features.

3.4 Relations between Stock and Commodity Markets

3.4.1 Linkages between Stock and Oil Markets

There is sizeable literature analysing the interdependence between commodities and stock markets. Oil, as one of the most important commodities in the world, is of great interest for investors and policy-makers. This natural and non-renewable resource has broad ramifications for financial market movement and economic performance. Specifically, large increases in oil prices are likely responsible for high inflation rate and economic recessions. Theoretical linkages between oil market and stock market have been well established. According to standard economic theory, stock market returns are directly affected by the future expected cash flows and indirectly influenced by discount rates used in the stock pricing formula. These two important factors are highly correlated with oil prices, and in this

way, oil prices can affect stock prices. As a result, increases in oil prices are expected to negatively affect the real output and cause the decrease of stock prices. A detailed analysis of this relationship is provided by Huang et al. (1996). Future oil prices can affect expected cash flows because oil is a real resource and an essential input to the production of many goods along with labour and capital, and therefore expected changes in energy prices are very likely to cause the changes in expected costs. Oil is a commodity, and changes in oil prices track the inflation rate, so expected oil prices also affect stock returns via the discount rate. As such a higher expected inflation rate is positively related to the discount rate and as a consequence is negatively related to stock returns. Moreover, when facing large inflationary pressures, the central banks may raise the interest rates, and consequently, higher interest rates tend to make the stock market less attractive and impact negatively on equity prices (Jiménez-Rodríguez, 2015). In addition, a rise in uncertainty about energy price also plays a role in firm-level investment decisions since increased uncertainty may delay implementing investment in capital equipment, reduce the positive effect of sales growth on investment and further depress aggregate stock prices (Yoon and Ratti, 2011; Pindyck, 1991; Bernanke, 1983).

The empirical research on the linkage between stock markets and oil price movements has only been investigated recently. Starting with the seminal work by Hamilton (1983), he initiated well-known research in economics focusing on the statistical correlation between the oil price shocks and macroeconomy in the US. He noted that 7 of 8 post-war recessions in the US had been preceded by a significant increase in the price of crude oil. He found no evidence that the inventories, capacity utilisation, the Bureau of Economic Analysis leading indicator series, interest rates and the stock market are able to predict the oil price shocks over 1948-1972. Oil prices not only impact on relevant macroeconomic variables but also may affect financial markets. Kling (1985) investigated the relationship between crude oil price and the stock market in the US between 1973 and 1982, concluding that the stock market was able to anticipate crude oil price changes after 1972. Also, crude oil prices had a significant lagged effect on the stock prices in some industries like the air transport, automobile, and domestic oil industries while shocks in crude oil prices generally were followed months later by significant declines in stock prices for these industries.

Jones and Kaul (1996) indicate that changes in oil prices have a significant impact on the output and real stock returns in the United States, Canada, Japan, and the United

Kingdom during the post-war period. However, they can only confirm the theoretical prediction of the negative relationship between oil price movement and stock market return in the US and Canadian markets, indicating that the effects of oil shocks on stock markets can be completely explained by their effects on contemporaneous and future real cash flows. Sadorsky (1999) conducts a vector auto-regression method to study the relationship between oil prices changes and stock returns in the US and finds that both oil prices and oil price volatility play important roles in affecting real stock returns. The results show that oil price movements are important in explaining movements in stock returns, suggesting that positive shocks to oil prices depress real stock returns. In addition, oil price movements can explain a larger fraction of the forecast error variance in real stock returns than do interest rates after 1986. He also observes that positive oil price volatility shocks explain a larger proportion of the forecast error variance in industrial production and real stock returns than do negative oil price volatility shocks, indicating oil price volatility shocks also have asymmetric effects on the economy. Extending previous work by testing for nonlinear linkages between the oil prices and the stock market, Ciner (2001) provides evidence that significant bi-directional nonlinear Granger causality exists between oil futures returns (both crude and heating oil) and stock index returns, consistent with the documented influence of oil on economic output. However, he finds no evidence that there is a linear Granger causality between them.

Basher and Sadorsky (2006) examine the impact of oil price changes on 21 emerging stock market returns over the period 1992–2005 using both unconditional and conditional risk analysis and find strong and robust evidence that oil price risk plays an important role in pricing emerging stock markets returns. More recently, some studies confirm the existence of return and volatility spillovers between world oil prices and stock markets in the US, Europe and Gulf Cooperation Council countries, indicating significant impact of oil price shocks on stock market returns (Park and Ratti, 2008; Mohanty et al., 2010; Arouri et al., 2011b; Arouri et al., 2011a; Fayyad and Daly, 2011; Cunado and Perez de Gracia, 2014). Nguyen and Bhatti (2012) employ both parametric and non-parametric methods to investigate market co-movement between oil price and stock market in China and Vietnam. They indicate a left tail dependence between global oil price and stock market in Vietnam, implying Vietnam's stock market will follow the downward trend of the oil market. However, evidence of any tail dependence between international oil price and the Chinese stock market cannot be found. Jammazi and Nguyen (2015) indicate that an oil shock in a stable price environment is likely to have larger consequences on stock returns than one in a volatile price environment.

This will occur specifically when testing for non-linearity in the relationship between real oil prices and real stock returns for Canada, Germany, the UK, and the US.

3.4.2 Relationship between Stock and Other Commodity Markets

Investment in commodities has grown rapidly in recent years. The popularity of commodity investment is because the correlations between commodity futures markets and traditional assets such as equity and bonds are expected to be low or negative, possibly resulting in higher diversification benefits. Different financial and economic factors which drive the value of commodities could contribute to the low correlation between commodity and other assets (Hammoudeh et al., 2014). Empirically, this is evidenced by some research showing that investing in the commodity futures can be used to diversify portfolio risks as an effective strategy. For example, Gorton and Rouwenhorst (2006) observe the commodity futures market performs better during unexpected inflation periods and a negative correlation between commodity markets and equity or bonds markets over a sample of 1959–2004. The diversification benefits of commodity markets are confirmed here. Büyüksahin et al. (2010) find that cross-market correlations and dynamic conditional correlations (DCCs) are almost zero during much of the sample time, indicating weak market co-movement between commodity futures and S&P500 index.

For the long-term perspective, little statistical evidence of a cointegration relationship can be found. Even during the GFC in 2008, the DCCs remain at a low level despite the increase in cross-correlations. The same conclusion is confirmed by Chong and Miffre (2010) who observe that the conditional correlations between 11 commodity futures and S&P500 returns tend to fall when traditional market risks rise. The portfolio diversification gains can also be confirmed in the study done by Belousova and Dorfleitner (2012) which indicate that investors can use commodity instruments (both physical commodity and commodity futures) as valuable investment tools to enhance the portfolio performance by changing exposure into individual commodities. For Indian commodity markets, low dynamic conditional correlations can be found between commodity futures and traditional asset indices returns (stock index, long-term bond index and Treasury bill index) by Lagesh et al. (2014).

More recently, as the rapid development of index fund dealing with commodities and more investment allocation in the commodity market enable it to be integrated with stock and

bonds market, some diversification benefits may be sacrificed (Tang and Xiong, 2012). While the majority of literature supports the diversification benefits of commodities, there are still contradictory results. For example, Daskalaki and Skiadopoulos (2011) in their findings challenge the alleged diversification benefits of commodities. Their analysis results confirm the superiority of optimal portfolios that include only the traditional asset classes in the vast majority of cases, even in the presence of transaction costs and the preserved diversification benefits out-of-sample could not be found. Silvennoinen and Thorp (2013) observe most correlations in stocks, bonds and commodity futures are near zero in the 1990s, increase around the early 2000s and reach peaks during the GFC, since the increasing interest of investors results in strong integration of commodities with conventional asset markets. As a result, diversification benefits of commodities against stock and bond markets were significantly reduced. Büyüksahin and Robe (2014) find evidence that the increased financialisation of commodity markets together with some macroeconomic fundamentals may also result in the integration between commodity markets and traditional assets markets. This possibly raises the prospect of correlations between commodities and conventional assets and eliminates diversification benefits.

3.5 Conclusion

The purpose of this chapter is to provide a comprehensive review regarding the interdependence between the stock markets and other financial markets, including equity market, index futures market and commodity market. The literature on spillover effects regarding the stock market and its volatility has produced a large amount of theoretical and empirical research, confirming that the stock market in one country is highly correlated to other financial markets. Several econometric methods including the ARCH/GARCH models have been employed to empirically examine the dynamic interactions between stock market and other financial markets. Several consensus have been reached. For example, (i) spillover effect between different stock markets has been observed; (ii) financial crises are generally found to enhance the spillover effect between stock markets; and (iii) stock index futures market usually has a price discovery role. However, there is still much debate regarding the spillover effect and information transmission between financial markets. Therefore, this study will provide further evidence on this relationship by conducting a comparative analysis of the Chinese stock market at a regional level. It also examines several

important financial liberalisation reforms in China that reflect the increased importance of China and its economy.

Chapter 4: Research Technique and Methodological Framework

4.1 Introduction

The purpose of this chapter is to review the econometric methodologies which have been used in examining the dynamics across financial markets. The Vector autoregression (VAR) model is an extension of a univariate autoregressive model that is able to capture linear interdependencies among multiple variables. It has been successfully applied to the analysis of multivariate financial time series. If cointegration relationship(s) among financial time series have been detected, the vector error correction model (VECM) can be applied. VECM is one of the most commonly used econometric models for financial time series analysis where the variables have a long-run stochastic trend. It is useful for estimating both short-term and long-term effects between time series. Volatility modelling and forecasting are also essential for financial analysis, since market volatility has unique and stylised characteristics, such as volatility clustering, mean reversion, persistence, etc. the ARCH and GARCH models since their introduction have been widely used in volatility modelling. Based on the basic GARCH models, some extensions are able to capture unique volatility features such as leverage effect. This chapter is organised as follows: section 4.2 discusses Vector Autoregressions (VAR); section 4.3 reviews some unit root tests and Vector Error Correction Model (VECM); section 4.4 provides a detail discussion on the GARCH family models; and finally, we conclude this chapter with a summary of the main themes covered here.

4.2 Vector Autoregressions (VAR)

Since the original works of Sims (1980), a Vector Autoregressions (VAR) model has become a standard econometric model for multivariate data analysis. Nowadays, VAR models are popular and widely used by empirical researchers to explore and explain economic and financial phenomena. A univariate autoregression (AR) model is a single-variable linear model which contains only one single equation. In the AR model, the current value of a variable is explained by its own lagged values, whereas a VAR model is an n -equation, n -variable linear model which is the generalisation of an AR model. This simple VAR framework, which is easy to use and to interpret, can systematically capture rich dynamics in

multiple time series (Watson, 1994). The VAR model is able to capture the interdependencies and evolution between multiple financial and economic time series. In a VAR model, each variable is explained by its own lagged values and the lags of all the remaining $n-1$ variables. As Sims (1980) argued in early papers, VAR can potentially provide a coherent and credible approach to data description, forecasting, structural inference and policy analysis. In particular, we have the following VAR equations:

$$Y_t = c + \Pi_1 Y_{t-1} + \Pi_2 Y_{t-2} + \dots + \Pi_p Y_{t-p} + \varepsilon_t \quad t=1, \dots, T, \quad (4.1)$$

where $Y_t = (y_{1t}, y_{2t}, \dots, y_{nt})'$ denotes an $n \times 1$ vector of time series variables, Π_i are $n \times n$ coefficient matrices, c is an $n \times 1$ vector of constants and ε_t is an $n \times 1$ unobservable zero-mean white noise vector process with time-invariant covariance matrix Σ :

$$\Sigma = \begin{pmatrix} \sigma_{\varepsilon_{1,t}}^2 & 0 & & 0 \\ 0 & \sigma_{\varepsilon_{2,t}}^2 & & 0 \\ & & \ddots & \\ 0 & 0 & & \sigma_{\varepsilon_{n,t}}^2 \end{pmatrix}$$

The simplest VAR process is the bivariate VAR (1) model which is represented as:

$$\begin{pmatrix} y_{1,t} \\ y_{2,t} \end{pmatrix} = \begin{pmatrix} c_1 \\ c_2 \end{pmatrix} + \begin{pmatrix} \pi_1^{11} & \pi_1^{12} \\ \pi_1^{21} & \pi_1^{22} \end{pmatrix} \begin{pmatrix} y_{1,t-1} \\ y_{2,t-1} \end{pmatrix} + \begin{pmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \end{pmatrix} \quad (4.2)$$

Equation (4.2) can be rewritten as:

$$\begin{cases} y_{1,t} = c_1 + \pi_1^{11} y_{1,t-1} + \pi_1^{12} y_{2,t-1} + \varepsilon_{1,t} \\ y_{2,t} = c_2 + \pi_1^{21} y_{1,t-1} + \pi_1^{22} y_{2,t-1} + \varepsilon_{2,t} \end{cases} \quad (4.3)$$

Using the lag operator, the VAR(p) can be written as:

$$\Pi(L)Y_t = c + \varepsilon_t \quad (4.4)$$

$$\text{where } \Pi(L) = I_n - \Pi_1 L_1 - \Pi_2 L_2 - \dots - \Pi_p L_p$$

If $\det(z) = \det(I_n - \Pi_1 z_1 - \Pi_2 z_2 - \dots - \Pi_p z_p) \neq 0$, for $z \in \mathbb{C}$, $|z| \leq 1$, The VAR(p) is stable. In other words, if all roots of the polynomial lie outside the complex unit circle, the VAR process is stable.

An important element in the specification of VAR models is the lag length selection of the VAR (Ozcicek and Douglas McMillin, 1999). As discussed by Lütkepohl (2005), the lag length for the VAR(p) model is frequently selected using model selection criteria. The general procedure is to fit VAR(p) models with orders $p = 0, \dots, p_{\max}$ and choose the lag structure that generates the minimum selection criteria as the optimal lag structure. The three most common information criteria are Akaike (AIC), Schwarz-Bayesian (BIC) and Hannan-Quinn (HQ):

$$\begin{aligned} AIC(p) &= \ln|\bar{\Sigma}(p)| + \frac{2}{T} (\text{Number of freely estimated parameters}) \\ &= \ln|\bar{\Sigma}(p)| + \frac{2}{T} (pK^2) \end{aligned}$$

$$\begin{aligned} HQ(p) &= \ln|\bar{\Sigma}(p)| + \frac{2\ln\ln(T)}{T} (\text{Number of freely estimated parameters}) \\ &= \ln|\bar{\Sigma}(p)| + \frac{2\ln\ln(T)}{T} (pK^2) \end{aligned}$$

$$\begin{aligned} BIC(p) &= \ln|\bar{\Sigma}(p)| + \frac{\ln(T)}{T} (\text{Number of freely estimated parameters}) \\ &= \ln|\bar{\Sigma}(p)| + \frac{\ln(T)}{T} (pK^2) \end{aligned}$$

where K is the dimension of the time series, T is the effective sample size, $\bar{\Sigma}$ is the estimated residual covariance matrix.

However, the unrestrictive Vector Autoregression (VAR) model requires stationarity of the underlying variables. If the time series are not stationary, spurious regression results may occur (Phillips, 1986; Granger and Newbold, 1974). Two methods, namely the vector error correction model (VECM) and Bayesian VAR can overcome the problems of spurious outcomes. VECM uses a transformed model to capture both short-term and long-term dynamics while the Bayesian method indicates there is no need to use a transformed model because differencing the levels data to achieve stationarity could throw away the information contained in the raw data. In order to capture the dynamics among the variables, the levels Vector Autoregression (VAR) model should be applied to determine the interrelationships among the underlying variables. Sims et al. (1990) suggest that the Bayesian approach does not need to consider non-stationarity of the time series and therefore is ideal for analysing non-stationary data. This is because the parameter estimates will not be affected by non-stationarity as the unrestrictive Ordinary Least Squares (OLS) estimates are. Canova and Ciccarelli (2004) indicate that Bayesian VARs could produce better forecasts than unrestricted VAR. In addition, Bayesian VAR could reduce the degrees of freedom issue and solve the over-fitting problems by introducing relevant prior information and eventually achieve a substantial improvement in forecasting performance over the classical VAR model (Abrego and Österholm, 2010). We start with the following VAR specification:

$$Y_t = b_0 + B_1 Y_{t-1} + B_2 Y_{t-2} + \dots + B_p Y_{t-p} + \varepsilon_t \quad t=1, \dots, T, \quad (4.5)$$

where Y_t is an $n \times 1$ vector of variables, ε_t is a $n \times 1$ vector of error terms which are independently, identically and normally distributed with variance-covariance matrix Σ ($\varepsilon_t \sim \text{IIN}(0, \Sigma)$), b_0 is a $N \times 1$ vector of intercepts and $B_i (i=1, \dots, p)$ is $n \times n$ matrices of parameters.

According to Koop and Korobilis (2010), if we define that Y is a $T \times N$ matrix which stacks the T observations on each dependent variable in columns next to one another, while y is an $NT \times 1$ vector which stacks all T observations on the first dependent variable, then all T

observations on the second, third, fourth, etc. dependent variable. E and ε are the error terms vectors for Y and y , respectively. The equation (4.5) can be rewritten as follows:

$$Y = XB + E \quad (4.6)$$

or

$$y = (I_n \otimes X)\beta + \varepsilon \quad (4.7)$$

where \otimes indicates the matrix Kronecker product, I_n is the identity matrix of dimension n , $x_t = (1, Y'_{t-1}, \dots, Y'_{t-p})$ and $X = (x_1, x_2, \dots, x_T)'$. X is $T \times K$ Matrix, where $K=1+N \times p$ is the number of coefficients in each equation of VAR and $B=(b_0, B_1, B_2, \dots, B_p)'$ and $\beta = \text{vec}(B)$ is an $nK \times 1$ vector which stacks all the VAR coefficients and the intercepts into a vector. The unknown parameters are β and Σ .

Following Ciccarelli and Rebucci (2003), we specify the likelihood function of Bayesian VAR model as:

$$L(Y|\beta, \Sigma) \propto |\Sigma|^{-1/2} \exp \left\{ -\frac{1}{2} \sum_t (Y_t - X_t \beta)' \Sigma^{-1} (Y_t - X_t \beta) \right\} \quad (4.8)$$

and the joint posterior distribution on the parameters can be obtained based on the Bayes theorem

$$\begin{aligned} p(\beta, \Sigma|Y,) &= \frac{p(\beta, \Sigma)L(Y|\beta, \Sigma)}{p(Y)} \\ &\propto p(\beta, \Sigma)L(Y|\beta, \Sigma) \end{aligned} \quad (4.9)$$

According to the definition of the conditional probability, the probability density function (pdf) of the parameters and data can be rewritten as follows:

$$\begin{aligned} p(\beta, \Sigma, Y) &= p(\beta, \Sigma)L(Y|\beta, \Sigma) \\ &= p(\beta, \Sigma|Y,)p(Y) \end{aligned} \tag{4.10}$$

Given that $L()$ denotes the likelihood function, $p()$ denotes the probability density function (pdf) and \propto denotes “proportional to”.

In terms of priors, the early work on Bayesian VAR was conducted by Doan et al. (1984) and Litterman (1986). They proposed a widely used prior by combining the likelihood function with the informative prior distributions and the prior is called the Minnesota (Litterman) prior. This is because it was developed at the Federal Reserve Bank of Minneapolis and the University of Minnesota. For the Minnesota (Litterman) prior, let us denote the unknown parameters of interest $\theta = (\beta, \Sigma)$, the Minnesota (Litterman) prior assumes that θ is:

$$\theta \sim N(\mu, V)$$

where $\mu=0$ suggests a zero mean model, but the prior covariance $V \neq 0$

We exclude the elements of V which correspond to exogenous variables, because the prior does not contain any information about the exogenous variables. Therefore the remainder of V is a diagonal matrix with the elements v_{ij}^l for $l = 1, \dots, p$:

$$v_{ij}^l = \begin{cases} \left(\frac{\lambda_1}{l^{\lambda_3}} \right)^2 & \text{for } (i = j) \\ \left(\frac{\lambda_1 \lambda_2 \sigma_i}{l^{\lambda_3} \sigma_j} \right)^2 & \text{for } (i \neq j) \end{cases} \tag{4.11}$$

where σ_i is the i -th diagonal element Σ .

The Minnesota (Litterman) prior simplifies the complicated problem to the choice of three coefficients λ_1 , λ_2 and λ_3 where λ_1 and λ_2 are overall tightness and λ_3 is the lag delay coefficient. The expectation (first moment) and covariance (second moment) of matrix B is given by the following equations based on Giannone et al. (2015):

$$E[(B_s)(B_s)_{ij}|\Sigma] = \begin{cases} 1 & \text{if } i = j \text{ and } s = 1 \\ 0 & \text{otherwise} \end{cases} \quad (4.12)$$

$$COV((B_s)_{ij}, (B_r)_{hm}|\Sigma) = \begin{cases} \lambda^2 \frac{1}{s^2} \frac{\Sigma_{ih}}{\psi_j/(d-n-1)} & \text{if } m = j \text{ and } r = s, \\ 0 & \text{otherwise} \end{cases} \quad (4.13)$$

4.3 Vector Error Correction Model (VECM).

Another form of VAR model which is able to identify certain long-run equilibrium relationships in the time series is the Vector Error Correction Model (VECM). Engle and Granger (1987) suggest that this model can solve spurious regression problems by differencing the levels data to achieve stationarity. Prior to estimating VECM, the cointegration relationship should be tested for the time series. Many economic and financial time series exhibit trending behaviour, for example, asset prices, exchange rates and GDP, etc., and therefore it is important to determine the appropriate form of trend in economic and financial series. Firstly, we have to test variables' stationarity, for which the unit root tests will be used. The null hypothesis of the unit root test is generally defined as the presence of a unit root. We start with the widely used Dickey-Fuller test (Dickey and Fuller, 1979). Here the following autoregressive model is considered:

$$Y_t = \rho Y_{t-1} + \varepsilon_t, t = 1, 2, \dots \quad (4.14)$$

where $Y_0 = 0$, ρ represents a real number, and ε_t are independent and normally distributed with zero mean and σ^2 variance ($\varepsilon_t \sim NID(0, \sigma^2)$). As $t \rightarrow \infty$, the time series Y_t converges to a stationary time series if $|\rho| < 1$. If $|\rho| \geq 1$, the time series is not stationary. The variance is $t\sigma^2$ with $|\rho| = 1$ while the variance grows exponentially as t increases if $|\rho| > 1$. If $\rho = 1$, the time series is called a random walk. The regression model (4.14) can be rewritten as:

$$\Delta Y_t = (\rho - 1)Y_{t-1} + \varepsilon_t = \beta Y_{t-1} + \varepsilon_t, t = 1, 2, \dots, \quad (4.15)$$

where Δ is the first difference operator.

As a result, testing for a unit root of model (4.14) is equivalent to testing $\beta = 0$. If we add a constant and/or deterministic time trend in model (4.15), equation (4.15) becomes as follows and we are then able to test for a unit root with drift or/and deterministic time trend:

$$\Delta Y_t = c + \alpha t + \beta Y_{t-1} + \varepsilon_t, t = 1, 2, \dots, \quad (4.16)$$

Said and Dickey (1984) augment the basic autoregressive (AR) unit root test to accommodate the general ARMA structure with unknown orders. Their test is referred to as the Augmented Dickey-Fuller (ADF) test and it is conducted using this equation:

$$\Delta y_t = \mu + \gamma t + \alpha y_{t-1} + \sum_{i=1}^k \beta_i \Delta y_{t-i} + \varepsilon_t \quad (4.17)$$

where: y_t = the financial time series to be tested

Δ = the first difference operator

t = the time trend term

k = the length of optimal lag

μ = the intercept term

ε_t = the white noise residual term

α = the unit root coefficient

Testing the null hypothesis y_t is I(1) becomes the test of $\alpha = 0$. The ADF t-statistic then becomes the usual t-statistic for testing $\alpha = 0$:

$$ADF_t = t_\alpha = \frac{\hat{\alpha}}{SE(\alpha)} \quad (4.18)$$

In addition, the Phillips-Perron (PP) test, a nonparametric model, is used to conduct the unit root test as an alternative method. The model is able to handle the serial correlation appropriately (Phillips and Perron, 1988; Phillips, 1987). The PP test corrects for any serial correlation and heteroskedasticity in the errors ε_t of the test regression by directly modifying the test statistics. The test regression for the PP tests is

$$Y_t = \rho Y_{t-1} + \varepsilon_t, t = 1, 2, \dots, \quad (4.19)$$

The OLS estimate of the autocorrelation parameter ρ (based on an n-observation time series) is shown as:

$$\hat{\rho}_n = \frac{\sum_{t=1}^n y_{t-1} y_t}{\sum_{t=1}^n y_t^2} \quad (4.20)$$

Two PP statistics⁸ are calculated as:

$$Z_\rho = n(\hat{\rho}_n - 1) - \frac{1}{2} \frac{n^2 \hat{\sigma}^2}{s_n^2} (\hat{\lambda}_n^2 - \hat{\gamma}_{0,n}) \quad (4.21)$$

$$Z_\tau = \sqrt{\frac{\hat{\gamma}_{0,n} \hat{\rho}_n - 1}{\hat{\lambda}_n^2}} - \frac{1}{2} (\hat{\lambda}_n^2 - \hat{\gamma}_{0,n}) \frac{1}{\hat{\lambda}_n} \frac{n \hat{\sigma}}{s_n} \quad (4.22)$$

⁸ Extract from STATA manual based on Hamilton (1994)

$$\hat{\gamma}_{j,n} = \frac{1}{n} \sum_{i=j+1}^n \hat{u}_i \hat{u}_{i-j}$$

$$\hat{\lambda}_n^2 = \hat{\gamma}_{0,n} + 2 \sum_{j=1}^q \left(1 - \frac{j}{q+1}\right) \hat{\gamma}_{j,n}$$

$$s_n^2 = \frac{1}{n-k} \sum_{i=1}^n \hat{u}_i^2$$

where \hat{u}_i is the OLS residual, k is the number of covariates in the regression, q is the number of Newey–West lags, and $\hat{\sigma}$ is the OLS standard error of $\hat{\rho}_n$.

Under the null hypothesis which asserts that $\rho = 0$, the two PP statistics have the same asymptotic distributions as the ADF t-statistic and normalised bias statistics. The PP tests are superior because the PP tests are robust to serial correlation or heteroskedasticity in the error term. Another advantage of the PP tests is that they do not require a specification of the lag length for the test regression.

The above tests are non-stationarity tests which are mainly for the null hypothesis that y_t is $I(1)$. However, Kwiatkowski et al. (1992) have developed statistical tests for the hypothesis of stationarity (y_t is $I(0)$) which are commonly called KPSS tests. The tests are designed to complement unit root tests, such as the Dickey-Fuller tests. The KPSS tests are able to distinguish between the series that appear to be stationary and the series that appear to have a unit root. The tests start with the following model:

$$Y_t = c + \xi t + r_t + \varepsilon_t, t = 1, 2, \dots, \quad (4.23)$$

where r_t is a random walk:

$$r_t = r_{t-1} + u_t, u_t \sim iid(0, \sigma_u^2) \quad (4.24)$$

The stationarity hypothesis is $\sigma_u^2 = 0$ against the alternative that $\sigma_u^2 > 0$ and therefore y_t is trend-stationary under the null hypothesis if ε_t is assumed to be stationary. The KPSS test statistic is the Lagrange Multiplier (LM) which is given by:

$$KPSS\ statistic = \frac{T^{-2} \sum_{t=1}^T s_t^2}{\hat{\sigma}_\varepsilon^2} \quad (4.25)$$

where $s_t^2 = \sum_{i=1}^t e_i$, $t = 1, 2, \dots, T$, and e_i are the residuals from the regression of y on an intercept and time trend. $\hat{\sigma}_\varepsilon^2$ represents the estimate of the error variance from this regression (the sum of squared residuals, divided by T).

The unit root tests are used to determine the order of integration. If the time series need to be differenced d times before it becomes stationary, we can say that the time series are integrated of order d and denoted as $X_t \sim I(d)$. If two or more series are individually integrated at the same order but some linear combination of them has a lower integration order, then the time series are said to be cointegrated. A simple but common example is where the individual time series are integrated at order one $I(1)$, an existing cointegration vector is able to make the linear combination of the time series stationary. Two commonly used methodologies are able to test the existence of significant cointegration relationships between the variables, firstly, Engle and Granger's two-step procedure (Engle and Granger, 1987); and secondly, the Johansen-Juselius test (Johansen and Juselius, 1990).

We look at Engle and Granger's two-step procedure. Engle and Granger (1987) proposed one of the first cointegration tests which is intuitive and easy to perform. Under the cointegration relationship, if two time series are non-stationary and cointegrated, then a linear combination of them must be stationary, as a result, the first step starts by estimating the following cointegration regression based on the application of OLS:

$$Y_t = c + \beta X_t + \varepsilon_t \quad (4.26)$$

$$\hat{\varepsilon}_t = Y_t - \hat{c} - \hat{\beta} X_t \quad (4.27)$$

where $\hat{\beta}$ and \hat{c} are OLS estimators of c and β and $\hat{\varepsilon}_t$ is the residual term.

If all variables are cointegrated in the above regression, the residual term $\hat{\varepsilon}_t$ should be stationary. Therefore, the second step in Engle and Granger's two-step procedure is to

conduct the unit root tests for the residual process of the above cointegrating regression. We set up the following ADF test:

$$\Delta \hat{\varepsilon}_t = \mu + \gamma t + \alpha \hat{\varepsilon}_{t-1} + \sum_{i=1}^k \beta_i \Delta \hat{\varepsilon}_{t-i} + \varepsilon_t \quad (4.28)$$

Under the null hypothesis of no cointegration relationships, the parameter β is zero, and thus the estimated residual term $\hat{\varepsilon}_t$ is I(1), otherwise the estimated residual term $\hat{\varepsilon}_t$ is I(0) with significant α in equation (4.28). However, if there are three or more variables, the possibility of more than one cointegration relationship leads to a weakness in Engle and Granger's two-step procedure, since it is not able to test the number of cointegration vectors (Watson and Teelucksingh, 2002).

Johansen and Juselius (1990) have developed a superior test for the cointegration relationship. They use the maximum likelihood function and their approach is more satisfying. They commence with the following vector autoregression (VAR):

$$X_t = \Pi_1 X_{t-1} + \dots + \Pi_k X_{t-k} + \mu + \Phi D_t + \varepsilon_t, t = 1, 2, \dots, T \quad (4.29)$$

where X_t is a $n \times 1$ vector of variables, ε_t is a $n \times 1$ vector of error terms $\varepsilon_t \sim IIN(0, \Lambda)$ and are centered seasonal dummies. This VAR can be expressed in first differenced form:

$$\Delta X_t = \Gamma_1 \Delta X_{t-1} + \dots + \Gamma_{k-1} \Delta X_{t-k+1} + \Pi X_{t-k} + \mu + \Phi D_t + \varepsilon_t \quad (4.30)$$

where $\Delta = 1 - L$, L is the lag operator, $\Gamma_i = \Pi_1 + \dots + \Pi_i - I$, $i = 1, \dots, k - 1$ and $\Pi = \Pi_1 + \dots + \Pi_k - I$

The existence of a cointegrating relationship can be confirmed by examining the rank of the coefficient matrix Π . The number of cointegrating vectors (r) equals the rank of the coefficient matrix Π . The matrix Π can be written as a vector of adjustment parameters and

cointegrating vectors $\Pi = \alpha\beta'$, where α is the matrix which represents the speed of adjustment parameters and β represents the matrix of cointegrating parameters. Two likelihood ratio statistics (trace statistic and maximum eigenvalue statistic) which are able to determine the number of cointegrating vectors are given by:

Trace statistic: $\lambda_{Trace}(r) = -T \sum_{i=r+1}^n \ln(1 - \hat{\lambda}_i)$, and

Maximum eigenvalue statistic: $\lambda_{Max}(r) = -T \ln(1 - \hat{\lambda}_{r+1})$

where T is the sample size and $\hat{\lambda}_i$ is the i th largest canonical correlation. The trace test assumes the null hypothesis of at most r_0 cointegrating vectors against the alternative hypothesis that $r_0 < rank(\Pi) \leq n$ where n represents the possible cointegrating vectors. The maximum eigenvalue test is a test where the null hypothesis is that of $rank(\Pi) = r_0$ against the alternative hypothesis of $r + 1$ cointegrating vectors.

According to Granger's representation theorem, if two time series are cointegrated, then there exists a valid error correction and a suitable estimation technique: a Vector Error Correction Model (VECM) can be applied using the multivariate cointegration framework (Johansen, 1991; Johansen, 1988). The Vector Error Correction Model (VECM) is able to adjust both short-term changes in time series and the errors from the long-term equilibrium. Let us assume that the long run relationship between two time series can be represented as:

$$Y_t = c + \beta X_t + \varepsilon_t \quad (4.31)$$

The VECM is represented as follows:

$$\Delta Y_t = c_y + \gamma_{11} \Delta Y_{t-1} + \gamma_{21} \Delta X_{t-1} + \alpha_1 \hat{\varepsilon}_{t-1} + \varepsilon_{1t} \quad (4.32)$$

$$\Delta X_t = c_x + \gamma_{12} \Delta Y_{t-1} + \gamma_{22} \Delta X_{t-1} + \alpha_2 \hat{\varepsilon}_{t-1} + \varepsilon_{2t} \quad (4.33)$$

given that $\hat{\varepsilon}_{t-1} = Y_{t-1} - \hat{c} - \hat{\beta} X_{t-1}$, $\hat{\varepsilon}_{t-1}$ is the lagged error correction term ECT_{t-1} that can be interpreted as the speed of short-term adjustment factors. It measures how fast the two

time series react to the deviation from the long-term equilibrium. At the same time, the coefficients γ_{11} , γ_{12} , γ_{21} and γ_{22} measure the short-term adjustment on the changes of variables.

4.4 GARCH Models Framework

Financial market volatility is important for risk management, options and futures pricing and financial market regulation. Over the last several decades, forecasting and modelling volatility in financial time series has attracted attention in financial research. There are various properties of volatility as a measurement of uncertainty in financial markets. Mandelbrot (1963) and Fama (1965) noted volatility clustering effects and kurtosis and skewness of the stock return distribution. Mean reversion is also a common property of financial market volatility. Fama and French (1988) noted mean reversion effects when analysing US stock market. Asymmetry effect, also called leverage effect which was found by Black (1976) and Christie (1982) is another property of financial market volatility. In addition, numerous studies show that volatility has long memory (volatility persistence). Ding et al. (1993) documented long memory of volatility and proposed a fractionally integrated model. Due to various properties of financial market volatility, it is not easy to model and forecast volatility accurately. Improving the performance of volatility forecasting models therefore becomes the aim of researchers and market participants. Consequently, there are a large number of methods to measure, model and forecast volatility. Engle (1982) introduced the ARCH model and Bollerslev (1986) generalised the ARCH framework to GARCH. The (G)ARCH family models then became popular and widely used in volatility modelling.

4.4.1 Autoregressive Conditional Heteroskedasticity (ARCH)

In order to solve the heteroskedasticity problems in financial time series, the Autoregressive Conditional Heteroskedasticity (ARCH) model was introduced to predict the conditional variance of financial time series by Engle (1982). This is the first model which delivered a systematic framework for volatility modelling. In an ARCH (q) model, the conditional variance of residual value (conditional volatility) depends on q lagged square error term and

can be formulated via a maximum likelihood procedure. Thus one step ahead forecasting of volatility becomes possible. Many studies have demonstrated the successful application of ARCH models in numerous financial time series, including inflation rates, exchange rates, and so on. Thus the ARCH model has proved useful in capturing many stylised properties of financial time series, such as volatility clustering, fat tail and leptokurtic, etc. However, the ARCH model also has some disadvantages. For example, it is difficult to estimate parameters when ARCH model has higher orders. The general form of ARCH(q) with respect to a mean process represented as:

$$\varepsilon_t = \sigma_t z_t \quad (4.34)$$

with the conditional variance given by:

$$h_t = a_0 + a_1 \varepsilon_{t-1}^2 + a_2 \varepsilon_{t-2}^2 + \dots + a_q \varepsilon_{t-q}^2 = a_0 + \sum_{i=1}^q a_i \varepsilon_{t-i}^2 \quad (4.35)$$

where $a_0 > 0, a_i \geq 0, i > 0$, z_t is a random variable with white noise process (an independent and identically distributed process with mean 0 and variance 1) and σ_t is the time-varying standard deviation.

The log-likelihood function can be written as:

$$l = \frac{1}{T} \sum_{t=1}^T l_t \quad (4.36)$$

$$l_t = -\frac{1}{2} \left(\log \sigma_t^2 + \frac{\varepsilon_t^2}{\sigma_t^2} \right) \quad (4.37)$$

where l denotes the average log likelihood and l_t represents the log likelihood of the t th observation and T is the sample size.

The mean equation can vary and two commonly used mean processes are given as:

Constant mean equation:

$$y_t = c + \varepsilon_t \quad (4.38)$$

Autoregressive AR(p) model:

$$y_t = \alpha_0 + \sum_{i=1}^p \alpha_i y_{t-1} + \varepsilon_t \quad (4.39)$$

4.4.2 Generalised Autoregressive Conditional Heteroskedasticity (GARCH)

Financial and economic time series often violate the assumption of homoskedasticity, and the conditional variance seems to depend on its recent lags and previous conditional variance. In response, the Generalised ARCH (GARCH) model first proposed by Bollerslev (1986) is able to solve the ARCH model's long lag structure and the negative coefficient problems. In the GARCH model, the conditional variance is modified so that it has a linear relationship with the lagged squared residual value from the mean equation and the lagged conditional variance. The GARCH model therefore allows the conditional variance to change as a function of both past errors and past conditional variances. Actually, the GARCH model turns the AR process of the conditional variance in an ARCH model to a general ARMA process. Thus the GARCH model requires fewer parameters compared with an ARCH model when modelling the volatility process. Empirical research shows that the GARCH model is more parsimonious compared with the ARCH model (Poon and Granger, 2003). For these reasons, it has become an important and popular econometric time series model for volatility forecasting. Although the GARCH model is superior to the ARCH model, it still has some limitations. For example, the traditional GARCH model is a kind of symmetric model not able to capture the asymmetric effect in the financial time series. Also, the error terms distribution is assumed to be normally distributed which may not be the actual distribution of the financial time series. The GARCH (p,q) is given by:

$$\begin{aligned} \varepsilon_t | \Psi_{t-1} &\sim N(0, h_t), \\ h_t &= a_0 + \sum_{i=1}^q a_i \varepsilon_{t-i}^2 + \sum_{j=1}^p b_j h_{t-j} \\ &= a_0 + A(L)\varepsilon_t^2 + B(L)h_t \end{aligned} \quad (4.40)$$

where ε_t denote a real-valued discrete-time stochastic process, Ψ_t is the information set through time t, $p \geq 0, q \geq 0, a_0 > 0, a_i \geq 0, i = 1, \dots, q, b_j \geq 0, j = 1, \dots, p$.

If $p=0$, the GARCH process downgrades to the ARCH(q) process; if $p=q=0$, then the process simply becomes white noise. The simplest, but nevertheless a very popular and useful GARCH model, is a GARCH(1,1) process, shown as follows:

$$h_t = a_0 + a_1 \varepsilon_{t-1}^2 + b_1 h_{t-1} \quad (4.41)$$

where $a_0 > 0, a_1 \geq 0$ and $b_1 \geq 0$

In order to estimate the GARCH regression model, a maximum likelihood estimation method is used and the log-likelihood function is:

$$L_T(\theta) = T^{-1} \sum_{t=1}^T l_t(\theta) \quad (4.42)$$

$$l_t(\theta) = -\frac{1}{2} \log h_t - \frac{1}{2} \varepsilon_t^2 h_t^{-1} \quad (4.43)$$

where T is the sample observations

Here the persistence of a GARCH model is calculated by summing the persistent parameters $\sum_{i=1}^q a_i + \sum_{j=1}^p b_j$. If the persistent parameters sum up to one, $\sum_{i=1}^q a_i + \sum_{j=1}^p b_j = 1$, then the GARCH process has a unit root and the normal GARCH model becomes an Integrated GARCH (IGARCH) model.

4.4.3 GJR GARCH

Some models promote what is called the asymmetric effect (leverage effect). If the leverage effect exists, the market volatility increases more following market falls than market rises in

the same magnitude. In some cases, there is a strong relationship between market performance and volatility. Changes in market returns tend to be negatively correlated with changes in the volatility of returns. This can be explained as follows: when the market falls, risk increases and volatility increases. In contrast, when the market rises, risk increases and volatility tends to decline. Therefore the volatility can be asymmetric for some financial data, which is termed the asymmetric effect or the leverage effect. However, both the ARCH and the GARCH models assume that positive and negative shocks have the same impacts on volatility. To be able to overcome this weaknesses in the ARCH and GARCH models, Glosten et al. (1993) develop an asymmetric GARCH model called GJR GARCH where positive and negative shocks which represent good news and bad news have different impact on volatility forecasting. Engle and Ng (1993) compare several GARCH volatility models which allow for asymmetry for the impact of news on volatility and indicate that GJR GARCH is the best parametric model. The conditional variance of GJR GARCH can be shown as:

$$\sigma_t^2 = a_0 + \sum_{i=1}^q a_i \varepsilon_{t-i}^2 + \varphi_i \varepsilon_{t-i}^2 d_{t-i} + \sum_{j=1}^p b_j \sigma_{t-j}^2 \quad (4.44)$$

where ε_t is i.i.d. $\sim D(0, \sigma_t^2)$, d_{t-i} is a dummy variable, when $\varepsilon_{t-i} < 0$, $d_{t-i} = 1$ whereas $\varepsilon_{t-i} > 0$, $d_{t-i} = 0$

and the simplest form is GJR GARCH(1,1) given by:

$$\sigma_t^2 = a_0 + a_1 \varepsilon_{t-1}^2 + \varphi \varepsilon_{t-1}^2 d + b_1 \sigma_{t-1}^2 \quad (4.45)$$

Positive shocks thus have an impact of a_1 on the conditional variance while negative shocks have an impact of $a_1 + \varphi$. When estimating the GJR GARCH model with the stock market index returns, φ is typically found to be positive, which means that the volatility increases proportionally more following negative shocks than positive shocks. It therefore captures the asymmetric effect very well.

4.4.4 Exponential GARCH (EGARCH)

One GARCH model which is also able to capture the asymmetric effect is the Exponential GARCH (EGARCH) model, developed by Nelson (1991). This model specifies the conditional volatility in logarithmic form so there is no restriction on the parameters to avoid negative volatility. This specification can capture the asymmetric effect, which means a negative shock leads to a higher conditional variance in the subsequent period than a positive shock (Poon and Granger, 2003). Instead of modelling the conditional variance directly, EGARCH models the natural logarithm of the variance, so that no parameters restrictions are required to ensure the positive conditional variance. The conditional variance equation can be formulated as:

$$\log(\sigma_t^2) = a_0 + \sum_{i=1}^q a_i g(\varepsilon_{t-i}) + \sum_{j=1}^p b_j \log(\sigma_{t-j}^2) \quad (4.46)$$

$$g(\varepsilon_t) = \theta \varepsilon_t + \gamma [|\varepsilon_t| - E|\varepsilon_t|]$$

where ε_t is i.i.d. $\sim D(0, \sigma_t^2)$

The two components of $g(\varepsilon_t)$ are $\theta \varepsilon_t$ and $\gamma [|\varepsilon_t| - E|\varepsilon_t|]$, each with zero mean. If $\varepsilon_t > 0$, $g(\varepsilon_t)$ is linear in ε_t with slope $\theta + \gamma$, while if $\varepsilon_t < 0$, $g(\varepsilon_t)$ is linear in ε_t with slope $\theta - \gamma$. As a result, the conditional variance (log volatility) is able to respond asymmetrically to the rises and falls in financial markets. Thus the EGARCH model is able to model volatility persistence, mean reversion as well as the asymmetrical effect. It also allows the negative innovations to have a greater impact on volatility than the standard GARCH.

4.4.5 GARCH-in-Mean (GARCH-M)

The above group of GARCH type models is used to modify the variance equation to capture such effects as the leverage effect. Engle et al. (1987) introduce an ARCH-in-Mean (ARCH-M) for modelling the relationship between risk and return in three interest rates data sets. This model extends the ARCH model to modify the mean equation by adding conditional variance variables so that the conditional variance can affect the mean. The ARCH-M model can also

simply be extended to GARCH-M if the conditional variance follows a GARCH process. In GARCH-M, three heteroskedasticity terms σ_t , σ_t^2 and $\log\sigma_t$ are introduced into the mean equation in order to reflect the returns' dependence on risks or volatility. The three variations in the mean equation (AR form) are as follows:

$$X_t = c + \sum_{i=1}^q \gamma_i X_{t-i} + \varphi \sigma_t^2 + \varepsilon_t \quad (4.47)$$

$$X_t = c + \sum_{i=1}^q \gamma_i X_{t-i} + \varphi \sigma_t + \varepsilon_t \quad (4.48)$$

$$X_t = c + \sum_{i=1}^q \gamma_i X_{t-i} + \varphi \log \sigma_t^2 + \varepsilon_t \quad (4.49)$$

The conditional variance equation is same as normal GARCH model:

$$\sigma_t^2 = a_0 + \sum_{i=1}^q a_i \varepsilon_{t-i}^2 + \sum_{j=1}^p b_j \sigma_{t-j}^2$$

4.4.6 VECH GARCH

Multivariate GARCH models were first analysed and estimated empirically by Bollerslev et al. (1988). They proposed a straightforward extension of the univariate GARCH models to a so-called VECH GARCH model. In the VECH GARCH model, the conditional variance-covariance matrix depends on its lagged matrices and the lagged error terms matrices. The VECH specification of a multivariate GARCH model is given by

$$vech(H_t) = C + \sum_{i=1}^q A_i vech(\varepsilon_{t-i} \varepsilon'_{t-i}) + \sum_{j=1}^p B_j vech(H_{t-j}) \quad (4.50)$$

$$\varepsilon_t | \psi_{t-1} \sim N(0, H_t)$$

The conditional variance-covariance matrix is given by the positive definite $d \times d$ matrix H_t .

H_t depends on the lagged error terms $\varepsilon_{t-i}, i=1, \dots, q$, and the lagged conditional variance-covariance matrices $H_{t-i}, i=1, \dots, p$. $\text{vech}(\cdot)$ denote the operator that stacks the lower triangular part of a symmetric $d \times d$ matrix into a $d(d+1)/2$ dimensional vector, ω, A_i and B_j are $d(d+1)/2 \times d(d+1)/2$ dimensional parameter matrices.

The conditional log-likelihood function for a single time period t is:

$$L_t(\theta) = -\frac{d}{2} \log 2\pi - \frac{1}{2} \log |H_t(\theta)| - \frac{1}{2} \varepsilon_t(\theta)' H_t^{-1}(\theta) \varepsilon_t(\theta) \quad (4.51)$$

where θ is the parameters vector

The log-likelihood function is the sum of $L_t(\theta)$ given by:

$$L(\theta) = \sum_{t=1}^T L_t(\theta) \quad (4.52)$$

If $d=2$, the multivariate GARCH becomes the simplest bivariate VECH GARCH model and the conditional variance equation is expressed as:

$$\begin{bmatrix} \sigma_{11,t}^2 \\ \sigma_{12,t}^2 \\ \sigma_{22,t}^2 \end{bmatrix} = \begin{bmatrix} c_1 \\ c_1 \\ c_1 \end{bmatrix} + \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1,t-1}^2 \\ \varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ \varepsilon_{2,t-1}^2 \end{bmatrix} + \begin{bmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \\ b_{31} & b_{32} & b_{33} \end{bmatrix} \begin{bmatrix} \sigma_{11,t-1}^2 \\ \sigma_{12,t-1}^2 \\ \sigma_{22,t-1}^2 \end{bmatrix} \quad (4.53)$$

Since the simplest VECH GARCH model is involved with 21 parameters estimation, VECH GARCH could lead to a large number of parameters estimation as the number of variables increases. A natural simplification for the above equation is to assume that matrices A_i and B_i are diagonal. The VECH model then becomes the diagonal representation as:

$$\begin{bmatrix} \sigma_{11,t}^2 \\ \sigma_{12,t}^2 \\ \sigma_{22,t}^2 \end{bmatrix} = \begin{bmatrix} c_1 \\ c_1 \\ c_1 \end{bmatrix} + \begin{bmatrix} a_{11} & 0 & 0 \\ 0 & a_{22} & a_{23} \\ 0 & 0 & 0 \end{bmatrix} + \begin{bmatrix} \varepsilon_{1,t-1}^2 \\ \varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ \varepsilon_{2,t-1}^2 \end{bmatrix} + \begin{bmatrix} b_{11} & 0 & 0 \\ 0 & b_{22} & b_{23} \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} \sigma_{11,t-1}^2 \\ \sigma_{12,t-1}^2 \\ \sigma_{22,t-1}^2 \end{bmatrix} \quad (4.54)$$

In the diagonal VECH GARCH specification, the conditional variance and covariance depend only on their own past values and past error terms, ignoring the interdependence between different variables.

4.4.7 BEKK GARCH

In 1995, Engle and Kroner (1995) introduced a BEKK model to simplify the estimation process by reducing the number of parameters. The BEKK representation can be written below as:

$$H_t = C'C + \sum_{k=1}^K C_{1k}x_t x_t' C_{1k} + \sum_{k=1}^K \sum_{i=1}^q A'_{ik} \varepsilon_{t-i} \varepsilon_{t-i}' A_{ik} + \sum_{k=1}^K \sum_{i=1}^p G'_{ik} H_{t-i} G_{ik} \quad (4.55)$$

where x_t is an exogenous variable

The key feature is that the positive definite variance-covariance matrices are generated by unrestricted parameterisations, since the quadratic representation automatically guarantees that H_t is positive definite. It also economises on the parameters by imposing restrictions both within and across equations, compared with the VECH representation. The joint likelihood function is expressed in the following way:

$$L = \sum_{t=1}^T L_t \quad (4.56)$$

$$\text{where } L_t = \frac{n}{2} \ln(2\pi) - \frac{1}{2} \ln(H_t) - \frac{1}{2} \varepsilon_t' H_t^{-1} \varepsilon_t$$

The simplest version is the bivariate BEKK GARCH(1,1) without exogenous variables which is described as:

$$H_t = C'C + A' \varepsilon_{t-1} \varepsilon_{t-1}' A + G' H_{t-1} G \quad (4.57)$$

where $H_t = \begin{bmatrix} \sigma_{11,t}^2 & \sigma_{12,t}^2 \\ \sigma_{21,t}^2 & \sigma_{22,t}^2 \end{bmatrix}$, $C = \begin{bmatrix} c_{11} & c_{12} \\ 0 & c_{22} \end{bmatrix}$, $A = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}$ and $G = \begin{bmatrix} g_{11} & g_{12} \\ g_{21} & g_{22} \end{bmatrix}$

In the above model, the diagonal elements of matrices $A(a_{11}$ and $a_{22})$ and $G(g_{11}$ and $g_{22})$ capture the effect of previous shocks and historical volatility on the current conditional variance, respectively. On the other hand, the off-diagonal elements of matrices $A(a_{12}$ and $a_{21})$ and $G(g_{12}$ and $g_{21})$ measure the volatility spillovers across the markets.

4.4.8 CCC GARCH

Bollerslev (1990) introduced the bivariate GARCH assuming constancy of the conditional correlation. This model proposed a constant conditional correlation matrix which can simplify the estimation and inference. For this reason, it is called CCC GARCH and it is given by:

$$Y_t = E(Y_t|\psi_{t-1}) + \varepsilon_t \quad (4.58)$$

$$VAR(\varepsilon_t|\psi_{t-1}) = H_t \quad (4.59)$$

where ψ_{t-1} is the information set at time t

If we denote $h_{ij,t}$ the ij^{th} element in the matrix H_t , the conditional correlation between two time series $y_{i,t}$ and $y_{j,t}$ is given by:

$$\rho_{ij,t} = \frac{h_{ij,t}}{\sqrt{h_{ii,t}h_{jj,t}}} \quad (4.60)$$

where $-1 \leq \rho_{ij,t} \leq 1$

We rewrite each conditional variance as:

$$h_{ii,t} = \omega_i \sigma_{i,t}^2 \quad (4.61)$$

where ω_i is a positive time invariant scalar.

The full conditional variance-covariance matrix H_t can be partitioned as:

$$H_t = D_t R D_t \quad (4.62)$$

where D_t denotes $N \times N$ diagonal matrix with elements $\sigma_{1,t}, \sigma_{2,t}, \dots, \sigma_{N,t}$. R is an $N \times N$ time invariant $\rho_{ij} \sqrt{\omega_i \omega_j}$.

The likelihood function is:

$$L(\theta) = -\frac{TN}{2} \log 2\pi - \frac{T}{2} \log |R| - \sum_{t=1}^T \log |D_t| - \frac{1}{2} \sum_{t=1}^T \epsilon_t' R^{-1} \epsilon_t \quad (4.63)$$

where $\epsilon_t = R^{-1} \varepsilon_t$

This model assumes the conditional correlation is constant over time. As a result, the variation in the conditional covariance is based on the changes of each individual corresponding conditional variance. This model is called Constant Conditional Correlation GARCH (CCC GARCH).

4.4.9 DCC GARCH

In the real world, however, the conditional correlation rarely becomes time invariant. In most cases, the conditional correlation tends to be time variant because the economic and financial activities change over time and further influence the financial markets volatility. Engle (2002) proposed the Dynamic Conditional Correlation GARCH (DCC GARCH) which can examine correlation dynamics among assets. Very similar to CCC GARCH, the conditional covariance matrix H_t in the DCC GARCH can be written as:

$$H_t = D_t R D_t \quad (4.64)$$

where D_t denotes $N \times N$ diagonal matrix with elements $\sigma_{1,t}, \sigma_{2,t}, \dots, \sigma_{N,t}$. R is an $N \times N$ time variant $\rho_{ij,t}$.

$$\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t}q_{jj,t}}} \quad (4.65)$$

where $q_{ij,t} = \bar{\rho}_{ij} + \alpha(\varepsilon_{i,t-1}\varepsilon_{j,t-1} - \bar{\rho}_{ij}) + \beta(q_{ij,t-1} - \bar{\rho}_{ij}) = (1 - \alpha - \beta)\bar{\rho}_{ij} + \alpha\varepsilon_{i,t-1}\varepsilon_{j,t-1} + \beta q_{ij,t-1}$

$$R = \text{diag}(\sqrt{q_{11,t}}, \sqrt{q_{22,t}}, \dots, \sqrt{q_{nn,t}})^{-1} Q_t \text{diag}(\sqrt{q_{11,t}}, \sqrt{q_{22,t}}, \dots, \sqrt{q_{nn,t}})^{-1}$$

$$Q_t = \bar{Q}(1 - \alpha - \beta) + \alpha(\varepsilon_{t-1}\varepsilon'_{t-1}) + \beta Q_{t-1}$$

\bar{Q} is the unconditional correlation matrix

The DCC GARCH model can be estimated by using the Quasi-Maximum Likelihood Estimation (QMLE) suggested by Engle (2002) and the log-likelihood function can be written as the sum of a volatility component and a correlation component:

$$L(\theta, \phi) = L_V(\theta) + L_C(\theta, \phi) \quad (4.66)$$

The volatility component is

$$L_V(\theta) = -\frac{1}{2} \sum_{t=1}^T (n \log(2\pi) + \log |D_t| + r_t' D_t^{-2} r_t) \quad (4.67)$$

and the correlation term is

$$L_C(\theta, \phi) = -\frac{1}{2} \sum_{t=1}^T (\log |R_t| + \varepsilon_t' R_t^{-1} \varepsilon_t - \varepsilon_t' \varepsilon_t) \quad (4.68)$$

where θ denotes the parameters in D, ϕ denotes the additional parameters in R, T denotes the number of observations, and n denotes the number of equations.

4.5 Conclusion

This chapter has summarised some advanced econometric methodologies which have been used in examining the dynamics across different financial markets. Extending the univariate AR model, the VAR model is able to capture linear relationships among different time series. The unrestricted VAR has some requirements on the stationarity of the underlying variables,

otherwise it will lead to the spurious outcomes. In contrast, the Bayesian VAR does not require the stationarity of the time series. It incorporates some priors and produces better forecasts than unrestricted VAR. On the other hand, VECM can solve the problems of spurious outcomes by differencing the time series to achieve stationarity before regressing the underlying variables. It can therefore capture both the short-term and long-term effects. To test the stationarity of the time series, some unit root tests should be applied. The ADF and PP tests test the hypothesis of non-stationarity while the KPSS test tests the hypothesis of stationarity. Moving to the second moment, both ARCH and GARCH models are able to capture heteroskedasticity in the volatility modelling and forecasting. Some GARCH family models, for instance, EGARCH and GJR GARCH, can capture the leverage effect or asymmetric effect. This means that a negative shock leads to a higher conditional variance than a positive shock. These univariate GARCH models focus only on the volatility of a single time series. In order to examine the volatility dynamics structure among multiple time series, multivariate GARCH versions are proposed to model both the variance and covariance between different financial time series. The BEKK GARCH model overcomes the weaknesses of the VECM version and simplifies the estimation process. The DCC GARCH model is preferred in the real world compared to the CCC GARCH model, because it allows for the time-variant conditional correlation.

Chapter 5: Spillover Effect between Shanghai and Hong Kong Stock Markets: Evaluating the Impact of Shanghai-Hong Kong Stock Connect

5.1 Introduction

Economic globalisation and increasing process of financial liberalisation make the international financial markets to become more integrated and correlated than ever before. Many authors (see for example, Bekaert and Harvey (1997)) have argued that openness in financial systems can increase international financial linkages and enhance stock markets correlations. Strong linkages between different stock markets globally can reduce the isolation of local markets, increase the ability to react rapidly to news from other markets and reduce the benefits of international diversification. A spillover occurs when price changes in one market produce a lagged impact on the other markets. The spillover effect can exist among different countries and also among different financial markets within one country. For example, much research since the US October Crash (the famous Black Monday 19/10/1987), has focused on the spillover effect between different stock and equity markets. Many researchers have observed spillover effects in relations to returns and volatility between different financial markets. Some studies have found short-term or long-term interdependence and causality of the returns among different stock markets. In this regard, Eun and Shim (1989) use daily stock returns to examine financial innovation transmission mechanisms and observe return spillovers from the US to nine largest stock markets (including Hong Kong and Australia). In addition to the influence on market returns, the flow of information can have a major influence on volatility patterns. For example, Hamao et al. (1991) document asymmetric volatility spillovers among the US, the UK and Japan and indicate that Japan is the most sensitive market. Therefore, understanding the return and volatility spillover effects across different markets is important, as it can enable the investors, governments and financial institutions to have a better understanding of the dynamic relationships among different stock markets and impacts of flow of information across markets. Understanding the spillover effects is also helpful in devising market policies, making asset and investment allocation decisions and in designing appropriate hedging strategies. Although the existing literature focuses on developed financial markets, it is important to extend spillover effect analyses to emerging markets as they develop and

become bigger players in the global economy. It is this aspect that China, being the world's largest emerging financial market, becomes suitable research market to re-examine return and volatility spillover dynamics.

China, as the largest developing country and the second largest economy in the world, now plays an increasingly important role in the global economy. The economic reforms which started in 1978 have led to huge changes in the Chinese economy and financial markets. During the early 1990s, China established two stock markets, namely Shanghai stock market and Shenzhen Stock market. Both stock markets experience rapid development and have become very influential regionally and globally. The capitalisation of the Chinese stock market surpassed Japan in 2007, however, China still has not fully opened up its financial markets to the rest of the world and still there exist some restrictions and unique characteristics in the Chinese stock market. However, in the process of integrating its financial markets, the Chinese government has taken several steps to liberalise its financial markets. For example, China divides its stock markets into different categories, where A-share market is for Chinese domestic investor and B-share market is for foreign investors. In order to balance advantages and disadvantages of fully opening up Chinese financial markets to the world, China has developed two programs: QDII (Qualified Domestic Institutional Investors) which allow only qualified domestic institutional investors to invest abroad and QFII (Qualified Foreign Institutional Investors) permitting only qualified foreign institutional investors to invest in Chinese domestic financial markets.

As a result of these changes, the Chinese financial market is now closely linked with the rest of the world. On the other hand, Hong Kong is one of the largest and most liquid financial markets in Asia. Hong Kong stock market, just behind China and Japan in terms of market capitalisation, is China's closest financial hub and has a significant economic, political, and geographical interrelationship with the Mainland. Therefore, the regions have close ties and are expected to exhibit high levels of market linkages. Given the presence of similar investor groups and cross-listed regional companies, the connection between Mainland China and Hong Kong has a significant influence on Hong Kong return (Yi et al., 2009). In order to link Shanghai and Hong Kong stock markets, a pilot program (Shanghai-Hong Kong Stock Connect) was launched on 17 November 2014. Restrictions on both domestic and international investors were relaxed and it is expected that the two stock markets will become more integrated. Given the launch of Shanghai-Hong Kong Stock

Connect and the availability of high-frequency data, it is timely to investigate the interdependence and linkages between Chinese mainland and Hong Kong stock markets. Although some studies have been done on spillover effect between China and other countries, for example, Johansson and Ljungwall (2009) and Zhou et al. (2012), very few have examined the impact of a significant event on the return and volatility spillover between China and Hong Kong. Furthermore, it should be noted that Shanghai-Hong Kong Stock Connect provides the first opportunity to retail investors outside Mainland China to trade in the Chinese A-share market.

This event will result in a significant increase in the capital flow between Shanghai and Hong Kong stock exchanges in both directions. This motivates the research and provides a real opportunity to examine whether the mean and volatility spillover effect changes after the introduction of Shanghai-Hong Kong Stock Connect. While focusing specifically on the Shanghai-Hong Kong Stock Connect, this study also aims to fill the gap in the literature by examining the Stock Connect's influence on returns and price volatility. We use the stock market price indexes to investigate the integration of Shanghai and Hong Kong stock markets and consider the price movement, mean and volatility spillover effects, and the volatility behaviour of the market integration before and after this event. We break the sample into two sub-periods: *Pre* and *Post* Shanghai-Hong Kong Stock Connect periods using various GARCH models. Our analyses contribute to the literature by shedding new light on the dynamic relationships between Shanghai and Hong Kong stock markets.

The remainder of this chapter is organised as follows. Section 5.2 introduces the Shanghai-Hong Kong Stock Connect program. Section 5.3 discusses the preliminary literature on the mean and volatility spillover effect between different stock markets. Section 5.4 describes data used in this study and provides descriptive statistics while Section 5.5 describes the methodological framework utilised by our research. Section 5.6 presents the empirical analysis. Section 5.7 further discusses the results and provides some policy recommendations and finally section 5.8 concludes the paper.

5.2 The Status of Shanghai-Hong Kong Stock Connect

A major change in the structure of Chinese stock markets was underway since the time the Shanghai-Hong Kong Stock Connect program was launched. On 10 April 2014, China

Securities Regulatory Commission (CSRC) and the Securities and Futures Commission (SFC) made a joint announcement to approve, in principle, the development of the pilot program (Shanghai-Hong Kong Stock Connect) to establish mutual access between Mainland China and Hong Kong stock markets. Seven months later, the program was officially launched on 17 November 2014. Shanghai-Hong Kong Stock Connect provides a cross-boundary investment channel between Shanghai and Hong Kong stock markets so that investors in each stock market can trade stocks listed in the other market through the local clearing house and brokers. This is a landmark event in the reforms of the Chinese stock markets which was able to relax restrictions and reshape financial structures of both Chinese and Hong Kong stock markets. For the first time, Shanghai-Hong Kong Stock Connect is able to provide a feasible, controllable and expandable channel for mutual markets access between the Mainland China (Shanghai) and Hong Kong for a broad range of investors, paving the way for further opening up of Chinese financial markets and RMB internationalisation (HKEX, 2015b). This pilot program is expected to significantly increase the capital flow between Shanghai and Hong Kong stock markets in both directions given that the Chinese mainland investors will have the chance to invest in major companies listed on Hong Kong Stock Exchange. On the other hand, Hong Kong and international investors will get access to Shanghai A-share market in a less restrictive manner than ever before. This arrangement is expected to lead to both outward and inward financial markets liberalisation and enable intensive interactions between Shanghai and Hong Kong stock markets.

After the launch of Shanghai-Hong Kong Stock Connect, eligible Chinese mainland investors can purchase eligible shares listed on the Hong Kong Stock Exchange (HKSE) via their own local brokers, while Hong Kong and international investors can purchase eligible shares listed on Shanghai Stock Exchange (SSE) through their local brokers as well. In terms of eligible stocks, only certain stocks in Shanghai A-share market will be included in Northbound Trading of Shanghai-Hong Kong Stock Connect at the initial stage. Other products like bonds, Exchange Traded Funds (ETF), B-shares and other securities are not included at this stage. This trading arrangement also includes all the constituent stocks (which are reviewed from time to time) of the SSE 180 Index, the SSE 380 Index, and the SSE listed A-shares that are not included as constituent stocks of the above indices but which have corresponding H-shares listed on HKSE except those which are not traded in RMB and under risk alert. The number of total eligible securities is estimated to be 568 (as at 10 Apr 2014) and those shares account for about 90% of all SSE A-Shares in terms of market capitalisation

and about 80% of all SSE A-Shares in terms of average daily turnover.⁹ For eligible stocks to be included in Southbound Trading, only equities listed on Main Board will be included in Shanghai-Hong Kong Stock Connect. At the initial stage, trading under this pilot program will be subject to an Aggregate Quota (Maximum Cross Boundary Investment Quota) together with a Daily Quota. The Northbound Aggregate Quota and Daily Quota are set at RMB 300 billion and RMB 13 billion respectively, while the Southbound Aggregate Quota and Daily Quota are set at RMB 250 billion and RMB 10.5 billion respectively.¹⁰

There are several benefits for international investors to trade through Shanghai-Hong Kong Stock Connect. Firstly, investors outside of Mainland China can participate in one of the fastest growing and the world's second largest economy and invest in unexploited market. It has been argued that multinational corporation and foreign direct investment are attracted to China due to its enormous market potential when more economic sectors and regions are opened up (Tseng and Zebregs, 2002). Secondly, this program provides an opportunity for all investors to diversify their investment portfolio with stocks from the Shanghai stock market as it covers a large number of SSE listed shares. It also provides new opportunities for international investors to invest with RMB since they do not need to have an account in Mainland China. In addition, all fund transfers will be processed in Hong Kong for safety and efficiency (HKEX, 2015a). Chinese domestic investors can also benefit from this program. Obviously, the implementation of Shanghai-Hong Kong Stock Connect provides a new channel for both international and domestic investors to access both Shanghai and Hong Kong stock markets and promote business and export expansion. It is reasonable to expect that these gradual steps towards a comprehensive financial liberalisation in China will continue cause significant increases in the integration of Chinese financial markets with the rest of the world.

5.3 A Brief Review of Existing Literature

A spillover occurs when the price changes in one market produce a lagged impact on the other markets. Spillover effects can exist among different countries and also among different

⁹ Market cap statistics as at end of Mar 2014; Average Daily Turnover statistics are for Jan-Mar 2014. Source: Shanghai-Hong Kong Stock Connect For investing in SSE securities, https://www.hkex.com.hk/eng/market/sec_tradinfra/chinaconnect/Documents/Northbound_Flyer_e.PDF

¹⁰ Shanghai-Hong Kong Stock Connect Information Book for Investors (2015), http://www.hkex.com.hk/eng/market/sec_tradinfra/chinaconnect/Documents/Investor_Book_En.pdf

financial and equity markets within one country. Moser (2003) identifies three leading activities that could result in a spillover effect, namely international trade, counterparty defaults and portfolio rebalancing. Ross (1989) uses information transmission theory to explain the volatility spillovers and indicates that the spillovers between financial markets could be used to explain the process of information transmissions and efficiency of the markets because price and volatility are related to the rate of information flow. In addition, the process of liberalisation and globalisation of capital markets improve the ability for national markets to react rapidly to new information from international markets and hence increase the co-movement of international financial markets (Booth et al., 1997; Roll, 1992).

Various empirical papers have examined the interdependence and correlations among stock markets in developed and emerging markets. Eun and Shim (1989) have examined the international transmission mechanism of stock market movements using the Vector Autoregressive (VAR) system and data from the US and nine other large stock markets. They report strong evidence of market interdependencies and return shocks from the US to other major stock markets. King and Wadhvani (1990) used cross-market correlation coefficients methodology to find evidence of spillovers among the US, the UK and Japan. Hamao et al. (1991) analyse the daily open-to-close returns of the above three major stock markets, indicating that the volatility spillover effects emanating from Japan have been gathering strength over time, pointing to the growing importance of Japanese financial developments for other markets. In terms of the methodological approach, Bae and Karolyi (1994) demonstrate that the normal GARCH without asymmetric effect could understate the magnitude and persistence of shocks originating from New York or Tokyo to other markets as compared to results using the EGARCH approach. The latter could capture asymmetric effects better, suggesting that bad news from domestic and foreign markets appear to have a much larger impact on subsequent return volatility than good news. There are also many studies showing evidence of spillover effects among the developed stock markets like the US, the UK, Japan, Canada, Australia and some European markets (Karolyi, 1995; Koutmos and Booth, 1995; Booth et al., 1997; Alaganar and Bhar, 2002). Gagnon and Karolyi (2006) summarise several characteristics from the early existing research as: (1) the volatility of stock prices is time-varying; (2) when volatility is high, the price changes in major markets tend to become highly correlated; (3) correlations in volatility and prices appear to be causal from the United States to other countries especially before the Crash of 1987; (4) lagged spillovers of price changes and price volatility are found between major markets; and (5)

good news and bad news from one market seem to affect the other market's volatility differently. In fact, bad news increases volatility in the next market much more significantly than good news.

As the emerging markets become important investment destinations, researchers increasingly want to know how fast emerging markets are integrated with the rest of the world as they become more attractive to international investors. Evidence of spillover effect has been reported from developed markets (e.g. the US and Japan) to the Asian markets, including Hong Kong, Taiwan, Singapore, South Korea and Thailand before the Asian Financial Crisis (John Wei et al., 1995; Kim and Rogers, 1995; Hu et al., 1997; Liu et al., 1998). Miyakoshi (2003) uses the bivariate EGARCH model and observes that only the US (not Japan) can significantly influence Asian market returns, however, the volatility of the Asian market is influenced more by the Japanese market than the US. Wongswan (2006) uses high-frequency data revealing that macroeconomic information announcements in developed countries (the US and Japan) have a significant but short-lived impact on emerging markets (South Korea and Thailand) volatility and intraday volume. Gallo and Otranto (2008) report price spillover from the Hong Kong stock market to South Korea and Thailand. They also show evidence of interdependence with Malaysia and co-movement with Singapore. Their empirical evidence implies that Hong Kong financial market plays a dominant role and that these Asian countries are more linked with the Hong Kong stock market. Chiang et al. (2007) apply a dynamic conditional correlation model to nine Asian daily stock returns series to confirm a contagion effect during the Asian financial crisis. Their study identifies two phases of this crisis and finds a shift in variance during the crisis period. Engle et al. (2012) model the interrelations of equity market volatility in 8 East Asian countries before, during, and after the Asian currency crisis and observe that Hong Kong transmits greater risks to the others as a net creator of volatility.

The Global Financial Crisis (GFC) erupted in 2007-08 led to some studies focusing on the spillover effects. Cheung et al. (2009) examine the impact of this catastrophe on the interrelationships among global stock markets and find the enhanced leadership of the US market with respect to the UK, Hong Kong, Japan, Australia, Russia and China markets. Yilmaz (2010) indicate that volatility and return spillovers behave very differently during the crisis and non-crisis periods when he examines return and volatility spillovers across 10 major East Asian countries. Beirne et al. (2010) investigate volatility spillovers using data

from 41 countries. Their study shows that spillovers from regional and global markets are present in the vast majority of emerging markets and spillovers in mean returns dominate in emerging Asia and Latin America. However, it is reported that spillovers in variance appear to play a key role in emerging European markets. Singh et al. (2010) point out that there exists evidence of price and volatility spillovers among fifteen countries across North American, European and Asian stock markets when including the same day effect and indicate greater regional influence among Asian markets than European and the US markets. Samarakoon (2011) find bi-directional and asymmetric interdependence and contagion between the US and emerging markets with important regional variations, suggesting that interdependence is driven more by the US market shocks, while contagion is driven more by emerging markets shocks.

More recently, Kenourgios and Padhi (2012) investigate both equity and bond markets in emerging countries and find evidence of contagion during the Russian crisis, the Asian financial crisis, subprime crisis, but no evidence in the Argentine turmoil. Zheng and Zuo (2013) introduce a Markov switching causality method to find the evidence of spillover effects among most markets including the US, the UK, Germany, Japan and Hong Kong and indicate that bilateral volatility spillover effects are more prominent over turmoil or crisis episodes, especially during Asian financial crisis and subprime mortgage crisis periods. Lee (2013) examines the range-based volatility and finds that there are global spillover effects from the US to Taiwan and regional spillover effects from Japan to Taiwan. Hwang (2014) finds evidence of contagion among four Latin American countries (Argentina, Brazil, Chile and Mexico) and observes that there are structural changes in mean and volatility of the correlation coefficients.

However, the research on spillover effect between the Chinese financial market and others are limited when compared to research undertaken in other regions. Brooks and Ragunathan (2003) report no evidence of volatility spillover between Chinese A Share and B share markets. Wang and Firth (2004) indicate that the overnight returns on all the Greater China stock indices (Shanghai, Shenzhen, Hong Kong and Taipei) can be estimated by using information from at least one of the three developed markets' daytime returns (Tokyo, London and New York). They find that the contemporaneous return spillovers are generally uni-directional from more advanced major international markets to the Chinese stock markets. However, Lin et al. (2009) suggest that A Share indices have never been correlated with

world markets and that B Share indices exhibit a low degree of correlation with Western markets (0–5%) but a slightly higher degree of correlation with other Asian markets (10–20%). Wang and Wang (2010) examine stock market linkages among Greater China, the US and Japan in terms of the price and volatility spillover effects, suggesting that volatility spillovers are stronger than price spillovers between the Greater China markets and the developed markets of the US and Japan. Since 1997, when the political sovereignty of Hong Kong reverted to People's Republic of China, the integration of the two economies has steadily increased.

Only a few studies have examined the dynamic relationship between the Chinese stock market and Hong Kong stock market. Li (2007) uses an asymmetric BEKK GARCH framework to report evidence of uni-directional volatility spillovers from Hong Kong to Shanghai and Shenzhen, but no evidence of a direct linkage between Mainland China and the US stock market. To some extent, the research finding indicates a weak integration of the Chinese stock exchanges with the regional developed market. With the Mainland China adopting more open financial and economic policies, international investors could benefit from portfolio diversification as a result of adding stocks from Mainland China to the investment portfolio. In another study by Zhou et al. (2012), it is observed that volatility interactions among the Chinese, Hong Kong, and Taiwanese markets are more prominent than those among the Chinese, Western, and other Asian markets, indicating that Chinese financial markets are integrated in the Greater China region. However, the connections and correlations among Asian stock markets have become increasingly more evident in recent years.

Allen et al. (2013) report evidence of volatility spillovers from the Chinese stock market to its neighbours and trading partners, including Australia, Hong Kong, Singapore, Japan and the US. Their results confirm significant volatility spillovers across these markets in the pre-Global Financial Crisis period, but no significant evidence spillover effects from China to related markets during the crisis. Huang and Kuo (2015) use the trivariate BEKK GARCH model to investigate the trilateral relationship among China, Hong Kong and Taiwan stock markets from 2000 to 2010. The findings suggest that the Hong Kong and Taiwan stock markets are significantly affected by Mainland China, implying that the Mainland China stock market plays a leading role in information transmission. Given that Shanghai-Hong Kong Stock Connect was an important announcement in capital market

development and integrating China with the rest of the world, it is timely to empirically investigate the impact of such a breakthrough on price and volatility spillovers.

5.4 Data Description

This study uses the close price of Shanghai Stock Exchange Composite Index (SSEC) and Hong Kong Hang Seng Index (HSI) data recorded at 1-minute interval retrieved from SIRCA and Thomson Reuters Tick History (TRTH). We use the high-frequency data because we believe that the low-frequency data may not fully reflect the information transmission process within a short horizon when the speed of the information transmission is much faster. The sample period is from 2 July 2014 to 8 April 2015. From an econometric perspective and the property of the high-frequency data (1-minute interval), 7 months (a total of 43923 data observations) are large enough to yield meaningful estimation results without a serious small sample bias issue. Also, if the sample size is too small, we may not capture the impact of Shanghai-Hong Kong Stock Connect while if the sample size is too big, some other significant events may influence the estimate results. Therefore, we determine that 7 months are appropriate. Under our sample period, the launch of Shanghai-Hong Kong Stock Connect is the only significant financial liberalisation reform, so we can exclude the influence of other events. The one minute returns are calculated as the difference in natural logarithms of the closing prices of both indices ($R_{i,t} = P_{i,t} - P_{i,t-1}$, $i=SSEC, HSI$), where $R_{i,t}$ denotes the continuously compounded return for index i at time t , and $P_{i,t}$ denotes the natural logarithms of the closing price of index i at time t .

The sample is further divided into two sub-periods in order to investigate how the introduction of Shanghai-Hong Kong Stock Connect impacts both Shanghai and Hong Kong stock markets. The first subsample which is referred to as the Pre-Shanghai-Hong Kong Stock Connect period, is from 2 July 2014 to 14 November 2014. The second sub-period which is called the Post-Shanghai-Hong Kong Stock Connect period covers from 17 November 2014 to 8 April 2015. Usually, Shanghai Stock Exchange starts trading from 09:30 am (Beijing time, same hereinafter) to 11:30 am in the morning and from 01:00 pm to 03:00 pm in the afternoon from Monday to Friday except for holidays. However, Hong Kong stock exchange trades from 09:30 am to 12:00 am in the morning and then from 01:00 pm to 04:00 pm in the afternoon. To get reliable data, the index prices recorded before either Shanghai or

Hong Kong stock market opens or after either of them closes are excluded from the sample. Thus we only use the data from 09:30 am to 11:30 am and from 01:00 pm to 03:00 pm on a trading day. We also exclude the day when there is only one stock exchange open. After eliminating weekends and holidays, our final data includes 43923 1 minute price observations for the full sample period (22143 observations for Pre-Shanghai Hong Kong Stock Connect period and 21780 observations for Post-Shanghai Hong Kong Stock Connect period).

Brief descriptive statistics for the intraday 1-minute closing prices and returns of SSEC and HSI are provided in Table 5.1. The statistics reported include the number of observations, mean, median, maximum value, minimum value, standard deviation, measure of skewness, measure of kurtosis and Jarque-Bera (JB) statistics. The mean of SSEC return is larger than the mean of HSI return for the full sample period, Pre-Shanghai-Hong Kong Stock Connect period and Post-Shanghai-Hong Kong Stock Connect period, implying that Shanghai stock market is likely to provide a higher return. In terms of the standard deviation, the standard deviation for Shanghai stock market is larger than Hong Kong stock market for the full sample period and Post-Shanghai-Hong Kong Stock Connect period, suggesting that SSEC is more volatile than HSI during the above periods. This is reasonable because higher risk equals greater return. After comparing the statistics of Pre-Shanghai Hong Kong Stock Connect period and Post-Shanghai Hong Kong Stock Connect period, we can see that both the mean and the standard deviation of each market have increased after implementing the Shanghai-Hong Kong Stock Connect program. It means that this program could have some influence on the return and volatility behaviours of both stock markets. Based on the Jarque-Bera statistics, which tests for normality and goodness of fit, the closing prices and returns of both indices appear to be non-normally distributed (rejecting the null hypothesis for the normal distribution). We depict the price movements and returns of SSEC and HSI for the sample period in Figure 5.1. We observe that Shanghai Stock Exchange Composite Index had a dramatic increase from 2500 to 4500 and its return became more volatile after November 2014 when the Shanghai-Hong Kong Stock Connect program began. Also, the index levels indicate that the two financial time series most probably are not stationary and the returns tend to become stationary, which is a usual feature in global equity markets.

Figure 5. 1: Price Movements and Returns of SSEC and HSI

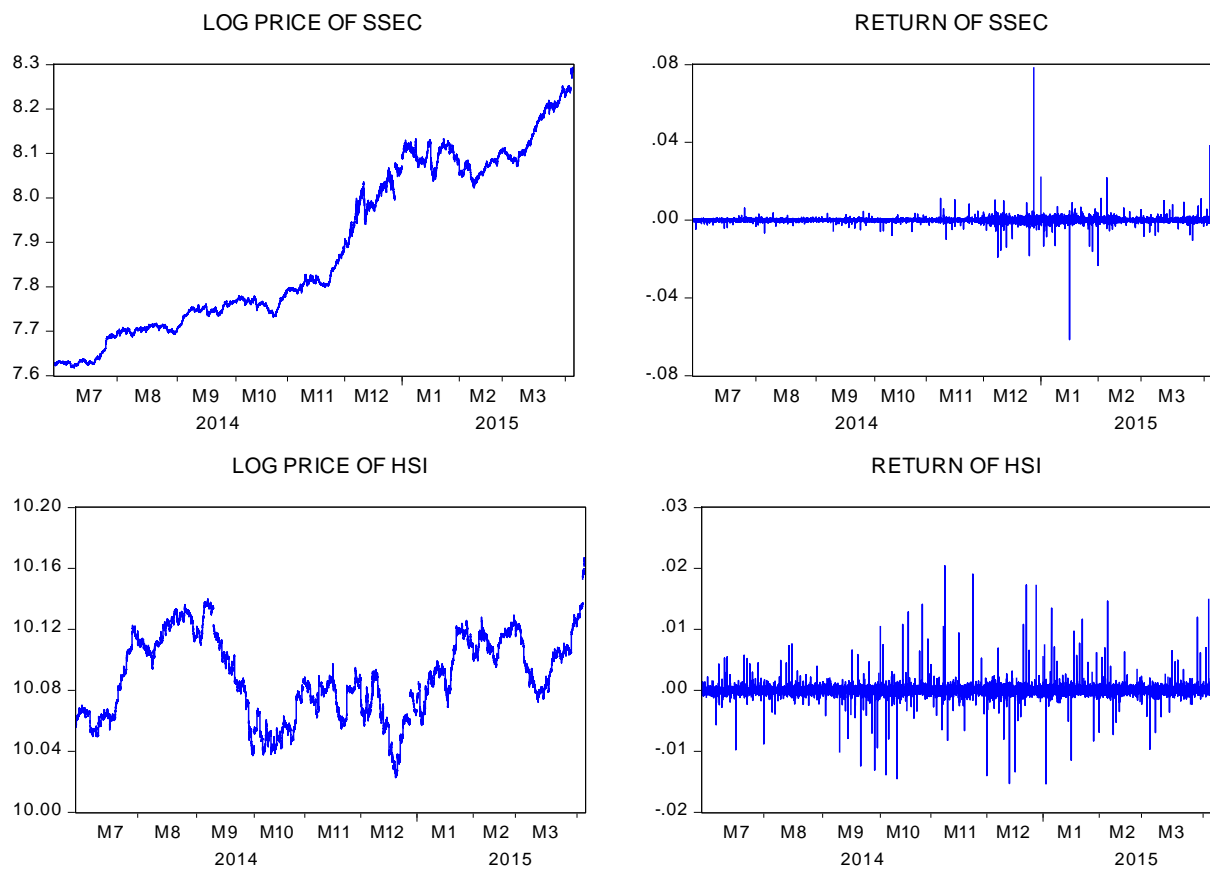


Table 5. 1: Summarised Descriptive Statistics

	Full Sample				Pre-Shanghai Hong Kong Stock Connect				Post-Shanghai Hong Kong Stock Connect			
	P_{SSEC}	P_{HSI}	R_{SSEC}	R_{HSI}	P_{SSEC}	P_{HSI}	R_{SSEC}	R_{HSI}	P_{SSEC}	P_{HSI}	R_{SSEC}	R_{HSI}
Observations	43923	43923	43922	43922	22143	22143	22142	22142	21780	21780	21780	21780
Mean	7.888641	10.08891	1.52E-05	2.47E-06	7.721023	10.0872	8.59E-06	1.40E-06	8.059053	10.09066	2.19E-05	3.56E-06
Median	7.808523	10.08702	1.96E-05	-3.54E-06	7.734113	10.08393	1.98E-05	-1.71E-06	8.079387	10.09084	1.93E-05	-5.32E-06
Maximum	8.293908	10.16687	0.078639	0.020413	7.827278	10.13994	0.011114	0.020413	8.293908	10.16687	0.078639	0.019057
Minimum	7.617537	10.02278	-0.061499	-0.01533	7.617537	10.03719	-0.00984	-0.014474	7.799014	10.02278	-0.061499	-0.01533
Std. Dev.	0.189569	0.02677	0.000864	0.000544	0.054955	0.02837	0.000404	0.000508	0.108611	0.024918	0.001157	0.000579
Skewness	0.274698	-0.030385	10.37952	3.417095	-0.336718	0.10969	-0.873385	1.666668	-0.637627	-0.178342	8.730442	4.581285
Kurtosis	1.601824	2.175542	2302.944	328.7961	2.175018	1.726128	74.55586	336.2063	3.244215	2.924074	1441.002	315.5261
Jarque-Bera	4130.098	1250.752	9.68E+09	1.94E+08	1046.358	1541.592	4726664	1.02E+08	1529.967	120.6865	1.88E+09	88714010

Note: P_{SSEC} and P_{HSI} denote the natural logarithms of Shanghai Stock Exchange Composite Index and Hong Kong Hang Seng Index, respectively. R_{SSEC} and R_{HSI} denote the continuously compounded returns for Shanghai Stock Exchange Composite Index and Hong Kong Hang Seng Index, respectively. The first return observation is calculated based on the first and second log price data, so one observation is naturally lost.

Table 5. 2: Unit Root Test
 Panel A: Full Sample Period

	ADF with Constant	Prob.	ADF with Trend	Prob.	PP with Constant	Prob.	PP with Trend	Prob.
P_{SSEC}	0.693612	0.9921	-1.810520	0.6999	0.679332	0.9918	-1.840584	0.6850
$\Delta P_{SSEC}(R_{SSEC})$	-78.71602	0.0001	-78.72565	0.0000	-166.0531	0.0001	-166.0341	0.0001
P_{HSI}	-1.474929	0.5466	-1.593387	0.7960	-1.394164	0.5869	-1.515418	0.8247
$\Delta P_{HSI}(R_{HSI})$	-200.0326	0.0001	-200.0323	0.0001	-199.8529	0.0001	-199.8519	0.0001

Panel B: Pre-Shanghai Hong Kong Stock Connect

	ADF with Constant	Prob.	ADF with Trend	Prob.	PP with Constant	Prob.	PP with Trend	Prob.
P_{SSEC}	-0.723133	0.8392	-2.333925	0.4148	-0.710288	0.8424	-2.328034	0.4180
$\Delta P_{SSEC}(R_{SSEC})$	-53.17510	0.0001	-53.17390	0.0000	-133.9329	0.0001	-133.9302	0.0001
P_{HSI}	-1.607590	0.4787	-1.779815	0.7148	-1.569353	0.4983	-1.741193	0.7329
$\Delta P_{HSI}(R_{HSI})$	-141.5884	0.0001	-141.5880	0.0001	-141.4574	0.0001	-141.4562	0.0001

Panel C: Post-Shanghai Hong Kong Stock Connect

	ADF with Constant	Prob.	ADF with Trend	Prob.	PP with Constant	Prob.	PP with Trend	Prob.
P_{SSEC}	-0.938619	0.7765	-1.841984	0.6842	-0.860496	0.8011	-1.793723	0.7081
$\Delta P_{SSEC}(R_{SSEC})$	-59.40365	0.0001	-59.40232	0.0000	-114.8932	0.0001	-114.8901	0.0001
P_{HSI}	-0.521320	0.8848	-2.139988	0.5227	-0.466079	0.8953	-2.115091	0.5368
$\Delta P_{HSI}(R_{HSI})$	-140.9578	0.0001	-140.9714	0.0001	-140.8624	0.0001	-140.8705	0.0001

Note: The ADF and PP tests test the null hypothesis of non-stationarity of the series (the time series have a unit root). The ADF and PP tests applied on are with constant and with trend. The lag selection for ADF test is based on Schwarz Info Criterion while the bandwidth selection for PP test is based on Newey-West Bandwidth.

5.5 Methodology Framework

5.5.1 The Analysis on Price Movement

The research methodologies include unit root and cointegration tests, Granger causality test, Vector Autoregressive (VAR) technique, Impulse Response Analysis, univariate GARCH and multivariate GARCH models. In order to determine whether the two financial time series are cointegrated, we have to test for the stationarity of the two time series and identify the level of integration. We determine the order of integration of P_{SSEC} and P_{HSI} using the Augmented Dickey-Fuller (ADF) test (Dickey and Fuller, 1981) and PP test (Phillips and Perron, 1988) to conduct our unit root tests. Table 5.2 presents the results of the unit root tests on SSEC and HSI and their first difference series for the full sample period, Pre- and Post-Shanghai Hong Kong Stock Connect periods. Our null hypothesis is that the financial time series has the unit root and we cannot reject the null hypothesis for price level of SSEC and HSI. From the results provided, the null hypothesis of unit roots cannot be rejected at the 1% level of statistical significance for both our series in the levels. However, the null is rejected and the estimated values are less than the critical values and P value is under 1% when first difference of these variables is taken, indicating that they are integrated of order one. Hence, it is concluded that P_{SSEC} and P_{HSI} are non-stationary and integrated of order one $I(1)$. If the two time series are found to be integrated of the same order, we can test for cointegration between them. Given that the two series are $I(1)$, we further use the Johansen-Juselius test (Johansen and Juselius, 1990) to conduct a cointegration analysis in order to determine whether P_{SSEC} and P_{HSI} have a long-run relationship. Starting with VAR structure we consider the following equation:

$$Y_t = A_0 + \sum_{i=1}^p A_i Y_{t-i} + \varepsilon_t \quad (5.1)$$

where

$$Y_t = \begin{pmatrix} P_{SSEC,t} \\ P_{HSI,t} \end{pmatrix}$$

This VAR can be rewritten as:

$$\Delta Y_t = A_0 + \Pi Y_{t-p} + \sum_{i=1}^{p-1} \Gamma_i \Delta Y_{t-i} + \varepsilon_t \quad (5.2)$$

where

$$\Pi = \sum_{i=1}^p A_i - I \text{ and } \Gamma_i = \sum_{i=1}^{p-1} A_i - I$$

The existence of a cointegrating relationship can be confirmed by examining the rank of the coefficient matrix Π . The number of cointegrating vectors (r) equals the rank of the coefficient matrix Π . Matrix Π can be written as a vector of adjustment parameters and cointegrating vectors $\Pi = \alpha\beta'$, where α is the matrix which represents the speed of adjustment parameters and β represents the matrix of cointegrating parameters. In order to determine the number of cointegrating vectors, the Johansen-Juselius test approach uses the following two likelihood ratio statistics - trace statistic and maximum eigenvalue statistic – which can be represented by:

$$\text{Trace statistic: } \lambda_{Trace}(r) = -T \sum_{i=r+1}^n \ln(1 - \hat{\lambda}_i)$$

$$\text{Maximum eigenvalue statistic: } \lambda_{Max}(r) = -T \ln(1 - \hat{\lambda}_{r+1})$$

where T is the sample size and $\hat{\lambda}_i$ is the i th largest canonical correlation. The trace test assumes the null hypothesis of r_0 cointegrating vectors against the alternative hypothesis that $r_0 < rank(\Pi) \leq n$ where n represents is the possible cointegrating vectors. The maximum eigenvalue test is a test where the null hypothesis is that $rank(\Pi) = r_0$ against the alternative hypothesis of $r_0 + 1$ cointegrating vectors. Our result is reported in Table 5.3.

For Pre-Shanghai-Hong Kong Stock Connect period, both trace and maximum eigenvalue statistics in all the four tests are not statistically significant at the 5% significance level. We therefore cannot reject the null hypothesis of no cointegration relationship. As a result, Johansen Juselius Cointegration tests strongly reject the existence of at least one cointegration vector and show clear evidence of no cointegration relationships between the two series for Pre-Shanghai Hong Kong Stock Connect period. This means that there is no specific long-term relationship between the two stock markets for that period. Our findings

here are in line with Cheng and Glascock (2005) who find no evidence of a cointegration relationship among the three Greater China Economic Area (GCEA) stock markets from 1993 to 2004. Zhu et al. (2004) also could not detect a cointegration relationship among the Shanghai, Shenzhen and Hong Kong stock markets from 1993 to 2001. Others who report similar findings include Huang et al. (2000) and Johansson and Ljungwall (2009). For the Post-Shanghai-Hong Kong Stock Connect period, the trace and maximum eigenvalue statistics - with no intercept and no trend test- reject H_0 : there is no cointegration vector at the 5% significance level and could not reject H_0 : there is at most one cointegration vector at the 5% significance level. This result means there is evidence of at least one cointegration relationship between the two series for the Post-Shanghai-Hong Kong Stock Connect period.

The contradictory results for the two periods suggest that Shanghai and Hong Kong stock markets seem to have a weak and unstable long-term relationship. Our results here suggest that the new program could strengthen the integration and co-movement between the two stock markets in the future. The new Shanghai-Hong Kong Stock Connect initiatives could accelerate the pace and dynamics of liberalisation of the Chinese stock market and improve the long-term investment environment. The results highlight the role of financial openness in financial integration between China and Hong Kong as argued by Su et al. (2007). They argue that increased financial openness has a stronger role in accounting for stock market co-movements between Mainland China and Hong Kong. Similarly, for the full sample period, the trace and the maximum eigenvalue statistics (in the no intercept and no trend test) indicate that there exists one cointegrating relationship between the two time series at the 5% significance level.

Table 5. 3: Johansen- Juselius Cointegration Tests

Panel A: Full Sample Period

Hypothesized No. of CE(s)	No Deterministic Trend in Data				Linear Deterministic Trend in Data			
	No Intercept, No Trend		Intercept, No Trend		Intercept, No Trend		Intercept, Trend	
	Trace Statistic	Prob.	Trace Statistic	Prob.	Trace Statistic	Prob.	Trace Statistic	Prob.
None	13.10577	0.0369	15.5828	0.1948	3.536803	0.9373	10.02451	0.9239
At most 1	0.601625	0.4993	1.91539	0.7945	0.001953	0.9615	3.319793	0.8366
	Max-Eigen Statistic	Prob.	Max-Eigen Statistic	Prob.	Max-Eigen Statistic	Prob.	Max-Eigen Statistic	Prob.
None	12.50414	0.0296	13.66741	0.1084	3.53485	0.9049	6.704717	0.9197
At most 1	0.601625	0.4993	1.91539	0.7945	0.001953	0.9615	3.319793	0.8366

Panel B: Pre-Shanghai Hong Kong Stock Connect

Hypothesized No. of CE(s)	No Deterministic Trend in Data				Linear Deterministic Trend in Data			
	No Intercept, No Trend		Intercept, No Trend		Intercept, No Trend		Intercept, Trend	
	Trace Statistic	Prob.	Trace Statistic	Prob.	Trace Statistic	Prob.	Trace Statistic	Prob.
None	7.949009	0.2406	12.9187	0.3704	5.71361	0.7291	14.19968	0.6411
At most 1	0.402297	0.5893	4.663391	0.3223	0.502744	0.4783	4.685601	0.6419
	Max-Eigen Statistic	Prob.	Max-Eigen Statistic	Prob.	Max-Eigen Statistic	Prob.	Max-Eigen Statistic	Prob.
None	7.546712	0.2056	8.255313	0.5175	5.210866	0.7150	9.514082	0.6707
At most 1	0.402297	0.5893	4.663391	0.3223	0.502744	0.4783	4.685601	0.6419

Panel C: Post-Shanghai Hong Kong Stock Connect

Hypothesized No. of CE(s)	No Deterministic Trend in Data				Linear Deterministic Trend in Data			
	No Intercept, No Trend		Intercept, No Trend		Intercept, No Trend		Intercept, Trend	
	Trace Statistic	Prob.	Trace Statistic	Prob.	Trace Statistic	Prob.	Trace Statistic	Prob.
None	16.26587	0.0104	18.60462	0.0831	11.29507	0.1940	17.03495	0.4124
At most 1	3.892448	0.0576	6.062778	0.1859	2.203992	0.1377	5.958834	0.4656
	Max-Eigen Statistic	Prob.	Max-Eigen Statistic	Prob.	Max-Eigen Statistic	Prob.	Max-Eigen Statistic	Prob.
None	12.37342	0.0313	12.54184	0.1567	9.091081	0.2786	11.07612	0.5055
At most 1	3.892448	0.0576	6.062778	0.1859	2.203992	0.1377	5.958834	0.4656

Note: Our lag length selection is based on Akaike Information Criterion (AIC) and nine lags are selected to process Johansen-Juselius Cointegration Tests.

We will use Granger causality test to examine the short-term relations between Shanghai and Hong Kong stock markets (Granger, 1969). According to the unit root test, the returns of Shanghai Composite Index and Hong Kong Hang Seng Index, R_{SSEC} and R_{HSI} are stationary. Hence the following VAR system is utilised to conduct causality tests:

$$R_{SSEC,t} = g_1 + \sum_{i=1}^p g_{11,i} R_{SSEC,t-i} + \sum_{i=1}^p g_{12,i} R_{HSI,t-i} + \varepsilon_{1,t} \quad (5.3)$$

$$R_{HSI,t} = g_2 + \sum_{i=1}^p g_{21,i} R_{SSEC,t-i} + \sum_{i=1}^p g_{22,i} R_{HSI,t-i} + \varepsilon_{2,t} \quad (5.4)$$

The first null hypothesis of Granger causality is that the return of SSEC does not Granger cause the return of HSI and the second null hypothesis of Granger causality is that the return of HSI does not Granger cause the return of SSEC. This is to test joint statistical significance of $g_{12,i}$ and $g_{21,i}$ respectively based on F-test. The F- statistics is calculated as follow:

$$F = \frac{(SSR_r - SSR_u)/n}{SSR_u/[T - (2n + 1)]} \quad (5.5)$$

where SSR_r is the sum of squared residuals from restricted equation and SSR_u is the sum of squared residuals from unrestricted equation. T is the number of observations while n is the number of lags. If the value of F exceeds the critical value, then the null hypothesis will be rejected. The lag selection is based on Akaike Information Criterion (AIC) which shows that the lag length of 8 is appropriate for both Pre-Shanghai Hong Kong Stock Connect period and Post-Shanghai Hong Kong Stock Connect period. If one or some of $g_{12,i}$ are not zero, we can assume that the return of Hong Kong Hang Seng Index Granger causes the return of Shanghai Stock Exchange Composite Index; If one or some of $g_{21,i}$ are not zero, we can assume that the return of Shanghai Stock Exchange Composite Index Granger causes the return of Hong Kong Hang Seng Index. If both of these events occur, it is said to be a feedback relationship between Shanghai and Hong Kong stock markets. In order to obtain additional insight into the two stock markets and their dynamic characteristics, we further conduct the impulse response analysis where the Cholesky decomposition is used to orthogonalize the underlying errors in order to know how the one market is destabilized by the shocks that arise from another market. The impulse response analysis is performed over two subsamples as defined in the previous section: Pre-and Post-Shanghai Hong Kong Stock

Connect periods. Impulse response functions which could describe the response trajectory are obtained by estimating the above VAR model (equation (5.3) and (5.4)) and 8 lags are chosen based on AIC.

5.5.2 The Analysis on the Volatility Behaviours

After analysing the behaviours of the price movements in the two markets, we examine the volatility behaviours by applying Generalized Autoregressive Conditional Heteroscedastic (GARCH) models in this section. In order to explore the impact of the Shanghai-Hong Kong Stock Connect program on the volatility of the two markets, this study initially uses the univariate GARCH model incorporated with a dummy variable and then considers a multivariate GARCH-style model. Engle (1982) introduced the Autoregressive Conditional Heteroskedasticity (ARCH) model to address the heteroskedasticity problem in the prediction of the conditional variance of financial time series. The ARCH process has an autoregressive structure on the conditional variance, which allows volatility shocks to persist over time and explains the volatility clustering. The GARCH model which was introduced later by Bollerslev (1986) overcomes ARCH model's long lag structure (overparametrisation) and the negative coefficient problems. Further, the conditional variance is modified to have linear relationships with the lagged squared residual value from the mean equation and the lagged conditional variance. The GARCH model turns the Autoregressive (AR) process of the conditional variance in ARCH model into Autoregressive Moving Average (ARMA) process. Empirical research shows that the GARCH model does not only provide a robust and reliable method of estimating volatility, but also has been found to fit time-varying volatility fairly well and is more parsimonious compared with the ARCH model (Poon and Granger, 2003). Therefore the successful application of GARCH model in numerous financial time series, including stock market index, inflation rate, exchange rate, etc., makes this approach an important, valuable and popular econometric time series model for volatility forecasting.

GARCH(1,1) is the simplest and one of the most popular models for volatility forecasting with conditional variance $\sigma_t^2 = a_0 + a_1 \varepsilon_{t-1}^2 + b_1 \sigma_{t-1}^2$. Because the GARCH model overcomes a number of weaknesses in the traditional volatility models which assume the variance keeps unchanged, it can effectively estimate the conditional volatility of many financial and economic time series such as stock price, futures price, exchange rates and bond prices. In 1993, Glosten, Jagannathan and Runkle introduced the GJR GARCH (henceforth) which allows for asymmetric effect in the response (leverage effect) (Glosten et al., 1993).

Therefore, the positive and negative shocks which represent good news and bad news have different impact on volatility forecasting. Under GJR GARCH framework, the conditional variance equation is given as: $\sigma_t^2 = a_0 + a_1 \varepsilon_{t-1}^2 + \varphi_1 \varepsilon_{t-1}^2 d_1 + b_1 \sigma_{t-1}^2$, where d_1 is a dummy variable, when $\varepsilon_{t-1} < 0$, $d_1 = 1$, when $\varepsilon_{t-1} > 0$, $d_1 = 0$. Based on the GJR GARCH model, we introduce a modified GJR GARCH model with the dummy variable. Firstly, we run the following mean equations $P_{SSEC,t} = c_{SSEC} + \lambda_{SSEC} P_{SSEC,t-1} + \varepsilon_{SSEC,t}$ and $P_{HSI,t} = c_{HSI} + \lambda_{HSI} P_{HSI,t-1} + \varepsilon_{HSI,t}$ respectively, and use Lagrange Multiplier Test to examine time-varying volatility (ARCH effect). The LM statistics reject the null hypothesis of no ARCH effect in the residual term of the above equation which indicates the presence of time-varying volatility in both Shanghai and Hong Kong stock markets. We then estimate the modified GJR GARCH model which is presented as follows:

The mean equation of GJR GARCH model for Shanghai stock market is:

$$P_{SSEC,t} = c_{SSEC} + \lambda_{SSEC} P_{SSEC,t-1} + \varepsilon_{SSEC,t}, \varepsilon_{SSEC,t} | \Omega_{t-1} \sim N(0, \sigma_{SSEC,t}^2) \quad (5.6)$$

The modified conditional variance equation for Shanghai stock market is:

$$\sigma_{SSEC,t}^2 = a_{SSEC,0} + a_{SSEC,1} \varepsilon_{t-1}^2 + b_{SSEC,1} \sigma_{t-1}^2 + \varphi_{SSEC,1} \varepsilon_{t-1}^2 d_1 + d_{SSEC} * DUMMY_t \quad (5.7)$$

The mean equation of GJR GARCH model for Hong Kong stock market is:

$$P_{HSI,t} = c_{HSI} + \lambda_{HSI} P_{HSI,t-1} + \varepsilon_{HSI,t}, \varepsilon_{HSI,t} | \Omega_{t-1} \sim N(0, \sigma_{HSI,t}^2) \quad (5.8)$$

The modified conditional variance equation for Hong Kong stock market is:

$$\sigma_{HSI,t}^2 = a_{HSI,0} + a_{HSI,1} \varepsilon_{t-1}^2 + b_{HSI,1} \sigma_{t-1}^2 + \varphi_{HSI,1} \varepsilon_{t-1}^2 d_1 + d_{HSI} * DUMMY_t \quad (5.9)$$

where Ω_{t-1} is the information set available at the time $t - 1$, $DUMMY_t = 1$ if $P_{SSEC,t}$ and $P_{HSI,t}$ are observed after 17 November 2014 when Shanghai-Hong Kong Stock Connect program was implemented, 0 otherwise. The ARCH effect is captured by the parameter $a_{SSEC,1}$ ($a_{HSI,1}$) while $b_{SSEC,1}$ ($b_{HSI,1}$) captures the GARCH effect, and $a_{SSEC,1} + b_{SSEC,1}$ ($a_{HSI,1} + b_{HSI,1}$) measures the persistence of the impact of shocks to the conditional variance. A GARCH (1,1) process is weakly stationary if $a_{SSEC,1} + b_{SSEC,1} < 1$ ($a_{HSI,1} + b_{HSI,1} < 1$). The coefficient d_{SSEC} (d_{HSI})

captures the incremental influence of Shanghai-Hong Kong Stock Connect program on the volatility of Shanghai and Hong Kong stock markets respectively. We use the modified GJR GARCH model with a dummy variable to estimate the volatilities of both Shanghai and Hong Kong stock markets for the whole sample period and our results are detailed in Table 5.9.

Another general version of the multivariate GARCH model introduced by Bollerslev et al. (1988) is the VECG GARCH model where the conditional variance and covariance are a function of all lagged conditional variance and covariance. The model is specified as follows:

$$h_t = C_0 + \sum_{i=1}^q A_i \eta_{t-i} + \sum_{j=1}^p B_j h_{t-j} \quad (5.10)$$

where $h_t = \text{vech}(H_t)$, $\eta_t = \text{vech}(\varepsilon_t \varepsilon_t^T)$, $\text{vech}(\cdot)$ denote the operator that stacks the lower triangular part of a symmetric $d \times d$ matrix into $d(d+1)/2$ dimensional vector, A_i and B_j are $d(d+1)/2$ dimensional parameter matrices. H_t denotes conditional variance-covariance matrix. However, the number of parameters for the VECG GARCH model is very large and thus difficult to estimate. Engle and Kroner (1995) introduced the BEKK (Baba, Engle, Kraft and Kroner) model to simplify the estimation process by reducing the number of parameters. The BEKK GARCH model can economise on the parameters by imposing restrictions both within and across equations. Therefore it can provide information on properties such as volatility spillover between markets, autoregressive tendencies, volatility persistence, and volatility clustering. The bivariate VAR-BEKK GARCH model in the mean equation is generally expressed as a VAR model which could capture the relationship between the two markets:

$$R_t = G_0 + \sum_{i=1}^p G_i R_{t-i} + \varepsilon_t, \quad \varepsilon_t | \Omega_{t-1} \sim N(0, H_t) \quad (5.11)$$

where R_t is a vector of returns for SSEC and HSI, $R_t = \begin{pmatrix} R_{SSEC,t} \\ R_{HSI,t} \end{pmatrix}$,

ε_t is a vector of Gaussian error, $\varepsilon_t = \begin{bmatrix} \varepsilon_{SSEC,t} \\ \varepsilon_{HSI,t} \end{bmatrix}$.

The conditional variance equations of BEKK GARCH(1,1) model can be outlined as:

$$H_t = C' C + A' \varepsilon_{t-1} \varepsilon_{t-1}' A + B' H_{t-1} B \quad (5.12)$$

$$H_t = \begin{bmatrix} c_{11} & 0 \\ c_{21} & c_{22} \end{bmatrix}' \begin{bmatrix} c_{11} & 0 \\ c_{21} & c_{22} \end{bmatrix} + \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}' \begin{bmatrix} \varepsilon_{1,t-1}^2 & \varepsilon_{1,t-1} \varepsilon_{2,t-1} \\ \varepsilon_{2,t-1} \varepsilon_{1,t-1} & \varepsilon_{2,t-1}^2 \end{bmatrix} \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} + \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}' H_{t-1} \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix} \quad (5.13)$$

The above equations can be expanded alternatively as follow:

$$h_{11,t} = c_{11}^2 + c_{21}^2 + a_{11}^2 \varepsilon_{1,t-1}^2 + 2a_{11}a_{21} \varepsilon_{1,t-1} \varepsilon_{2,t-1} + a_{21}^2 \varepsilon_{2,t-1}^2 + b_{11}^2 h_{11,t-1} + 2b_{11}b_{21} h_{12,t-1} + b_{21}^2 h_{22,t-1} \quad (5.14)$$

$$h_{22,t} = c_{22}^2 + a_{12}^2 \varepsilon_{1,t-1}^2 + 2a_{22}a_{12} \varepsilon_{1,t-1} \varepsilon_{2,t-1} + a_{22}^2 \varepsilon_{2,t-1}^2 + b_{12}^2 h_{11,t-1} + 2b_{12}b_{22} h_{12,t-1} + b_{22}^2 h_{22,t-1} \quad (5.15)$$

where H_t denotes conditional variance-covariance matrix, C is the matrix of intercept coefficients, A measures the effect of previous period shocks or news (ARCH effect), B measures the effect of previous conditional volatility (GARCH effect). In this model, the diagonal elements of matrices $A(a_{11}$ and $a_{22})$ and $B(b_{11}$ and $b_{22})$ capture the effect of own previous shocks and historical volatility to the current conditional variance, respectively. On the other hand, the off-diagonal elements of matrices $A(a_{12}$ and $a_{21})$ and $B(b_{12}$ and $b_{21})$ measure the cross-market effects of shock and volatility (the volatility spillovers). The above BEKK system can be estimated efficiently by maximising the conditional log-likelihood function, assuming a normal distribution of errors. The log-likelihood function of the joint distribution is the sum of all the log-likelihood functions of the conditional distributions which can be represented below as follows:

$$L = \sum_{t=1}^T L_t \quad (5.16)$$

$$L_t = \frac{n}{2} \ln(2\pi) - \frac{1}{2} \ln |H_t| - \frac{1}{2} \varepsilon_t' H_t^{-1} \varepsilon_t \quad (5.17)$$

In order to capture the asymmetric response of the volatility, Kroner and Ng (1998) incorporated asymmetric effect into their BEKK GARCH model where equation (5.12) becomes:

$$H_t = C' C + A' \varepsilon_{t-1} \varepsilon_{t-1}' A + B' H_{t-1} B + D' \eta_{t-1} \eta_{t-1}' D \quad (5.18)$$

$$H_t = \begin{bmatrix} c_{11} & 0 \\ c_{21} & c_{22} \end{bmatrix}' \begin{bmatrix} c_{11} & 0 \\ c_{21} & c_{22} \end{bmatrix} + \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}' \begin{bmatrix} \varepsilon_{1,t-1}^2 & \varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ \varepsilon_{1,t-1}\varepsilon_{2,t-1} & \varepsilon_{2,t-1}^2 \end{bmatrix} \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} + \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}' H_{t-1} \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix} + \begin{bmatrix} d_{11} & d_{12} \\ d_{21} & d_{22} \end{bmatrix}' \eta_{t-1} \eta_{t-1}' \begin{bmatrix} d_{11} & d_{12} \\ d_{21} & d_{22} \end{bmatrix} \quad (5.19)$$

where $\eta_{t-1} = \begin{bmatrix} \max(0, -\varepsilon_{SSEC,t-1}) \\ \max(0, -\varepsilon_{HSI,t-1}) \end{bmatrix}$

The matrix D captures the asymmetric property of the time-varying variance-covariance. The asymmetric effect is also called the leverage effect, a common feature of stock markets. If any coefficient in D is positive and significant, a normal asymmetric effect exists. Accordingly, a bad news will cause a larger volatility of stock markets than a good news which means the stock volatility tends to rise more in response to negative shocks (bad news) than positive shocks (good news), in the conditional variances and co-variances. If a negative and significant value occurs, it implies an opposite effect, which means that the bad news may reduce volatility and good news could increase the volatility. If insignificant, there is no such leverage effect and bad news could be treated equivalent to good news. We use the VAR-BEKK-GARCH (1, 1) model with asymmetric effect to estimate the conditional variance of the two markets and investigate spillover effects for the Pre-and Post-Shanghai Hong Kong Stock Connect periods respectively. The estimation is based on the Berndt, Hall, Hall, and Hausman (BHHH) algorithm and the results of this estimation are outlined in Table 5.8.

5.6. Major Findings and Results Analysis

5.6.1 Results on Analysis on Price Movement

5.6.1.1 Results on Granger causality, VAR and Impulse Response Analysis

In this section, the Granger causality relationship between Shanghai and Hong Kong stock markets will be discussed. According to Table 5.4, the Granger causality relationship between the returns of SSEC and HSI changes from bi-directional to uni-directional once Shanghai-Hong Kong Stock Connect is in effect. Specifically, prior to the Stock Connect program, we can reject both hypotheses which are Return of SSEC does not Granger Cause Return of HSI and Return of HSI does not Granger Cause Return of SSEC at the 1% level respectively, suggesting the existence of a bilateral causal relationship between Shanghai and

Hong Kong stock markets. However, during Post-Shanghai Hong Kong Stock Connect period, we can only reject the hypothesis that Return of SSEC does not Granger Cause Return of HSI at 1% level. The hypothesis that Return of HSI does not Granger Cause Return of SSEC cannot be rejected at 5%, implying that Return of HSI could not Granger Cause Return of SSEC after the Shanghai-Hong Kong Stock Connect program is introduced. Table 5.5 displays the parameters estimates of the VAR model which is one of the most popular forecasting techniques in financial market behaviours. During Pre-Shanghai Hong Kong Stock Connect period, the return behaviour for both Shanghai and Hong Kong stock markets depends on its own past values respectively, since some of the coefficients of their own lagged returns (lag1, 2, 3, 5, 6, 7 and 8 for SSEC and lag1 and 4 for HSI) are statistically significant at 5%. This result shows that Shanghai stock market is more autoregressive than Hong Kong stock market. In terms of the cross-market impact, the lagged returns of SSEC (lag1, 2, 5 and 7) are observed to predict the current return of HSI which are all significant at the 5% significance level.

On the other hand, the lagged returns of HSI (lag1, 3 and 8) are also good predictors for that of SSEC at the 5% significance level. The results show strong evidence of a bilateral causal feedback relationship between the two markets before Shanghai-Hong Kong Stock Connect program. This is in line with the results reported by Zheng and Chen (2013) who also find a bi-directional causality relationship and consistent with our Granger causality results. Looking at Post- Connect period, the returns of SSEC and HSI indicate autoregressive behaviour as most of the lagged SSEC's coefficients are statistically significant. However, most of the coefficients of HSI are statistically insignificant, implying that the Shanghai stock market has a stronger autoregressive dynamic compared with the Hong Kong stock market. Surprisingly, the cross-markets effects between the two markets are observed to be weaker. Only one lagged return in each market is seen to have a significant impact on the returns of the other market at the 5% significance level. The predictive power of the lagged returns of HSI for the current return of SSEC becomes less significant after this event, as all the coefficients of the lagged returns of HSI in SSEC equation are statistically insignificant except for lag 3. However, the lagged 3 coefficient is significant only at 5% and the P value is 4.79% which is just slightly below 5%. If at 10% level, we could ignore the impact from the lagged 3 return of HIS and conclude that there is no impact from lagged returns of HSI on SSEC. On the contrary, we observe that the lagged 1 return of SSEC has a significant influence on the return of HSI, since the coefficient is statistically significant at

the 1% significance level. Our results suggest that the information transmission from Shanghai to Hong Kong is faster than the opposite direction, because the lagged 1 coefficient is statistically significant for the effect from Shanghai to Hong Kong compared with the lagged 3 coefficient for Hong Kong to Shanghai. In addition, when we compare the significance level and absolute values of these two coefficients, we see that $g_{21,1}$ is larger and more significant than $g_{12,3}$ (0.049206 VS 0.030188, 1% VS 5%). As a result, the mean spillover effect from Shanghai to Hong Kong is more prominent than the opposite direction after in the Post-Connect period.

The evidence here is indicative of the strategic leadership role of Shanghai stock market plays following the initiation of Shanghai-Hong Kong Stock Connect. The results for the Post-Connect period are consistent with Lam and Qiao (2009) who argue that the Chinese stock markets are now playing the most influential role among the stock markets in the Greater China region, including Hong Kong stock market. However, other studies such as Tian (2008) report that the Mainland China stock markets continue to be heavily influenced by Hong Kong stock market. Overall, the stock returns are predictable in both Shanghai and Hong Kong stock markets by their own lagged returns for both periods, implying serial correlation is a strong feature in both markets but the cross-market effect becomes weaker after the Shanghai-Hong Kong Stock Connect program. Nonetheless, the mean spillover effect from Shanghai to Hong Kong is found to be faster and stronger than Hong Kong to Shanghai, since the lagged returns of HSI lose more predictive power for the current return of SSEC after the Shanghai-Hong Kong Stock Connect program. Our findings suggest that Shanghai-Hong Kong Stock Connect program does contribute to the leading role of Shanghai stock market.

Table 5. 4: Granger causality Test

	Pre-Shanghai Hong Kong Stock Connect		Post-Shanghai Hong Kong Stock Connect	
Null Hypothesis:	F-Statistic	Prob.	F-Statistic	Prob.
R_{SSEC} does not Granger Cause R_{HSI}	13.8077	3.00E-20	21.3498	1.00E-32
R_{HSI} does not Granger Cause R_{SSEC}	11.2746	5.00E-16	1.80179	0.0716

Note: The test procedure is based on bivariate VAR(8) model and the optimal lag length selection of 8 is based on AIC.

Table 5. 5: VAR Results

Pre-Shanghai Hong Kong Stock Connect				Post-Shanghai Hong Kong Stock Connect			
	R_{SSEC}		R_{HSI}		R_{SSEC}		R_{HSI}
$R_{SSEC}(-1)---g_{11,1}$	0.067193*	$R_{SSEC}(-1)---g_{21,1}$	0.080693*	$R_{SSEC}(-1)---g_{11,1}$	0.217001*	$R_{SSEC}(-1)---g_{21,1}$	0.049206*
	(0.0000)		(0.0000)		(0.0000)		(0.0000)
$R_{SSEC}(-2)---g_{11,2}$	0.167158*	$R_{SSEC}(-2)---g_{21,2}$	0.031265*	$R_{SSEC}(-2)---g_{11,2}$	0.040268*	$R_{SSEC}(-2)---g_{21,2}$	0.004075
	(0.0000)		(0.0006)		(0.0000)		(0.3141)
$R_{SSEC}(-3)---g_{11,3}$	0.091770*	$R_{SSEC}(-3)---g_{21,3}$	0.011672	$R_{SSEC}(-3)---g_{11,3}$	-0.029077*	$R_{SSEC}(-3)---g_{21,3}$	0.00392
	(0.0000)		(0.2074)		(0.0002)		(0.3329)
$R_{SSEC}(-4)---g_{11,4}$	0.013975	$R_{SSEC}(-4)---g_{21,4}$	0.004059	$R_{SSEC}(-4)---g_{11,4}$	-0.035291*	$R_{SSEC}(-4)---g_{21,4}$	0.006749
	(0.0519)		(0.6622)		(0.0000)		(0.0956)
$R_{SSEC}(-5)---g_{11,5}$	-0.029061*	$R_{SSEC}(-5)---g_{21,5}$	-0.022553*	$R_{SSEC}(-5)---g_{11,5}$	-0.020107*	$R_{SSEC}(-5)---g_{21,5}$	-0.000489
	(0.0001)		(0.0152)		(0.0112)		(0.9039)
$R_{SSEC}(-6)---g_{11,6}$	-0.027883*	$R_{SSEC}(-6)---g_{21,6}$	-0.002356	$R_{SSEC}(-6)---g_{11,6}$	-0.020628*	$R_{SSEC}(-6)---g_{21,6}$	0.002688
	(0.0001)		(0.7991)		(0.0093)		(0.5066)
$R_{SSEC}(-7)---g_{11,7}$	-0.028912*	$R_{SSEC}(-7)---g_{21,7}$	0.019257*	$R_{SSEC}(-7)---g_{11,7}$	-0.019547*	$R_{SSEC}(-7)---g_{21,7}$	-0.00189
	(0.0000)		(0.0350)		(0.0136)		(0.6402)
$R_{SSEC}(-8)---g_{11,8}$	-0.044408*	$R_{SSEC}(-8)---g_{21,8}$	0.002835	$R_{SSEC}(-8)---g_{11,8}$	-0.007971	$R_{SSEC}(-8)---g_{21,8}$	0.003876
	(0.0000)		(0.7554)		(0.3055)		(0.3290)
$R_{HSI}(-1)---g_{12,1}$	0.047818*	$R_{HSI}(-1)---g_{22,1}$	0.028213*	$R_{HSI}(-1)---g_{12,1}$	-0.012693	$R_{HSI}(-1)---g_{22,1}$	-0.005003
	(0.0000)		(0.0001)		(0.4057)		(0.5209)
$R_{HSI}(-2)---g_{12,2}$	-0.006687	$R_{HSI}(-2)---g_{22,2}$	-0.011251	$R_{HSI}(-2)---g_{12,2}$	0.007100	$R_{HSI}(-2)---g_{22,2}$	0.000558
	(0.2218)		(0.1117)		(0.6418)		(0.9429)
$R_{HSI}(-3)---g_{12,3}$	-0.011497*	$R_{HSI}(-3)---g_{22,3}$	-0.007882	$R_{HSI}(-3)---g_{12,3}$	0.030188*	$R_{HSI}(-3)---g_{22,3}$	-0.008917
	(0.0357)		(0.2652)		(0.0479)		(0.2523)
$R_{HSI}(-4)---g_{12,4}$	0.003754	$R_{HSI}(-4)---g_{22,4}$	-0.014151*	$R_{HSI}(-4)---g_{12,4}$	0.010519	$R_{HSI}(-4)---g_{22,4}$	-0.007182
	(0.4929)		(0.0455)		(0.4906)		(0.3565)
$R_{HSI}(-5)---g_{12,5}$	0.006285	$R_{HSI}(-5)---g_{22,5}$	0.002887	$R_{HSI}(-5)---g_{12,5}$	-0.006692	$R_{HSI}(-5)---g_{22,5}$	0.005654
	(0.2509)		(0.6832)		(0.6608)		(0.4676)
$R_{HSI}(-6)---g_{12,6}$	0.00788	$R_{HSI}(-6)---g_{22,6}$	0.000324	$R_{HSI}(-6)---g_{12,6}$	-0.028057	$R_{HSI}(-6)---g_{22,6}$	-0.027800*
	(0.1499)		(0.9635)		(0.0657)		(0.0004)
$R_{HSI}(-7)---g_{12,7}$	-0.003469	$R_{HSI}(-7)---g_{22,7}$	-0.01214	$R_{HSI}(-7)---g_{12,7}$	-0.022005	$R_{HSI}(-7)---g_{22,7}$	-0.004192
	(0.5259)		(0.0859)		(0.1490)		(0.5902)
$R_{HSI}(-8)---g_{12,8}$	0.010942*	$R_{HSI}(-8)---g_{22,8}$	-0.011723	$R_{HSI}(-8)---g_{12,8}$	-0.027464	$R_{HSI}(-8)---g_{22,8}$	-0.01032
	(0.0453)		(0.0971)		(0.0705)		(0.1830)
Constant--- g_1	0.00000673*	Constant--- g_2	3.72E-07	Constant--- g_1	0.0000192*	Constant--- g_2	2.05E-06
	(0.0106)		(0.9131)		(0.0116)		(0.5969)

Note: The estimated model is VAR(8) as shown in equations (3) and (4) and the lag length selection of 8 is based on AIC. The P value of the coefficient is given in parentheses and * indicates rejection of the null hypothesis at the 5% level of significance.

Figure 5.2 presents the results from our Impulse Response analysis based on bivariate VAR model for both Pre-and Post-Shanghai Hong Kong Stock Connect periods (see Panel A and Panel B respectively). Figure 5.2 traces out impulse response functions from one standard deviation shock in both markets to each other and the dashed lines in each graph are 95% confidence bands. For the Pre-Connect period, a shock in the Shanghai stock market has a strong positive effect on the return of HSI (0.000155 for the first follow up period), while Shanghai stock market exhibits a weak response to the shock from Hong Kong after the second follow up period (0.000023 for the second follow up period). In the Post-Connect period, the response of HSI to the shocks in Shanghai stock market increases to 0.000282 for the first follow up period. However, this stock market exhibits nearly no change in the response of shocks from the Hong Kong stock market, since the weak impact on the second period disappears. We see a stronger response from both markets to the shocks originating from their own market compared with the shocks from the other market, indicating that the information transmission process across markets is decaying. We also observe that the response has a short-lived feature since there are little changes after the fourth follow up period. Overall, we can see that a shock from the Shanghai stock market seems to have a stronger impact on Hong Kong stock market as opposed to the other way round (weak impact from Hong Kong to Shanghai stock market).

The short run dependence of market return in Hong Kong stock market to the shocks that arise from Shanghai stock market appears to be greatly increasing while the impact of the shocks in HSI on Shanghai stock market is weaker after the Shanghai-Hong Kong Stock Connect program. This means Hong Kong stock market tends to be more responsive to the shocks in Shanghai market which reacts less significantly to the shocks in Hong Kong. While our observation here is consistent with the results of Granger causality test and VAR analysis which also show that the Shanghai stock market dominates Hong Kong stock market after this event, suggesting that the leading role of Shanghai stock market increases. It is also indicative of the increased importance of Chinese stock markets in the Asia-Pacific region and its influence in information transmission. The detailed information on impulse response functions is provided in Table 5.6.

Table 5. 6: Impulse Response Functions

Period	Pre-Shanghai Hong Kong Stock Connect				Post-Shanghai Hong Kong Stock Connect			
	Response of R_{SSEC} to:		Response of R_{HSI} to:		Response of R_{SSEC} to:		Response of R_{HSI} to:	
	R_{SSEC}	R_{HSI}	R_{SSEC}	R_{HSI}	R_{SSEC}	R_{HSI}	R_{SSEC}	R_{HSI}
1	0.000392	0	0.000155	0.000482	0.001121	0	0.000282	0.000498
2	3.37E-05	2.30E-05	3.60E-05	1.36E-05	0.000240	-6.32E-06	5.37E-05	-2.49E-06
3	6.84E-05	-1.02E-06	1.42E-05	-3.18E-06	9.85E-05	2.19E-06	1.62E-05	-2.05E-08
4	4.48E-05	-2.00E-06	9.92E-06	-3.40E-06	7.13E-06	1.52E-05	7.65E-06	-4.36E-06
5	2.36E-05	3.32E-06	5.37E-06	-6.91E-06	-3.64E-05	8.79E-06	6.72E-06	-2.80E-06
6	5.59E-06	2.92E-06	-4.73E-06	1.35E-06	-4.23E-05	-6.72E-07	7.30E-07	3.30E-06
7	-1.39E-06	3.90E-06	-1.44E-08	1.76E-07	-5.01E-05	-1.43E-05	-6.38E-06	-1.37E-05
8	-1.08E-05	-1.10E-06	4.47E-06	-5.35E-06	-4.81E-05	-1.47E-05	-6.92E-06	-2.48E-06
9	-1.97E-05	5.19E-06	-2.30E-06	-5.32E-06	-3.50E-05	-1.79E-05	-2.40E-06	-5.87E-06
10	-8.28E-06	-5.96E-07	-1.76E-06	1.65E-07	-1.21E-05	-4.62E-06	-2.36E-06	-7.33E-07

Note: Impulse responses to Cholesky one standard deviation shock in VAR equations (5.3) and (5.4)

Table 5. 7: Results from GJR GARCH with Dummy Variable

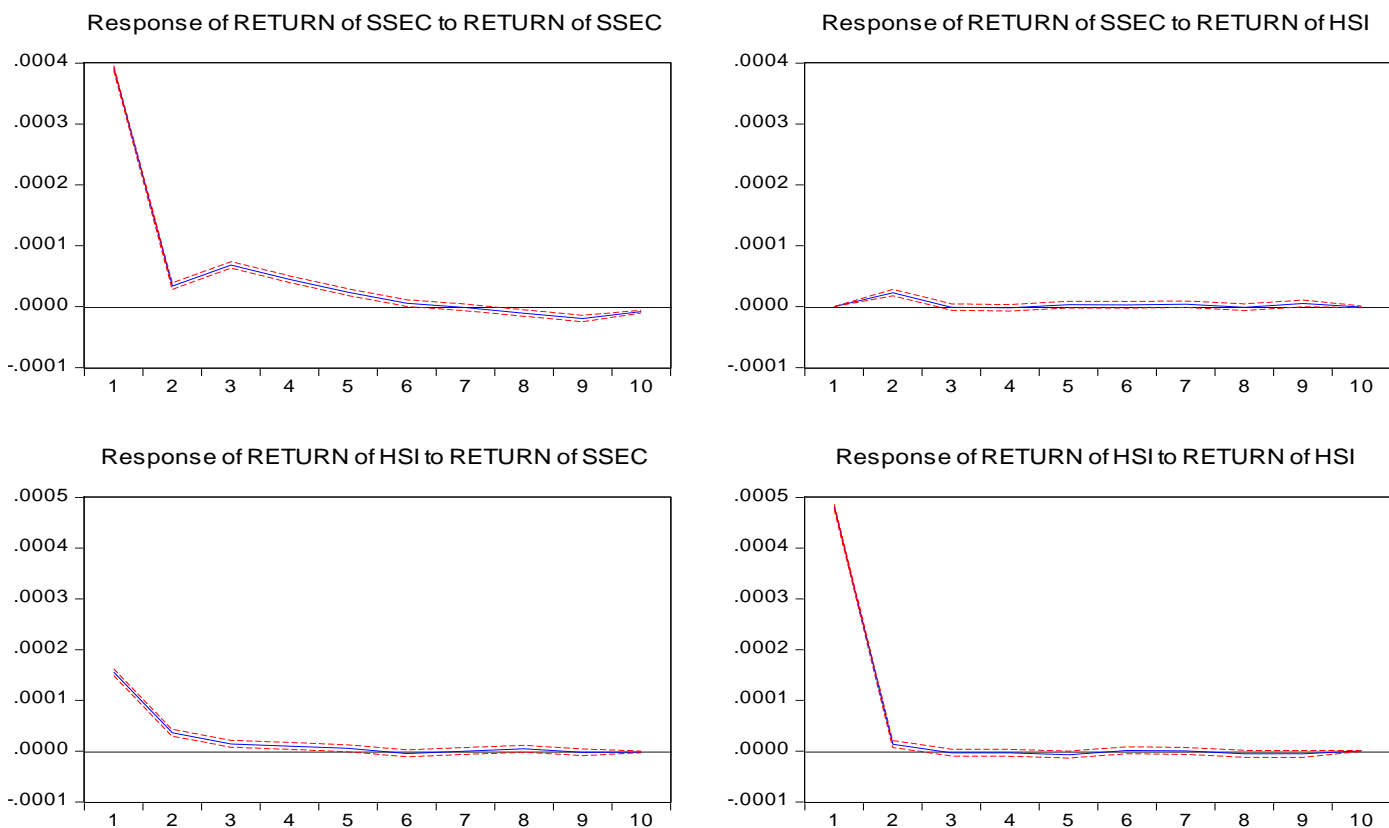
Shanghai Stock Market					Hong Kong Stock Market				
Variable	Coefficient	Std. Error	z-Statistic	Prob.	Variable	Coefficient	Std. Error	z-Statistic	Prob.
Mean Equation					Mean Equation				
c_{SSEC}	2.33E-06	0.000146	0.015912	0.9873	c_{HSI}	0.001208	0.000206	5.857927	0.0000
λ_{SSEC}	0.999999	1.89E-05	53017.12	0.0000	λ_{HSI}	0.999898	2.16E-05	46228.57	0.0000
Variance Equation					Variance Equation				
$a_{SSEC,0}$	5.64E-08	1.05E-09	53.79944	0.0000	$a_{HSI,0}$	1.75E-07	1.27E-08	13.71399	0.0000
$a_{SSEC,1}$	0.120175	0.002197	54.69594	0.0000	$a_{HSI,1}$	0.149989	0.006852	21.89127	0.0000
$\phi_{SSEC,1}$	-0.083679	0.005142	-16.2731	0.0000	$\phi_{HSI,1}$	0.049994	0.021212	2.356874	0.0184
$b_{SSEC,1}$	0.598982	0.004715	127.0301	0.0000	$b_{HSI,1}$	0.599991	0.017393	34.49627	0.0000
d_{SSEC}	6.86E-07	8.71E-09	78.84132	0.0000	d_{HSI}	4.82E-08	9.08E-10	53.09352	0.0000

Note: $(a_{SSEC,1}+b_{SSEC,1})$ and $1/(a_{SSEC,1}+b_{SSEC,1})$ are 0.719157 and 1.390517 for Shanghai respectively, while $(a_{HSI,1}+b_{HSI,1})$ and $1/(a_{HSI,1}+b_{HSI,1})$ for Hong Kong are 0.749980 and 1.333369 respectively.

Figure 5. 2: Impulse Response Analysis based on VAR

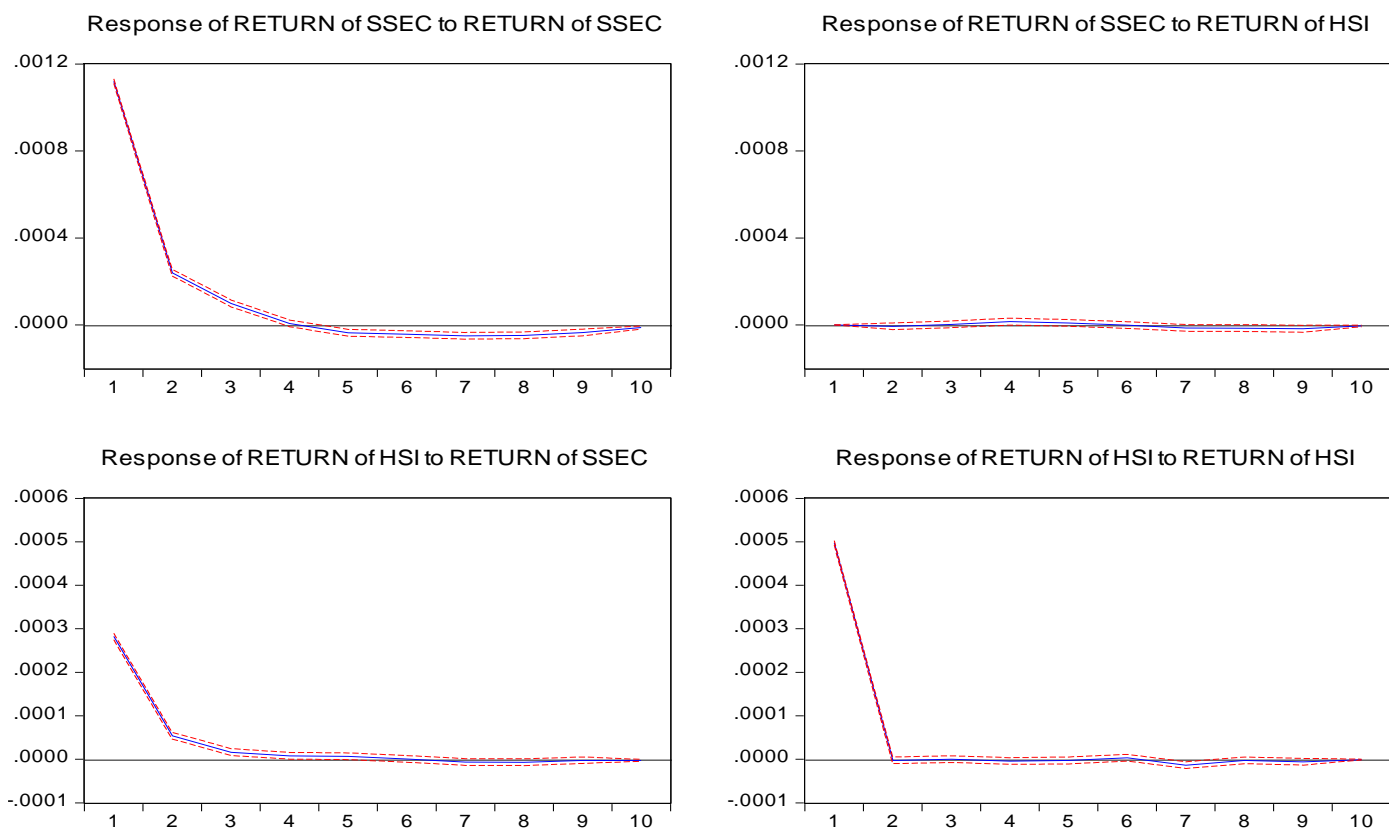
Panel A: Pre-Shanghai Hong Kong Stock Connect period

Response to Cholesky One S.D. Innovations ± 2 S.E.



Panel B: Post-Shanghai Hong Kong Stock Connect period

Response to Cholesky One S.D. Innovations ± 2 S.E.



5.6.2 Result on Analysis of the Volatility Behaviours

5.6.2.1 Results on GJR GARCH with Dummy Variable

Table 5.7 presents the volatility estimates for Shanghai and Hong Kong stock markets based on the GJR GARCH model with a dummy variable for the full sample period. All the coefficients are statistically significant at the 5% level except the constant coefficient in the mean equation of SSEC. Firstly, the coefficients λ_{SSEC} and λ_{HSI} are statistically significant in the mean equations, suggesting that there is a serial correlation in both Shanghai and Hong Kong stock markets, consistent with our VAR results in section 6.1.1. Moving to the conditional variance equations, coefficients $a_{SSEC,1}$ and $a_{HSI,1}$ measure the impact of the lagged square error term in the mean equation which relates to the impact of price changes of the previous period on the current volatility. If they are higher, the recent news could have a greater impact on the conditional volatility. The coefficients $b_{SSEC,1}$ and $b_{HSI,1}$ capture the impact of the lagged conditional volatility on the current conditional volatility and therefore indicate the effect of the old news (already available news) on the current conditional volatility. Generally, we do observe evidence of significant ARCH and GARCH effects on the conditional volatility of both stock markets since the coefficients $a_{SSEC,1}$, $a_{HSI,1}$, $b_{SSEC,1}$ and $b_{HSI,1}$ are statistically significant at the 1% significance level.

According to the results, both the recent news and old news appear to have slightly more impact on Hong Kong stock market compared with Shanghai stock market, because $a_{HSI,1} > a_{SSEC,1}$ and $b_{HSI,1} > b_{SSEC,1}$, implying that information transmission in Hong Kong is slightly more efficient than Shanghai but the difference seems to be narrowing. The sum $a_{SSEC,1}$ and $b_{SSEC,1}$ ($a_{HSI,1}$ and $b_{HSI,1}$) measures the persistence of the conditional volatility of Shanghai stock market (Hong Kong stock market), whereby if they are greater and closer to unity, the volatility is more integrated (or permanent) and therefore implies more persistence. We observe that the sum $a_{SSEC,1}$ and $b_{SSEC,1}$ is 0.719157, while the sum of $a_{HSI,1}$ and $b_{HSI,1}$ is 0.749980, suggesting that Hong Kong stock market is slightly more persistent. If the sum $a_{SSEC,1}$ and $b_{SSEC,1}$ ($a_{HSI,1}$ and $b_{HSI,1}$) is less than 1, the GARCH model is mean reverting and conditionally heteroskedastic, but has a constant unconditional variance (Engle, 2001). The unconditional variance, given by $1/(a_{SSEC,1} + b_{SSEC,1})$ and $1/(a_{HSI,1} + b_{HSI,1})$, is 1.390517 for

Shanghai and 1.333369 for Hong Kong. This shows that Shanghai stock market is more volatile than Hong Kong. This is expected because the latter is more open and developed compared to Chinese mainland stock markets.

The participation of foreign investors is more likely to improve market competitiveness, enhance information efficiency and increase liquidity level as they are better informed and engage more in portfolio investment. Now that the Chinese mainland stock market is opening up but has not been fully integrated to the world, we could observe higher volatility in Mainland China stock market as domestic individual investors could play more important roles. However, we observe the gap is quite small, implying that China is on its way to open its door to foreign investors and Shanghai-Hong Kong Stock Connect is one of the most important reforms in financial liberalisation. The coefficients $\varphi_{SSEC,1}$ and $\varphi_{HSI,1}$ capturing the asymmetric effects are statistically significant, suggesting both stock markets react differently to good news and bad news. The coefficient $\varphi_{SSEC,1}$ is negative, indicating that the conditional volatility of the Shanghai stock market is more sensitive to good news but more resistant to bad news. For Hong Kong stock market, the coefficient $\varphi_{HSI,1}$ is positive, pointing out that Hong Kong stock market intensifies in response to the bad news in the previous period. The dummy coefficients of both stock markets are positive and statistically significant. This evidence suggests that we can reject the null hypothesis that the introduction of Shanghai-Hong Kong Stock Connect program has no impact on the volatility behaviours of Shanghai and Hong Kong stock markets.

Given that the coefficient is positive, we believe that the introduction of Shanghai-Hong Kong Stock Connect program has increased the volatility level of both markets following the implementation of these changes. New changes have a significant positive impact on the expected conditional variances of both Shanghai and Hong Kong stock markets. This is not surprising as market openness allows foreign investment and encourages both individual and institutional investors to invest in Mainland China and Hong Kong in an innovative way. Moreover, the activeness of both markets fosters market efficiency which is improved through pooling of information and resources together. It is very reasonable to expect an open financial market to face a large number of risks, and therefore the possibility of international risk sharing increases in an open stock market. This is in line with some studies which find that the financial liberalisation could significantly increase the volatility of

stock markets in a large number of countries (Jaleel and Samarakoon, 2009; Bley and Saad, 2011; Afef, 2014). The reason why the financial liberalisation can contribute to the higher stock market volatility is that the foreign investor may be able to speculate in the domestic market with a short strategy and thus increase the stock volatility (Umutlu et al., 2010). Furthermore, financial integration makes the local markets more vulnerable to external crises since they are less insulated (Bley and Saad, 2011).

5.6.2.2 Estimation Results from VAR(8)-BEKK-GARCH(1,1)

Table 5.8 reports the parameters estimates on VAR(8)-BEKK-GARCH(1,1) with an asymmetric effect which could capture well the evolution of the means and conditional volatility of the two stock markets returns and their interactions. The VAR results are very similar to the VAR results provided earlier. The returns of both Shanghai and Hong Kong stock markets have a serial correlation feature as the current returns significantly depend on some of their past values.¹¹ For cross-market effect, the results indicate a bi-directional mean spillover effect. For Pre-Shanghai-Hong Kong Stock Connect period, there are 4 lagged returns of HSI (lag1, 2, 3 and 6) which are statistically significant at 5% for SSEC equation, implying a strong mean spillover effect from Hong Kong to Shanghai before Shanghai-Hong Kong Stock Connect. In contrast, we observe a weak mean spillover effect from the Shanghai to Hong Kong stock market as there is only one lagged return of SSEC (lag 6) which is statistically significant for Hong Kong stock market.

However, for the post-period, there is only one lagged return of HSI (lag1) that is statistically significant for SSEC equation compared with to three significant lagged coefficients of SSEC (lag1, 4 and 8) under HSI equation. This evidence is indicative of a strong mean spillover effect from Shanghai to Hong Kong. We observe significant changes in terms of mean spillover effect between these two markets and conclude that the mean spillover effect from Shanghai to Hong Kong became stronger than the opposite direction after Shanghai-Hong Kong Stock Connect. Our results here also indicate the initial leadership role of Shanghai stock market after the connect adoption as the information transmission efficiency for this stock market improves significantly following the Stock Connect adoption.

¹¹ For example, for Pre-Shanghai Hong Kong Stock Connect period, their own lagged 2, 3, 5, 6, 7 and 8 returns for SSEC and lagged 1 and 5 returns for HSI are statistically significant at 5% meanwhile the lagged 1, 3, 5 and 6 for SSEC and the lagged 1, 4 and 8 for HSI are statistically significant for the post-period.

This is unsurprising because the Chinese authority has already taken some steps to enhance financial openness and put in place measures to ensure an effective regulatory regime for the Mainland stock market. Our results here are consistent with Lam and Qiao (2009) who elaborate that the Chinese stock markets, in fact, play a most influential role among the stock markets in the Greater China region, including Hong Kong.

Moving to the conditional variance equations, Table 5.8 outlines the spillover effects of intraday volatilities between Shanghai and Hong Kong stock markets for Pre-and Post-Shanghai-Hong Kong Stock Connect periods on the basis of the BEKK-GARCH conditional variance-covariance equation model. The diagonal parameters (i.e., a_{11} and a_{22}) of the matrix A, which capture the past shock effects of each market on the current volatility (the dependence of the volatility in one market on its own lagged innovations), are statistically significant for both periods at the 5% significance level, implying that there are ARCH effects in both the Shanghai and Hong Kong stock markets for both periods. The diagonal parameters (b_{11} and b_{22}) of matrix B, which measure past volatility effects on the current conditional volatility in each market, are used to capture the GARCH effect. The coefficient b_{11} is found to be statistically significant for the Shanghai stock market in both periods, indicating there is strong GARCH effect in Shanghai stock market. However, the coefficient b_{22} is found to be statistically significant only in Post-Connect period for the Hong Kong stock market. The finding indicates that the GARCH effects only occur after Shanghai-Hong Kong Stock Connect and that the current conditional variances of HSI are considerably influenced by past conditional variance after this event.¹²

Since matrix A measures the effect of recent news, while matrix B captures the effect of old news, we observe that both types of news have similar impact on the conditional volatility of Shanghai stock market for both periods. This, however, is only on the conditional variance of Hong Kong stock market for Post-Connect period. Only recent news could influence the conditional volatility of Hong Kong stock market before the implementation of the stock connect program. This suggests that old news starts to become important after the introduction of Shanghai-Hong Kong Stock Connect as the capital flow from Mainland China may be contributing to the importance of old news. Looking at the volatility spillover effect, the off-diagonal parameters of the matrices A and B measure cross-market impacts, capturing shock spillovers and volatility spillovers between Shanghai and Hong Kong stock markets

¹² Other studies which have documented significant ARCH and GARCH effects in emerging markets include Beirne et al.(2013)

respectively. The coefficient a_{12} captures the cross-market effect from the error term of the Shanghai stock market to the conditional variance of Hong Kong stock market, while a_{21} captures the cross-market effect in the opposite direction. The variable b_{12} measures the cross-market effect from the lagged conditional variance of Shanghai stock market to the conditional variance of Hong Kong stock market, while b_{21} indicates the similar cross-market effect in the opposite direction. As per the estimated results for Pre-Connect period, parameters a_{21} and b_{21} are statistically significant at the 1% significance level, thereby suggesting that the lagged shocks and the historical conditional volatility in Hong Kong stock market is influencing the conditional variance of Shanghai stock market. In contrast, parameters a_{12} and b_{12} are statistically insignificant at the 1% significance level for Pre-Connect period, showing that the lagged shocks and the historical conditional volatility in Shanghai stock market do not have similar impacts on the current conditional volatility of Hong Kong stock market. We can therefore only observe the uni-directional shock and volatility spillover effect from Hong Kong to Shanghai before the Stock-Connect initiatives. This finding could be explained due to the fact that Hong Kong stock market is a well-developed and more open to the world. It can therefore absorb the information faster and more efficiently than the stock markets in Mainland China.

However, the coefficients a_{12} and b_{12} become statistically significant in the Post-Connect period but b_{21} coefficient becomes statistically insignificant. This implies that the spillover effect from Shanghai stock market to Hong Kong stock market (in terms of both the lagged shocks and the historical conditional volatility) occurs after the introduction of the Stock-Connect arrangement, but there exists only the shock spillover effect from Hong Kong to Shanghai. In terms of the absolute value, a_{21} (0.4822) is much larger than a_{12} (0.0385), implying a stronger shock spillover effect from Hong Kong to Shanghai. Since taking steps towards financial liberalisation and opening up of the Chinese stock markets to the world, the shock spillover effect reported in the empirical analysis is consistent with the financial liberalisation process and literature. The new findings in Table 5.8 show that the implementation of Shanghai-Hong Kong Stock Connect could improve information transmission running from Shanghai stock market to Hong Kong stock market in terms of volatility spillovers.

As the government continues opening up the Shanghai stock market to foreign investors, it will not be surprising that Hong Kong stock market starts losing its influential

power on the Chinese mainland stock market. In a more recent study, Huang and Kuo (2015) argue that Chinese mainland stock markets play a leading role in information transmission for Hong Kong and Taiwan stock markets. In terms of the asymmetric effect, coefficients d_{11} and d_{22} are negative and statistically significant in the Pre-Connect period but positive and statistically significant in the post period. We can see that both stock markets are very sensitive to good news but more resistant to bad news before the implementation of Stock-Connect program. However, after the two markets have become linked, they become to react more to bad news than good news. This implies that Shanghai-Hong Kong Stock Connect could influence the asymmetric effect in both stock markets.

Overall, we have seen that the contagion effects between Shanghai and Hong Kong stock markets experience a big change over the period and contemporaneous increases in the volatility spillover seem to be driven by Shanghai-Hong Kong Stock Connect. We see that the spillover effect in mean and volatility from Shanghai to Hong Kong are enhanced after Stock-Connect program, while the contagion effect from Hong Kong to Shanghai appear to be weaker in Post-Connect period than that in the Pre-Connect period. Our findings demonstrate that the Mainland China stock markets start to become more influential regionally. Yi et al. (2009) offer some reasons to interpret this phenomenon. Some policy direction about macroeconomic conditions, industry policies, economic growth and micro-market structures in Mainland China would certainly exert serious repercussions on Hong Kong stock market. Besides, there are also many large state-owned companies listed on the Hong Kong Stock Exchange (some are cross-listed in both markets) which could contribute to market shocks passing from Mainland China to Hong Kong. As a result, the Chinese stock market could lead to information absorption compared to the Hong Kong stock market. In addition, the heavy dependence of the economy of Hong Kong on Mainland China and the rising number of cross-listed companies on both markets also make contributions to the leading role of Chinese mainland stock markets.

Since both international and domestic investors incorporate the volatility spillover relationship into their portfolio allocation, so this study sheds lights on how investors can benefit from diversification. The evidence of volatility spillover is associated with the rise in correlation which indicates declining benefit from market diversification between Shanghai and Hong Kong, because they tend to move together. Our results help investors to better understand the changes of the origin and drivers of both the shock and volatility spillovers.

Even if China starts to influence the Hong Kong stock market, the magnitude is relatively small, thus investors still can benefit from the asset diversification between these two stock markets. However, it is suggested for investors to reconsider asset allocation across different markets geographically or/and different assets classes to achieve optimal portfolio diversification and increase the potential diversification benefit.

Table 5. 8: VAR(8)-BEKK-GARCH(1,1) with Asymmetric Effect Results

Pre-Shanghai Hong Kong Stock Connect					Post-Shanghai Hong Kong Stock Connect						
Mean Equation					Mean Equation						
	R _{SSEC}		R _{HSI}			R _{SSEC}		R _{HSI}			
R _{SSEC} (-1)---g _{11,1}	5.57E-03	(0.3989)	R _{SSEC} (-1)---g _{21,1}	0.0373	(0.1274)	R _{SSEC} (-1)---g _{11,1}	0.5647*	(0.0000)	R _{SSEC} (-1)---g _{21,1}	0.1003*	(0.0000)
R _{SSEC} (-2)---g _{11,2}	0.1566*	(0.0000)	R _{SSEC} (-2)---g _{21,2}	0.0224	(0.2849)	R _{SSEC} (-2)---g _{11,2}	-0.0161	(0.3471)	R _{SSEC} (-2)---g _{21,2}	3.21E-03	(0.6507)
R _{SSEC} (-3)---g _{11,3}	0.1014*	(0.0000)	R _{SSEC} (-3)---g _{21,3}	9.66E-03	(0.6525)	R _{SSEC} (-3)---g _{11,3}	-0.0720*	(0.0000)	R _{SSEC} (-3)---g _{21,3}	2.37E-03	(0.7543)
R _{SSEC} (-4)---g _{11,4}	9.82E-03	(0.0961)	R _{SSEC} (-4)---g _{21,4}	0.0417	(0.0829)	R _{SSEC} (-4)---g _{11,4}	-7.63E-03	(0.5110)	R _{SSEC} (-4)---g _{21,4}	0.0225*	(0.0056)
R _{SSEC} (-5)---g _{11,5}	-0.0216*	(0.0000)	R _{SSEC} (-5)---g _{21,5}	-0.0326	(0.0992)	R _{SSEC} (-5)---g _{11,5}	-0.0321*	(0.0000)	R _{SSEC} (-5)---g _{21,5}	-6.01E-03	(0.3449)
R _{SSEC} (-6)---g _{11,6}	-0.0332*	(0.0000)	R _{SSEC} (-6)---g _{21,6}	-0.0642*	(0.0001)	R _{SSEC} (-6)---g _{11,6}	-0.0290*	(0.0046)	R _{SSEC} (-6)---g _{21,6}	-4.85E-03	(0.3795)
R _{SSEC} (-7)---g _{11,7}	-0.0330*	(0.0000)	R _{SSEC} (-7)---g _{21,7}	0.0206	(0.3942)	R _{SSEC} (-7)---g _{11,7}	-0.0127	(0.2985)	R _{SSEC} (-7)---g _{21,7}	1.69E-03	(0.7732)
R _{SSEC} (-8)---g _{11,8}	-0.0402*	(0.0000)	R _{SSEC} (-8)---g _{21,8}	-0.0211	(0.3764)	R _{SSEC} (-8)---g _{11,8}	0.0170	(0.0721)	R _{SSEC} (-8)---g _{21,8}	0.0163*	(0.0000)
R _{HSI} (-1)---g _{12,1}	0.0536*	(0.0000)	R _{HSI} (-1)---g _{22,1}	0.0335*	(0.0330)	R _{HSI} (-1)---g _{12,1}	0.1832*	(0.0000)	R _{HSI} (-1)---g _{22,1}	0.0167	(0.0995)
R _{HSI} (-2)---g _{12,2}	0.0209*	(0.0000)	R _{HSI} (-2)---g _{22,2}	-8.21E-03	(0.6259)	R _{HSI} (-2)---g _{12,2}	0.0444	(0.0547)	R _{HSI} (-2)---g _{22,2}	-4.03E-03	(0.7339)
R _{HSI} (-3)---g _{12,3}	0.0117*	(0.0156)	R _{HSI} (-3)---g _{22,3}	0.0258	(0.1130)	R _{HSI} (-3)---g _{12,3}	0.0367	(0.1190)	R _{HSI} (-3)---g _{22,3}	-0.0178	(0.1558)
R _{HSI} (-4)---g _{12,4}	7.84E-03	(0.1300)	R _{HSI} (-4)---g _{22,4}	-0.0291	(0.0777)	R _{HSI} (-4)---g _{12,4}	-0.0471	(0.0762)	R _{HSI} (-4)---g _{22,4}	-0.0494*	(0.0000)
R _{HSI} (-5)---g _{12,5}	7.55E-03	(0.0720)	R _{HSI} (-5)---g _{22,5}	0.0366*	(0.0045)	R _{HSI} (-5)---g _{12,5}	0.0196	(0.3211)	R _{HSI} (-5)---g _{22,5}	0.0171	(0.0712)
R _{HSI} (-6)---g _{12,6}	0.0102*	(0.0170)	R _{HSI} (-6)---g _{22,6}	0.0151	(0.3081)	R _{HSI} (-6)---g _{12,6}	-0.0282	(0.2588)	R _{HSI} (-6)---g _{22,6}	-0.0234	(0.0545)
R _{HSI} (-7)---g _{12,7}	1.79E-03	(0.6757)	R _{HSI} (-7)---g _{22,7}	-8.87E03	(0.6422)	R _{HSI} (-7)---g _{12,7}	-0.0161	(0.4459)	R _{HSI} (-7)---g _{22,7}	-0.0125	(0.2965)
R _{HSI} (-8)---g _{12,8}	2.58E-03	(0.5139)	R _{HSI} (-8)---g _{22,8}	-0.0252	(0.1542)	R _{HSI} (-8)---g _{12,8}	-0.0160	(0.4832)	R _{HSI} (-8)---g _{22,8}	-0.0135	(0.2555)
Constant---g ₁	1.26E-05*	(0.0000)	Constant---g ₂	2.48E-06	(0.7788)	Constant---g ₁	2.34E-05	(0.0592)	Constant---g ₂	1.04E-05	(0.0850)

Table 5.8: VAR(8)-BEKK-GARCH(1,1) with Asymmetric Effect Results (Continued)

Pre-Shanghai Hong Kong Stock Connect			Post-Shanghai Hong Kong Stock Connect		
Variance Equation			Variance Equation		
c_{11}	8.56E-05	(0.0818)	c_{11}	1.18E-03*	(0.0000)
c_{21}	7.65E-04	(0.1107)	c_{21}	4.04E-04*	(0.0000)
c_{22}	2.44E-05	(0.9986)	c_{22}	2.26E-04*	(0.0000)
a_{11}	0.2360*	(0.0000)	a_{11}	0.1288*	(0.0000)
a_{12}	-0.0149	(0.4521)	a_{12}	0.0385*	(0.0000)
a_{21}	-0.0806*	(0.0000)	a_{21}	0.4822*	(0.0000)
a_{22}	0.2842*	(0.0000)	a_{22}	0.0272*	(0.0126)
b_{11}	0.6477*	(0.0000)	b_{11}	-0.0874*	(0.0062)
b_{12}	0.0873	(0.1850)	b_{12}	-0.1321*	(0.0000)
b_{21}	0.1959*	(0.0000)	b_{21}	0.0383	(0.7404)
b_{22}	0.0449	(0.4693)	b_{22}	0.7931*	(0.0000)
d_{11}	-0.1466 *	(0.0000)	d_{11}	0.1927*	(0.0000)
d_{12}	0.1870*	(0.0000)	d_{12}	-0.0129*	(0.0040)
d_{21}	-0.0318*	(0.0032)	d_{21}	-0.1741*	(0.0000)
d_{22}	-0.2269 *	(0.0000)	d_{22}	0.2350*	(0.0000)

Note: This table shows the estimates of the multivariate VAR(8)-BEKK-GARCH(1,1) model with asymmetric effect. The parameters c_{ij} , a_{ij} , b_{ij} , d_{ij} and $g_{ij,t}$ are the elements of the matrices C, A, B, D and G, as presented in Section 5.2. The model is estimated by the BHHH method and there is no convergence in 50 iterations. * indicates rejection of the null hypothesis at the 5% level of significance.

5.7 Further Discussion and Policy Implications

There are some important policy implications from our empirical analysis. Based on our empirical results, we find that Shanghai stock market plays a more dominant role in the information transmission after the implementation of Shanghai-Hong Kong Stock Connect. The enhanced information flows from the empirical analysis may reflect the fact that Mainland China and Hong Kong are closely linked with each other. It has widely been reported that Hong Kong's economy heavily relies on Mainland China and a substantial part of foreign direct investment (FDI) in Hong Kong comes from Mainland China (Yi et al., 2009). In addition, a large number of large state-owned Chinese mainland companies are listed on Hong Kong Stock Exchange and some are cross-listed in both markets. This may contribute to passing market shocks from Mainland China to Hong Kong and influence the leading power in the information absorption of the Chinese stock markets. Thus, the important government policies, macroeconomic information as well as market structures changes in Mainland China would definitely exert a greater influence on Hong Kong stock market. As a result, changes on policy directions and news on macroeconomics outcomes in Mainland China will be treated as a significant signal and used as part of the dynamics forecasting of the Hong Kong stock market outcomes and investor sentiments.

One important implication is that Hong Kong and international investors may be able to use the Shanghai stock market as a market predictor. Once a crisis happens there, investors based in Hong Kong could react faster and reduce any potential loss from their investment portfolio. However, with the new Stock-Connect initiatives, the Shanghai and Hong Kong stock markets may tend to move together. As a result, some investment diversification benefits could be compromised and investors may be forced to reallocate some investments to other markets in order to protect their portfolios in the long run. Investor sentiment may also influence the movements of stock markets. For example, if there are prolonged positive (negative) sentiments in Mainland China stock markets, the shocks and investor reactions could propagate to Hong Kong and most likely cause a similar increase (decrease) in its stock market outcomes, since Chinese mainland stock markets are mainly driven by market sentiment. Our research analysis here will be useful to international portfolio managers, investment service providers and policy-makers.

It is observed that the openness of the Chinese stock market to Hong Kong and the rest of the world could improve the rate of information flow and increase market efficiency as

foreign participation increases. Our investigation here provides one of the earliest empirical evidence on these two Chinese regional markets suggesting that the opening of Chinese financial markets has improved the information and operational efficiency of the local markets. In addition, the empirical results in our research reveal that the Chinese stock markets have been experiencing stronger and more stable ties with Hong Kong stock market in recent years. We believe that Shanghai-Hong Kong Stock Connect did consolidate the regional position of Shanghai as a regional financial centre and that the financial liberalisation of Chinese mainland stock markets does make a positive contribution to the development of the Chinese economic growth and its financial system. It is therefore important that China continues opening its financial markets globally so that its financial markets can be more integrated to the rest of the world and become more innovative and competitive.

Given the recent growth in financial globalisation, it is critical that China continues to develop its financial markets, both from the perspectives of institutional and regulatory reforms, so that the risk associated with large capital inflows can be managed better. However, the Shanghai-Hong Kong Stock Connect program does have some limitations so far. For example, only certain stocks in both stock exchanges can be traded through this program. As the Chinese economy and financial markets continue to develop, China should consider gradually releasing some of the restrictions on this program so that more listed companies will be allowed to trade freely until the markets are fully open to the world. In addition, such trading will be subject to an aggregate quota together with a daily quota. Once the quota is reached, Chinese authority must take some actions to deal with this issue, such as closing the door or lifting up the quota. As a result, it will influence the market efficiency and operation. Therefore the Chinese authority should make plans to further open Chinese mainland stock markets before that happens.

The success of Shanghai-Hong Kong Stock Connect is accelerating the gradual internationalisation of RMB, because it provides direct access to RMB denominated A share market and broadens the use of RMB. This program provides a very important data gathering experience for further reforms in the liberalisation of Chinn's mainland financial markets. This learning experience will be critical to the success of the forthcoming Shenzhen-Hong Kong Stock Connect, Exchange-Traded-Funds (ETFs) Connect, Futures Connect and Bond Connect. Shanghai-Hong Kong Stock Connect incorporates potentially successful guidelines

for future market openness programs, but other issues need to be considered before future Connect initiatives are launched. As the Chinese financial market continues to be integrated with the world, the country's policy-makers are facing an increasingly complex situation in which both domestic and overseas shocks can affect local stock markets. With the opening up of the Chinese stock market, both foreign and local investors will benefit from information sharing and risk management strategies and become more active in their participation. However, the desired financial liberalisation should follow a proper sequential process in order to avoid greater risk exposure and crisis. The gradual move and transition towards more open and developed markets based on a well-functioning financial system should also be supported by required changes in legal and institutional frameworks. The Chinese authority needs to set up better regulation to limit local and foreign arbitrage trading and encourage the trading with long-term investment purpose in order to guarantee a safe, reliable, efficient financial system.

5.8 Conclusion

This study aims to examine the impact of Shanghai-Hong Kong Stock Connect on the dynamic relationship between the Shanghai and Hong Kong stock markets. Our empirical research comprehensively analyses the return and volatility behaviours of Shanghai and Hong Kong stock markets using various quantitative methods. We use cointegration tests, Granger causality tests and the VAR model to examine the dynamics in the returns of Shanghai and Hong Kong stock markets and further, we conduct Impulse Response Analysis. We also look at the volatility of the two stock markets by applying both univariate and multivariate GARCH models including GJR GARCH and BEKK GARCH models. A high-frequency data (1 minute's interval) of Shanghai and Hong Kong stock markets indices is utilised to analyse the dynamic market behaviours. The dataset is from 02/07/2014 to 08/04/2015 which is about 4 months before and after the implementation of the Shanghai-Hong Kong Stock Connect program. Looking at the influence of Shanghai-Hong Kong Stock Connect, our empirical results show strong evidence that this program could enhance the leading role and increase the predictive power of Shanghai stock market.

First of all, we find a significant long-term cointegration relationship between Shanghai and Hong Kong stock markets in the Post-Connect period while we observe no

cointegration relationship between these two markets prior to this program. This initial assessment suggests that the integration and co-movement between the two stock markets have strengthened following the initiative connecting the Shanghai and Hong Kong stock markets and other financial market policy changes. Secondly, we observe that the return spillover effect from Shanghai to Hong Kong is faster and stronger than that from Hong Kong to Shanghai in the Post-Connect period. Our impulse response analysis conducted as part of sensitivity tests shows that Hong Kong stock market tends to be more responsive to the shocks in Shanghai, while Shanghai stock market reacts less significantly to the shocks in Hong Kong after the Stock Connect program. Thirdly, our findings indicate that the implementation of Shanghai-Hong Kong Stock Connect program has increased the conditional volatility level of both stock markets, since it opens the door to foreign investment and attracts both individual and institutional investors to participate in both Shanghai and Hong Kong stock markets. Not surprisingly, this result implies that opening up the Shanghai and Hong Kong stock markets could increase the risk level in them. Fourthly, based on the VAR BEKK model, we see an enhanced spillover effect in terms of mean and volatility from Shanghai to Hong Kong and weaker contagion effects from Hong Kong to Shanghai after Shanghai-Hong Kong Stock Connect. This empirical evidence seems to suggest that the Chinese mainland stock markets could significantly affect Hong Kong stock market through return and volatility spillover effects. It can also play a leading role in information transmission regionally which is in line with international centre hypothesis (Eun and Shim, 1989).

As the Chinese financial market continues to be integrated with the world, policy-makers are facing an increasingly complex situation in which both domestic and overseas shocks can affect local stock markets and investors may sacrifice some diversification benefits. Our study has important policy implications for portfolio managers. In line with Heymans and Da Camara (2013), we observe that as investor sentiments change following economic and policy shocks, individuals and portfolio managers may find it necessary to readjust their hedging strategies in order to protect their wealth. The success of Shanghai-Hong Kong Stock Connect provides valuable operational experience for further reforms on financial liberalisation of the Chinese stock markets. The launch of Shanghai-Hong Kong Stock Connect is just a starting point and part of the national opening up strategy. With the opening up of Chinese stock market, both foreign and local investors will benefit from information sharing and risk management strategies and become more active in their

participation. However, the adopted financial liberalisation should follow a proper sequential process in order to avoid greater risk exposure and crisis. The gradual move and transition towards more open and developed markets based on financial system should also be supported by required changes in the legal and institutional framework. We believe Shanghai-Hong Kong Stock Connect has consolidated the position of Shanghai as a dominant regional financial centre and that the financial liberalisation of Chinese mainland stock markets does make a positive contribution to the development of Chinese economic growth and financial system. Raine and Adams (2015) point out that Shanghai-Hong Kong Stock Connect's solid operational record within its first year could foreseeably cause it to serve as a model for other cross-border trading channels into Mainland China and other developing markets with significant regulatory barriers to foreign investment.

Chapter 6: Financial Linkages, Information Transmission and Market Co-movement: Evidence from China and Asia-Pacific Stock Markets

6.1 Introduction

In this era of international financial integration, the determinants of stock market co-movements and the nature of intra-region market dependencies have attracted considerable attention in the international finance literature. Importantly, the modern portfolio manager must seek to understand the links between surges in capital flows, financial crisis and international portfolio selection as well as spillover effects. This is especially the case when the price changes in one market produce a lagged impact on the other markets. The literature has examined spillover effects across regions and provides empirical evidence indicating that the spillover effect exists. Empirical analyses of spillover effects are useful in revealing the nature of volatility transmission and how this affects international portfolio diversification decisions and risk management strategies of international firms (Majdoub and Mansour, 2014).

A greater understanding of spillover effects could also enable investors to better model stock performance, reduce financial risks, achieve optimal portfolio allocation and respond to changes in asset pricing. During the times of financial crises, we observe increased probability of financial contagion that results in shocks being transmitted from one stock market to another. Contagious markets effects generally reduce the benefits of international diversification. Following the US Market Crash in October 1987, research has attempted to understand the international and regional factors that drive volatility across international financial markets. The global financial transmission process and interdependence between international stock markets appear to have increased in recent years. Despite there being some complexities in the financial transmission process, we have empirical evidence of return and volatility spillover effects from the US to major economies such as the UK, Japan and other OECD stock markets, reflecting the world-dominating position of the US stock market and the strength of the equity market relationship between US and foreign markets (Hamao et al., 1990; Eun and Shim, 1989; Theodossiou and Lee, 1993).

Many emerging economies have carried out reforms to liberalise their capital markets in the last decade. They are now more integrated with the rest of the world and their markets respond rapidly to adverse shocks from international markets and key foreign macroeconomic announcements. We therefore predict significant co-movements in asset prices internationally, even though emerging markets may be less efficient than more developed stock markets. Bekaert and Harvey (1997) indicate that the liberalisation of capital markets often increases their international linkage and enhances stock markets correlations so as to influence asset returns and risk-sharing among investors.

As data becomes more readily available, the strength of shock transmission to international equity markets and how stock market valuation and asset prices react to changes in global 'monetary environment' will continue to be examined more efficiently. The need to enhance portfolio returns calls for further research on stock market integration and co-movement between emerging markets and developed economies in relation to: firstly, differences in the holdings of foreign capital stocks; and secondly, the degree of financial integration across emerging markets. This research has the potential to explain differences in the intensity of spillovers across countries and the strength of cross-market linkages over time. Ng (2000) examines the volatility spillovers from Japan and the US to six Pacific-Basin emerging stock markets and shows that some liberalisation events (such as capital market reforms and country fund launching) are able to affect the relative importance of the world factor (the US) and the regional market factor (Japan) over time. In addition, the degree of integration among international stock markets tends to change over time, especially during financial crises.

Following the US October Crash, the occurrence of more recent financial crises, such as the Asian Financial Crisis in 1997 and the Global Financial Crisis in 2008, has testified that international stock markets are now more interdependent. Given the increased frequency of financial crises in recent years, researchers, practitioners and policy-makers are attempting to gain a fuller understanding of the nature of inter-market volatility and the process of shock transmission across different regions. It is thus becoming important to understand channels of volatility transmission following international financial contagion. Yang et al. (2003) report that both long-run cointegration relationships and short-run causal linkages among the US, Japanese, and ten Asian emerging stock markets were strengthened during the 1997-1998 Asian financial crisis. They highlight that these markets become more integrated after the

crisis. Yiu et al. (2010) also highlight the effects of the GFC during 2007-2008 on the Asian stock markets.

The rapid pace of China's economic development and profound changes in policy direction, with an emphasis on financial market reforms has also boosted research interest. Those factors are expected to enhance regional economies and have a significant impact on the global economy. The economic reforms which began in 1978 laid down the foundation of the Chinese economic transformation and the establishment of The Chinese stock market in the early 1990s. Both the Shanghai and Shenzhen stock exchanges have evolved rapidly to support international capital flows and wider risk diversification. Subsequently, the Chinese government has pursued market-oriented economic reforms and capital account liberalisation.

As capital accounts have become more influential regionally and globally and market capitalisation and trading volumes have increased in recent years, these two markets are a critical component of the Chinese financial system since they provided new channels for investment. Statistics from Chinese Securities Regulatory Commission (CSRC), as of 2014, show that the total number of companies listed on the Shanghai Stock Exchange (SSE) and the Shenzhen Stock Exchange (SZSE) is 2613 with an annual increase of 124. The total market capitalisation on the two stock exchanges amounted to RMB 37.25 trillion in 2014, ranking the second in the world after the US¹³.

As a socialist market economy with an economic and social infrastructure that is unique to China, the country's stock market is also not like those major developed economies. For example, two types of stocks are traded in China, where A shares are restricted only for Chinese domestic investor and B shares can be bought and sold by foreign investors. As a result, the Chinese stock market is not fully integrated with the rest of the world. As the Chinese economy and financial market continue to grow, the Chinese government also took several actions to liberalise its financial markets. Two programs have been initiated - QDII (Qualified Domestic Institutional Investors) and QFII (Qualified Foreign Institutional Investors) – so that qualified domestic institutional investors can invest abroad and qualified foreign institutional investors can invest in Chinese domestic financial markets. The recently introduced Shanghai-Hong Kong Stock Connect program is also expected to accelerate liberalisation of the Chinese stock market and enhance the international stature of the local currency (RMB). These selected but important financial market reforms are aimed at 'going

¹³ Source: China Security Regulatory Commission Annual Report (2014)

global', allowing the Chinese stock markets to play a leading role and enhance country's influence on the global financial markets. Following China's membership to the WTO in 2001, the country has significantly increased its interactions with the Asia-Pacific countries, gaining a larger role in international trade and exerting its influence on the world stage.

A number of studies show that Chinese financial markets have been impacted directly or indirectly by international stock markets. For instance, Fan et al. (2009) outline that there has been a significant trend of long-term co-movement between the Chinese and overseas stock markets since 1999, implying that China's leading role in fostering intra-Asian-trade is undeniably on the rise over time. While China's remarkable economic progress in the past three decades may have depended heavily on exports, this evolution has propelled economic growth in other neighbouring Asian countries to support regional integration. As a result, China's stock market boom since the late 1990s has had a large influence on the economies in the Asia-Pacific region and the country's leading role in strengthening intra-Asian-trade was undeniably in the ascendant.

Additionally, through playing a key role in Asian economic integration and regional financial stability, China is quickly becoming the Asia-Pacific region's economic centre of gravity. As the second largest economy and the largest emerging market economy, China is the world's number one trading partner and the principal engine of regional and global economic growth, currently accounting for about 18% of world economic activity (Das, 2012). Given China's growing domination, the influences of the Chinese financial markets can hardly be ignored. However, the literature on Asian economic integration has paid increasing attention to trade integration but the impact on Asian-Pacific financial integration has not been much explored (Arora, 2010). Many countries in the Asia-Pacific region have experienced remarkable economic growth through intra-regional trade and financial linkages with China. Added to which, rapid economic liberalisation and continuous financial sector reforms in the Asia-Pacific region have led deeper financial ties and encouraged portfolio investment and participation of institutional investors.

Based on the regional interdependences and a high degree of integration within the Asia-Pacific region, Shu et al. (2015) note that the spillover between China and Asia-Pacific economies may occur through investment changes in expectations and risk appetite channels. We therefore seek to examine the interactions between China and other economies in the Asia-Pacific region and examine how the direct financial linkages to China influence

portfolio rebalancing, capital flows, volatility and risk appetite investment in the region. Although the literature examines the volatility spillover effect internationally and regionally, reporting some evidence of equity markets integration, only a few studies examine co-movements and mechanisms of volatility transmission among Asia-Pacific stock markets using dynamic forecasting models. The recent Chinese stock market crash (2015-2016) supports our interest in examining spillover influences in the Asia-Pacific markets, especially implications for hedging, pricing securities, asset allocation and investment trading strategies. Additionally, it is important to analyse the spillover from China's monetary policy shocks to examine volatility linkages in terms of the source, magnitude and evolution of daily volatility spillovers following the recent Global Financial crisis (GFC).

We investigate the extent to which financial shocks and turbulence originating from China is transmitted among Asia-Pacific markets. We assess whether financial markets in Asia-Pacific countries in the 2015-16 crash show similar behaviours from the perspectives of the presence of persistent effects and volatility asymmetry. Which Asian region might suffer more as a result of this financial turmoil? We have few studies concentrated on the influential regional power of China on the interdependence between Chinese and other stock markets in recent years. Therefore, our research will fill this gap and contribute to the existing literature in the following ways. Firstly, our study considers possible linkages between China and the regional developed and emerging markets simultaneously, shedding light on the interactions dynamics between China and other stock markets. Secondly, we apply dynamic GARCH models to investigate 11 groups of pairwise stock markets which include China and one of the Asian-Pacific markets to explore the spillover effects between them and whether close partnership and collaboration might insulate countries from the crisis. Thirdly, while using a sample period covering the most recent Chinese stock market crash, and we examine the influence of this financial turbulence on the behaviour of the Chinese domestic and international investors for the first time.

We also evaluate how the impact on Asia-Pacific markets may change during this period of high risk and whether price and price volatility effects are homogenous across the countries in the region.¹⁴ Stock markets in our study represent different stages of development and capitalisation in the Asia-Pacific region, including the more mature and

¹⁴ Our sample is representative in terms stages of financial market development and capitalisation, including more mature, stable economies and emerging markets given the intensity of financial integration within the region.

emerging stock markets because of the intensively financial integration within the region. Therefore, our results will have important policy implications for markets participants and policy-makers in other emerging economies.

The remainder of this chapter is organised as follows. Section 6.2 introduces the Chinese stock market and recent Chinese stock market crash. Section 6.3 discusses the preliminary literature on the mean and volatility spillover effect between different stock markets. Section 6.4 describes data used in this study and the descriptive statistics. Section 6.5 describes the methodological framework of this study. Section 6.6 presents the empirical results. After that we have a policy implementation part and conclusion in section 6.7.

6.2 The Brief Introduction of Chinese Stock Market

Along with the fast growth of its economy, the Chinese stock market has expanded tremendously since the establishment of the Shanghai Stock Exchange and Shenzhen Stock Exchange in the 1990s. The Shanghai Stock Exchange (SSE), which is directly governed by the CSRC, was founded on 26th November 1990 and started formal operation on 19th December the same year. The Shenzhen Stock Exchange (SZSE), another institution under the supervision of the CSRC was officially opened on 1st December 1990. By the end of 2014, the total number of companies listed on the Shanghai Stock Exchange and the Shenzhen Stock Exchange are 2613 with an annual increase of 124. The total market capitalisation on the two stock markets amounted to RMB 37.25 trillion, equivalent to 58.53% of the country's GDP, ranked second in the world following the US.¹⁵ The huge capitalisation makes the Chinese stock market more influential regionally and globally. Panels A and B of Figure 6.1 outline recent trends in the number of domestic listed companies and the total market capitalisation of SSE and SZSE as a percentage of the Chinese GDP from 1992 to 2014.

A unique characteristic of the Chinese stock market is its market segmentation feature which also attracts great attention of academic. There are two categories of shares in the Chinese stock market, namely A Share and B Share. The A-share market is denominated in Chinese currency RMB and is restricted to ownership by Chinese domestic citizens, while the B-share market (denominated in US dollar for Shanghai Stock Exchange and denominated in

¹⁵ Source: China Security Regulatory Commission Annual Report (2014)

HK dollar for Shenzhen Stock Exchange) is open only to foreign investors. Before February 2001, A-Share and B-Share markets were completely divided. However, in February 2001, CSRC announced a new guideline which allowed Chinese non-institutional residents with a foreign currency deposit account to trade in the B share market (Weber and Zhang, 2012). The double listing nature of the Chinese stock market results in a partially segmented financial market environment, although the government has taken several steps to liberalise financial operations. A series of financial liberalisation measures were taken by the Chinese authority to open up the capital market and improve the financial regulations after joining the WTO in 2001. In November 2002, CSRC and the People's Bank of China jointly announced 'provisional measures on the administration of domestic securities investments of qualified foreign institutional investors' which were implemented on 1st December 2002. While the QFII scheme fosters international capital inflow into Mainland China, the QDII scheme was officially launched in April 2006 to allow domestic investors to make an investment in the international securities markets. Moreover, the national currency (RMB) is not fully convertible and the capital and financial accounts are still regulated. By the end of 2006, the State Administration of Foreign Exchange (SAFE) had approved 15 commercial banks for overseas wealth management on behalf of clients with quotas of US\$ 13.4 billion. A further 15 insurance companies were licensed for overseas investment with quotas of US\$ 5.174 billion and one fund management company for a quota of overseas investment as much as US\$ 0.5 billion.¹⁶ Implementation of these reforms indicates a gradual relaxation of restrictions on both domestic and international investors to encourage international financial integration.

Despite these positive developments, the Chinese stock market crash began in June 2015 following a sharp slowdown in Chinese economic growth. Following weeks of volatility and swings in share valuation, the Shanghai composite index lost about 25% of its value within a month (Salidjanova, 2015). On the back of this extraordinary fall in the Chinese stock market, the index fell from 5178 on 12th June 2015 to 2850 on 26th August 2015 with almost half of the value lost. After that, the Chinese stock markets started to recover and the index reached over 3600 points at the end of December 2015. However, in January 2016, the stock markets experienced a steep sell-off because of the new circuit

¹⁶ Further details on these new guidelines are provided in State Administration of Foreign Exchange Annual Report (2006).

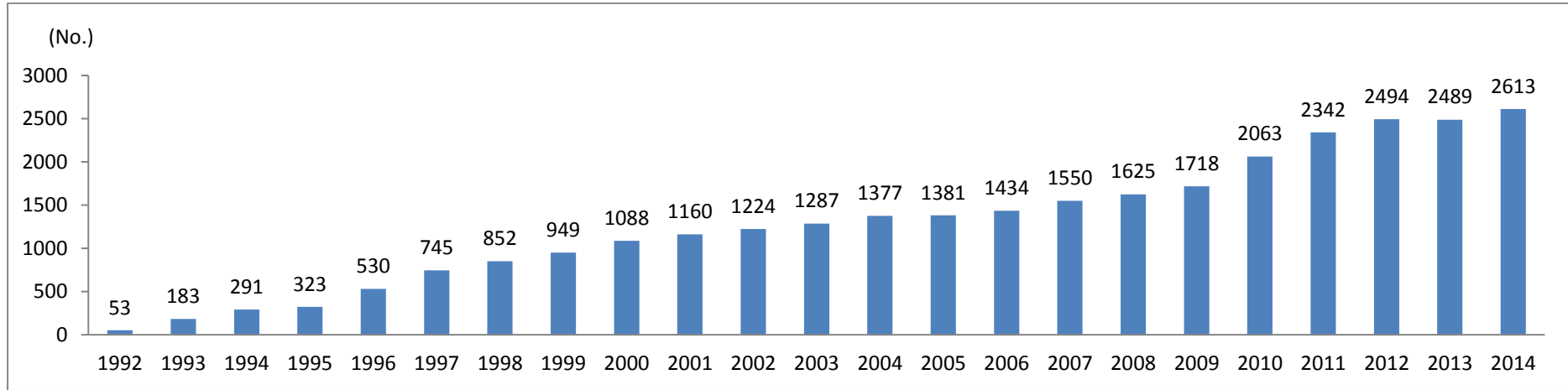
breakers system¹⁷. On 4th January 2016, the first trading day of 2016 and the first day of operation for circuit breakers, the first 15 minutes, CSI 300 Index fell 5% and triggered the first circuit breakers which paused the trading for 15 minutes. After the trading resuming, CSI 300 fell by another 2% and triggered the second circuit breaker which suspended the trading for the rest of the day. On Thursday (7th January 2016) the CSI 300 Index dropped 5% in the first 13 minutes and fell another 2% in just one minute after 15 minutes suspension, triggering a complete suspension for the day with just 30 minutes trading for the whole day. As a result, Chinese regulators decided to suspend circuit breakers in order to smooth the trading operation on 8 January (just 4 days after its introduction)¹⁸. Nevertheless, the stock markets still kept falling and SSEC went down to about 2600 points at the end of January. This market crash and share turmoil in China will impact not only on the wealth of Chinese investors but also largely on Asia-Pacific economies. As stated by Dimitriou et al. (2013), portfolio managers will have to revise their risk management and asset allocation strategies during this time of crisis. Moreover, this economic and financial downturn will influence investors' assessment on the region's economic outlook and lead to a ripple effect across the Asia-Pacific stock markets. The share market turmoil in China therefore motivates us to investigate the interdependence between the Chinese stock market and other stock markets in the Asia-Pacific region and our study will shed light on the rising influence of the Chinese stock market.

¹⁷ A move of 5 per cent of the CSI 300 Index in either direction from the index's previous close will trigger a 15-minute trade suspension across the country's stock markets; a 7 per cent rise or fall in the CSI 300 Index will prompt a trading halt in the Shanghai and Shenzhen stock exchanges for the rest of the day. Source: http://www.sse.com.cn/aboutus/mediacenter/hotandd/c/c_20151204_4019218.shtml and http://www.sse.com.cn/lawandrules/sserules/trading/universal/c/c_20151204_4019335.shtml

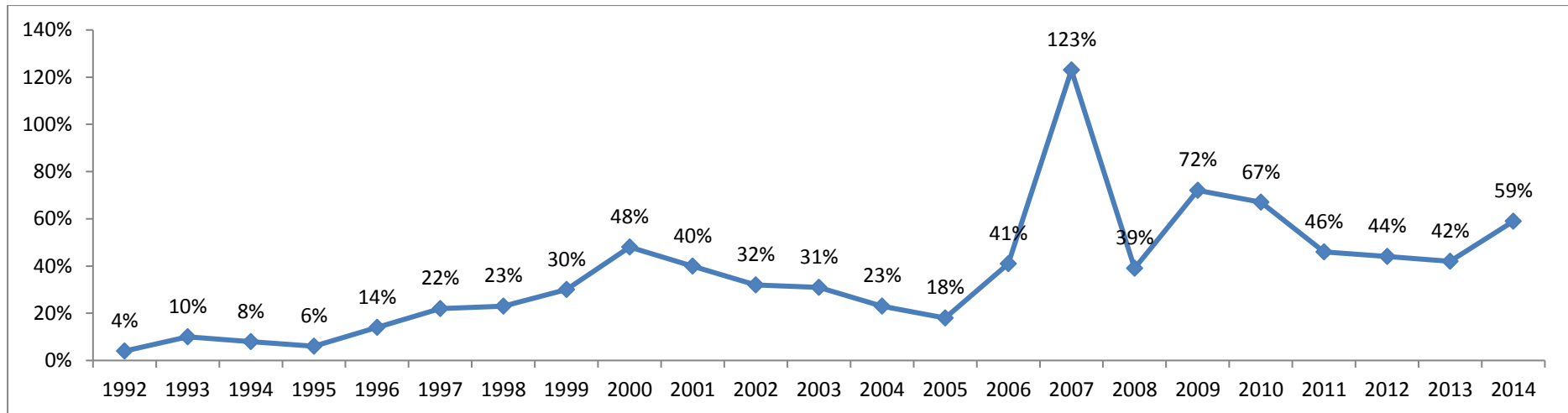
¹⁸ China suspends circuit breakers on stock exchanges to 'maintain market stability', from <http://www.abc.net.au/news/2016-01-08/china-suspends-circuit-breaker-mechanism/7075454>

Figure 6. 1: Information about Number of Listed Companies and Market Capitalisation

Panel A: Number of Domestic Listed Companies



Panel B: Total Market Capitalisation of SSE and SZSE as Percentage of GDP



Source: China Security Regulatory Commission Annual Report (2014)

6.3 Literature review

Return and volatility are two essential characteristics of financial assets. Fama (1970) indicates that asset prices fully reflect all the available information in an efficient market. Accordingly, the changes in the markets prices are involved with the incorporation of new information. Later, Ross (1989) pointed out that the volatility of financial asset prices is a measure of information flow as it is directly related to the rate of information flow to the market, implying that the volatility is more important than the price changes in terms of information transmission. Special linkages such as financial ties, free capital movements and similar movements in countries' income, dual lists of companies result in the indirect link between international stock markets and strengthen the common movement of stock prices (Ripley, 1973). As explained by Yamamoto (2014), stock market contagion can be transmitted through different channels. This includes the correlated information channel, the liquidity channel, the cross-market hedging channel and the wealth effect channel. In addition, Moser (2003) indicates that the co-movement between international stock markets can be explained by three leading activities, namely international trade, counterparty defaults and portfolio rebalancing.

After the US October Crash in 1987, there is a growing literature on the information transmission between different stock markets. Studies on the interdependencies between international stock markets have been concentrated on analysing how news from one stock market influences another market's performance and investors' behaviour. For example, Eun and Shim (1989) examine the international transmission mechanism of stock market movements by estimating the VAR system, showing that the innovations in the US could be rapidly transmitted to other nine stock markets. This result reflects the dominant position of the US in the world economy and indicates that it is the most important producer of information. Since the volatility is directly related to the rate of information flow, understanding the volatility behaviours is important for risk management and more studies focused on the volatility spillover effects. The phenomenon of volatility spillover is the interdependence among different markets' volatility, suggesting that the volatility in one market is able to influence another market's volatility. Hamao et al. (1990) examined the daily opening and closing price of major indices in Japan, the UK and the US by applying GARCH models and report evidence of price volatility spillovers from New York to Tokyo, London to Tokyo, and New York. King and Wadhvani (1990) enquire why almost all stock

markets fell together during the US October Crash in 1987. They use this event as empirical evidence to point out that a “mistake” in one country could be transmitted to another country and an ‘unexpected’ occurrence of financial distress in one country can rapidly spread to another market, leading to greater spillover or contagion in financial markets.

Theodossiou and Lee (1993) find evidence of uni-directional return and volatility spillovers from relatively advanced markets (like the US) to less advanced markets. In contrast, Lin et al. (1994) find evidence of bi-directional spillovers between the US and Japanese stock markets for cross-market interdependence in returns and volatilities. Examining the asymmetric impact of good news and bad news, Bae and Karolyi (1994) explore the joint dynamics of overnight and daytime volatility of the Japanese and the US stock markets over the 1988-1992 period by applying the asymmetric GARCH model. They point out that bad news from domestic and foreign markets appear to have a much larger impact on subsequent return volatility than good news. Koutmos and Booth (1995) find strong evidence that the volatility spillovers are much more pronounced when the news is bad, implying that the volatility transmission mechanism is asymmetric (negative innovations can increase volatility in the market more than positive innovations). These findings suggest that stock markets are sensitive to news originating in other markets, especially when the news is adverse.

Focusing on the Asian market, the US stock market was found to play a more dominated role in the information transmission compared with the Japanese stock market in the 1990s. John Wei et al. (1995) find that the Tokyo market has less influence than the New York market over the Taiwanese and Hong Kong markets and the Taiwanese stock market is more sensitive than the Hong Kong stock market to the price and volatility behaviour of the advanced markets. Hu et al. (1997) examine the co-movement between two developed markets (the US and Japan) and four emerging markets in the South China Growth Triangular (Hong Kong, Taiwan, Shanghai and Shenzhen). They show that the emerging stock markets are significantly correlated with the return volatility of the US market, implying that geographical and economic ties do not necessarily lead to stronger spillover effects across markets. Liu and Pan (1997) find similar results showing that mean and volatility spillover effects originate from the US and Japan and spread to four Asian markets (Hong Kong, Singapore, Taiwan, and Thailand). The US market is more influential than the Japanese market in transmitting returns and volatilities to the four Asian markets, but the observed

spillover effects are unstable and increase substantially after the US stock market crash in 1987. Similarly, Ng (2000) observes that both regional (Japan) and world (the US) factors are important for market volatility in the Pacific–Basin region and the world influence factor (the US) is stronger than the regional factor.

In contrast, other researchers find that the regional financial centre behaves as a leading exporter and is more important in explaining the evolution of financial spillovers and transmission of shocks (see Kim and Rogers, 1995). Masih and Masih (1999) also confirm the leading role of regional financial centre (Hong Kong) and provide strong support for the view that the Asian stock markets fluctuations are explained mostly by their regional markets rather than by the advanced markets. Miyakoshi (2003) also discovers that the volatility of the Asian market is influenced more by the Japanese market than by the US and there exists an adverse influence of volatility from Asian markets to the Japanese market.

As the Chinese economy grows fast and its financial markets play an increasingly important role in the Asia-Pacific region, we cannot ignore the significant function of the Chinese financial market. However, research on the spillover effect between the Chinese financial markets and other markets is limited compared to more advanced stock markets. Wang and Firth (2004) find evidence that the overnight returns on all the Greater China stock indices (Shanghai, Shenzhen, Hong Kong and Taipei) can be estimated by using information from at least one of the three developed markets' daytime returns (Tokyo, London and New York). They observe contemporaneous uni-directional spillovers from more advanced major international markets to the Chinese stock markets.

Some studies find no link between China and the other markets, implying a weak integration of the Chinese stock market with the world. Based on weekly data, Chow and Lawler (2003) conclude that there is no evidence of a positive correlation between the Shanghai and New York stock markets, suggesting that they are not integrated. Cheng and Glascock (2005) could not find a cointegration relationship between China and four stock markets under this study (the US, Japan, Hong Kong and Taiwan). In contrast, the test results of Bahng and Shin (2004) indicate the existence of one cointegrating vector, implying that a long-run equilibrium relationship holds among the Greater China economic bloc which includes Mainland China, Hong Kong and Taiwan. Li (2007) finds the evidence of small magnitude uni-directional volatility spillovers from Hong Kong to Shanghai and Shenzhen.

Johansson and Ljungwall (2009) show evidence of mean and volatility spillover from the Taiwanese stock market to Chinese mainland stock markets.

However, as the Chinese economy and financial markets grow rapidly, the Chinese stock market has become an important regional financial hub in the northeast and south Asia region recent years, and it has become more closely linked to the regional developed markets. More recently, under the background that both the number of listed companies and the market capitalisation increase dramatically, several market liberalisation policies have been implemented with the outcome that the market has increased to influence its neighbours with strengthening economic ties. As the regional influence of the Chinese stock market grows, it is expected that there will be a significant integration and influence between Chinese markets and Asia-Pacific markets. Li (2012) finds that the Chinese stock market is linked to the US market through bi-directional spillovers and to the South Korean and Japanese markets via uni-directional transmissions from China during 1992–2010. In addition, the Chinese stock market does not exert influence on overseas markets before the liberalisation period, implying that market liberalisation and institutional reforms are able to increase the spillovers from China to global and regional markets. Zhou et al. (2012) and Allen et al. (2013) show empirical evidence of volatility spillover from China to its neighbours and major trading partners, indicating that Chinese financial markets are integrated in the Greater China region in recent years.

Wang (2014) points out that the GFC has strengthened the linkages among East Asia stock markets and increased the integration of the Chinese stock market with other East Asian markets during post-GFC turmoil period. Huang and Kuo (2015) note that the Hong Kong and Taiwan stock markets are significantly affected by Mainland China, implying that the Mainland China stock market is starting to exert important regional influence among Asia's stock markets. Even for the more advanced Japanese stock market, Nishimura et al. (2015) highlight that the Chinese stock market has a large impact on the Japanese stock market via China-related firms in Japan, and that there could also be similar relationships with other countries. Thus it is appropriate and timely to examine the influential power of the Chinese stock markets regionally and further to provide financial implications to investors. This chapter aims to analyse the transmission of the 2015 Chinese financial crash and determine whether China has significant regional influence among Asia-Pacific stock markets during the periods of financial distress.

6.4 Data and Structural Break Tests

This empirical analysis uses daily data from *Datastream* which consists of the closing price of daily stock market indices from China and the 11 largest Asia-Pacific stock markets. The indices in our research are Shanghai Stock Exchange Composite Index for China, Hang Seng Index for Hong Kong, TAIEX for Taiwan, Straits Times Index for Singapore, KLCI Index for Malaysia, NIKKEI 225 Index for Japan, KOSPI Index for South Korea, S&P/ASX 200 Index for Australia, IDX Composite for Indonesia, S&P/NZX 50 Index for New Zealand, NIFTY 500 Index for India and SET Index for Thailand. The reason for selecting the China and Asia-Pacific stock markets is the substantial interest of the increased importance of China in Asia-Pacific region and the expected linkage between those stock markets and the Chinese stock market. These Asia-Pacific countries and regions have greater economic ties with China and comparable economic structure in terms of development in the capital market. They have adopted similar policies towards opening up their financial systems. These policies aim to encourage free international capital movement and fuel economic growth. The Asia-Pacific stock markets have also been deeply affected by the 1997 Asian financial crisis which was preceded by years of outstanding economic performance. The sample period extends from 1 December 2014 to 29 January 2016 which is the most recent data and covers the recent Chinese stock market crash. In total, our sample consists of 287 observations for each market after eliminating weekends and public holidays. We examine the effect of the Chinese stock market crash by splitting the full sample into two periods: pre-crash (bullish) and post-crisis (bearish) periods to specify the crisis phase and provide deeper insights into the regional spillover dynamics. The first sub-sample ranges from 1 December 2014 to 11 June 2015, providing 130 observations while the crisis period runs from 12 June 2015 to 29 January 2016 with 157 observations. While taking the daily closing price of each index, the daily return is calculated as the first difference of the natural logarithm of the daily closing price as:

$$R_{i,t} = Y_{i,t} - Y_{i,t-1}$$

where $R_{i,t}$ denotes the daily return for index i at time t , and $Y_{i,t}$ denotes the natural logarithms of the closing price of index i at time t

Figure 6.2 illustrates the dynamics of the data for the Chinese and eleven Asia-Pacific stock markets' log-transformed indices over the sample period. The black vertical line indicates the break date 12 June 2015 which corresponds to the highest level of Shanghai Stock Exchange Composite Index. As shown in Figure 6.2, Shanghai Stock Exchange Composite Index kept increasing during the first sub-sample period until it reached the top position on 12 June 2015 and then experienced a significant decline. The Asia-Pacific stock markets also share this similar trend with the Chinese stock market. The corresponding market returns are shown in Figure 6.3 where we can observe the volatility clustering of stock market returns. The main descriptive statistics of these markets for the full sample period are presented in Table 6.3. The statistics reported include the mean, the median, the maximum value, the minimum value, the standard deviation, the measure of skewness, the measure of kurtosis, the Jarque-Bera (JB) statistics and the number of observations. Only the average return of China and New Zealand are positive while the other stock markets show negative market returns. The standard deviation which is a measure of volatility indicates that the Chinese stock market is the most volatile market (from Panels A and B). Consistent with Zhou et al. (2012), this suggests that investment in China seems to be riskier than other Asia-Pacific markets. Conversely, the New Zealand stock market is found to be the least volatile market with the lowest standard deviation. From returns data, market skewness suggests that the data distribution is asymmetrical while sample kurtosis of all the stock indices is more than 3, which means the distribution is highly leptokurtic with fat tails compared with the Gaussian distribution. The stylised characteristics such as volatility clustering, fat tail, leptokurtic and non-normal distribution confirm the appropriateness of using GARCH family models.

Our break date is 12 June 2015 which corresponds to the date when Shanghai Stock Exchange Composite Index reached its highest level and then crashed. In order to examine the appropriateness of the break date, we undertake Lee and Strazicich (2003)¹ and Perron (1989) tests to investigate the presence of structural breaks in the Shanghai Stock Exchange Composite Index. These two tests allowing for up to two structural breaks were conducted to help us re-examine the choice of the period before and after the crisis through endogenously determining breakpoints in the data. In particular, the test results for both methodologies

¹ The Lagrange multiplier (LM) unit root tests developed by Lee and Strazicich (2003) are able to test two structural breaks in the trend without suffering from spurious problems according to El Ghini and Saidi (2017).

confirm the break date is around the peak time, suggesting the appropriateness of our breakpoint choice.

To examine the appropriateness of our breakpoint choice based on the Chinese stock market crash in 2015, we use two reliable structural break tests that have been successfully used for financial time series. The first one is based on the methodology developed by Perron (1989) which adjusts the ADF test by including dummy variables in the OLS regression. He considered three models of the structural break at a time T_B ¹ ($1 < T_B < T$) under the null and the alternative hypotheses and the unit-root null hypotheses are:

Model (A): Trending data with intercept break

$$y_t = c + \beta t + \theta DU_t + dD_t + \alpha y_{t-1} + \sum_{i=1}^k c_i \Delta y_{t-i} + \varepsilon_t$$

Model (B): Trending data with trend break

$$y_t = c + \beta t + \gamma DT_t + dD_t + \alpha y_{t-1} + \sum_{i=1}^k c_i \Delta y_{t-i} + \varepsilon_t$$

Model (C): Trending data with intercept and trend breaks

$$y_t = c + \beta t + \theta DU_t + \gamma DT_t + dD_t + \alpha y_{t-1} + \sum_{i=1}^k c_i \Delta y_{t-i} + \varepsilon_t$$

where $DU_t = 1$, if $t \geq T_B$, 0 otherwise; $D_t = 1$, if $t = T_B + 1$, 0 otherwise; $DT_t = t - T_B$, if $t \geq T_B$, 0 otherwise. We employ the model (C) which incorporates both intercept and trend breaks and the results are documented in Table 6.1.

¹ We use 12 June 2015 as the break date.

Table 6. 1: Perron Test Result

Variable	Coefficient	Std. Error	t-Statistic	Prob.
α	0.9346	0.0188	49.7981	0.0000
c	0.5223	0.1487	3.5120	0.0005
β	0.0003	0.0001	2.9288	0.0037
θ	-0.0239	0.0068	-3.5309	0.0005
γ	-0.0004	0.0001	-2.7490	0.0064
d	0.0312	0.0255	1.2236	0.2221

Lee and Strazicich (2003) adopt an endogenous two-break Lagrange Multiplier (LM) unit root test to allow for up to two breaks in the deterministic trend under both the null and alternative hypotheses. The result is provided in Table 6.2. The tests follow a data-generating process (DGP):

$$y_t = \delta' Z_t + e_t, e_t = \beta e_{t-1} + \varepsilon_t$$

where Z_t is a vector of exogenous variables and $\varepsilon_t \sim iid N(0, \sigma^2)$. Consider the following two structural breaks: Model A allows for two breaks in levels and is described by $Z_t = [1, t, D_{1t}, D_{2t}]'$ where $D_{jt} = 1, if t \geq T_{Bj} + 1, j = 1, 2$, and 0 otherwise and T_{Bj} denotes the date of break. Model C allows two shifts in both levels and trend and is shown as $Z_t = [1, t, D_{1t}, D_{2t}, DT_{1t}, DT_{2t}]'$, where $DT_{jt} = t - T_{Bj}, if t \geq T_{Bj} + 1, j=1,2$, and 0 otherwise.

The two-break LM unit root test statistic can be estimated by regression based on the LM (score) principle:

$$\Delta y_t = \delta' \Delta Z_t + \Phi \tilde{S}_{t-1} + u_t,$$

Where $\tilde{S}_t = y_t - \tilde{\Psi}_x - Z_t \tilde{\delta}$, $t=2, \dots, T$; $\tilde{\delta}$ denotes the coefficients from the regression of Δy_t on ΔZ_t ; $\tilde{\Psi}_x$ is $y_1 - Z_1 \tilde{\delta}$ and y_1 and Z_1 are the first observations of y_t and Z_t . The null hypothesis of a unit root is:

$$H_0: \Phi = 0$$

and the two LM test statistics are:

$$\tilde{\rho} = T \tilde{\Phi}$$

$$\tilde{\tau} = t - \text{statistic testing the null hypothesis } \Phi = 0$$

According to the Perron test results, we can see both intercept and trend coefficients are statistically significant at the 1% level, implying that both level and trend structural breaks exist and our break date selection is appropriate. Moving to the LS test, the results indicate that there are two trend structural breaks during our full sample period since the corresponding coefficients are statistically significant at 1%. The estimated break dates are 24th June 2015 and 13th October 2015 respectively. The coefficient for the first break date (24th June 2015) is most significant with the highest T-statistic, implying an important structural break around the estimated date which is within the market peak time period. Since the estimated date is very close to our break date and it therefore confirms the appropriateness of our breakpoint choice within an acceptable range.

Table 6. 2: Lee and Strazicich Structural Break Test Result

Variable	Coefficient	T-Statistic
S(1)	-0.0921*	-3.6758
Constant	0.0083*	3.4354
D(24Jun2015)	-0.0226	-0.9028
DT(24Jun2015)	-0.0209*	-4.2269
D(13October2015)	-0.0181	-0.7208
DT(13October2015)	0.0213*	3.2180

Note: * indicates the 5% significance level.

Table 6. 3: Descriptive Statistics Summary

Panel A: Log Price

	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Observations
China	8.180685	8.162571	8.549921	7.884449	0.148389	0.600328	2.729370	18.11468 (0.0001)	287
Australia	8.599848	8.595024	8.696627	8.484980	0.056457	0.028881	1.895816	14.61977 (0.0007)	287
Hong Kong	10.07880	10.08170	10.255650	9.827802	0.096438	-0.116619	2.584476	2.715261 (0.2573)	287
Indonesia	8.493143	8.497819	8.616729	8.323730	0.080181	-0.095348	1.611687	23.48352 (0.0000)	287
India	8.826466	8.826889	8.901850	8.714740	0.038446	-0.306707	2.646503	5.993963 (0.0499)	287
Japan	9.848135	9.854026	9.945974	9.681422	0.063467	-0.300424	1.904349	18.67257 (0.0001)	287
South Korea	7.600052	7.597436	7.684053	7.511967	0.036587	0.134357	2.339197	6.085216 (0.0477)	287
Malaysia	7.449846	7.451108	7.529836	7.334421	0.043365	-0.121158	2.181830	8.707086 (0.0129)	287
New Zealand	7.996660	8.001375	8.054278	7.936346	0.023802	-0.245333	2.546415	5.339314 (0.0693)	287
Singapore	8.059802	8.102704	8.171868	7.837041	0.085669	-0.678141	2.277501	28.23968 (0.0000)	287
Thailand	7.278138	7.301991	7.387641	7.110557	0.070183	-0.55411	2.329553	20.06208(0.0000)	287
Taiwan	9.092286	9.108742	9.207649	8.910632	0.071429	-0.337684	1.890722	20.16917 (0.0000)	287

Note: The figure in parentheses is the p -value

Panel B: Return

	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Observations
China	0.000074	0.002882	0.056036	-0.088732	0.025560	-0.950077	4.575548	72.60753 (0.0000)	286
Australia	-0.000138	0.000000	0.036908	-0.041765	0.010985	-0.157138	3.812401	9.041930 (0.0109)	286
Hong Kong	-0.000600	-0.000365	0.069870	-0.060183	0.013918	0.141756	6.743157	167.9250 (0.0000)	286
Indonesia	-0.000393	0.000000	0.061411	-0.040530	0.010958	0.178808	7.865940	283.6793 (0.0000)	286
India	-0.000295	0.000000	0.021980	-0.069468	0.010321	-1.246767	9.478883	574.3075 (0.0000)	286
Japan	-0.000014	0.000181	0.074262	-0.047151	0.014456	0.294301	6.430882	144.3990 (0.0000)	286
South Korea	-0.000096	0.000000	0.029124	-0.024967	0.008443	0.090534	4.156077	16.31749 (0.0003)	286
Malaysia	-0.000224	0.000000	0.042962	-0.027380	0.007725	0.455793	6.804904	182.4237 (0.0000)	286
New Zealand	0.000280	0.000569	0.015886	-0.025335	0.005284	-0.445835	4.597443	39.88388 (0.0000)	286
Singapore	-0.000801	-0.000303	0.054437	-0.043905	0.008938	0.219078	9.849524	561.3698 (0.0000)	286
Thailand	-0.000710	-0.000438	0.031486	-0.048422	0.009329	-0.222126	5.863597	100.0708(0.0000)	286
Taiwan	-0.000422	-0.000075	0.035175	-0.049569	0.010165	-0.269395	5.771062	94.96484 (0.0000)	286

Note: The figure in parentheses is the p -value

Figure 6. 2: Stock Market Indices

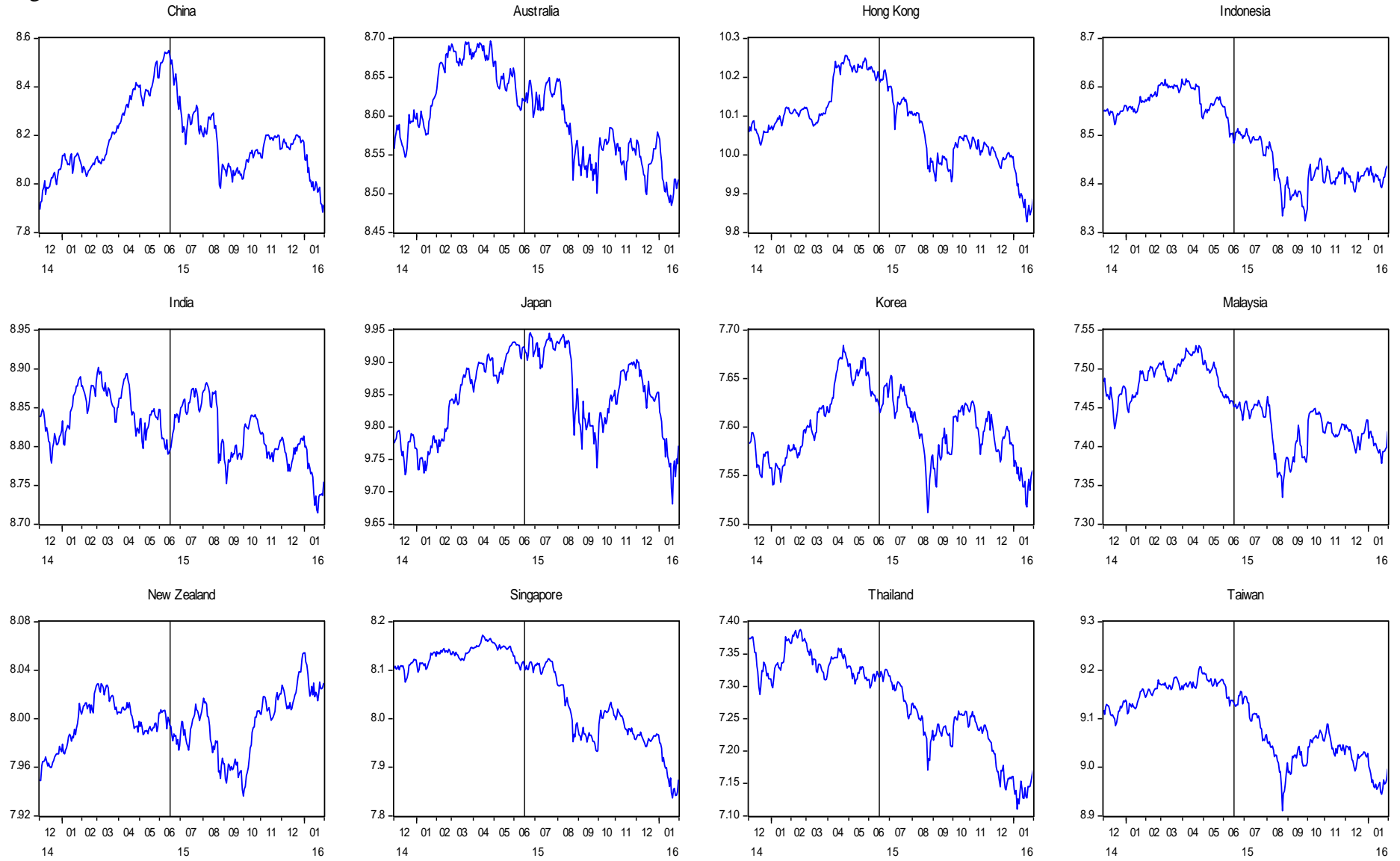
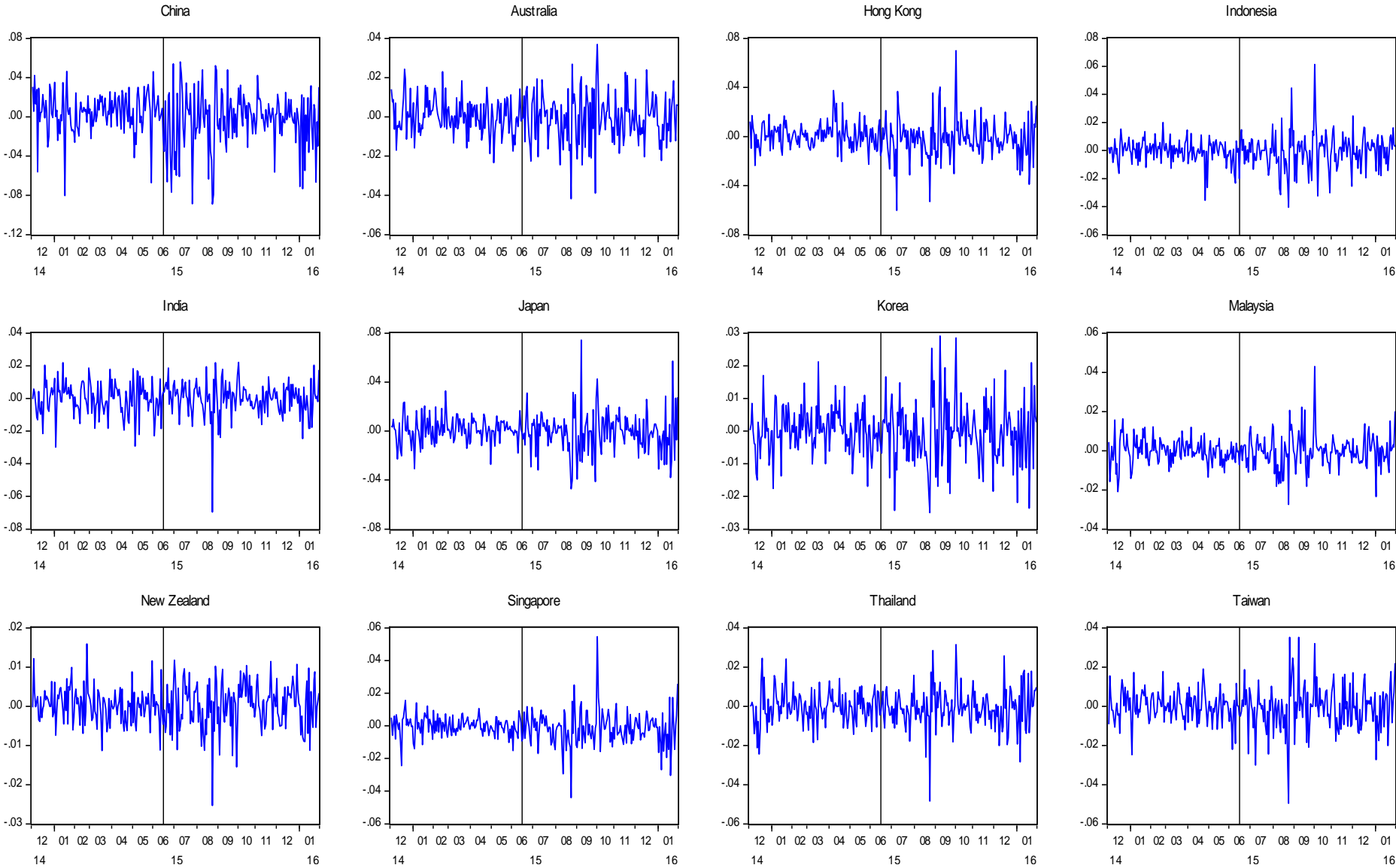


Figure 6. 3: Stock Markets Daily Returns



6.5 Methodological Framework

6.5.1 Unit Root and Cointegration Tests

We initially perform the Augmented Dickey-Fuller (ADF) unit root test (Dickey and Fuller, 1981) to examine the properties of the financial series. The estimable ADF test equation is specified as:

$$\Delta y_t = \mu + \gamma t + \alpha y_{t-1} + \sum_{i=1}^k \beta_i \Delta y_{t-i} + \varepsilon_t \quad (6.1)$$

where: y_t = the financial time series to be tested

Δ = the first difference operator

t = the time trend term

k = the length of optimal lag

μ = the intercept term

ε_t = the white noise residual term

α = the unit root coefficient

The lowest value of the Schwarz's information criterion (SIC) is used to determine the length of optimal lag in the ADF regression. In addition, the nonparametric Phillips-Perron (PP) test which is able to handle the serial correlation properly (Phillips and Perron, 1988) is also used. The results of these two methods are provided in Table 6.4. Based on our unit roots results, we can conclude that all the stock markets indices are integrated of order one $I(1)$ ¹. For more discussion, see the section 6.1.

We next test for the existence of any long-run cointegration relationship between the stock indices using Johansen's methodology (Johansen and Juselius, 1990). We consider an autoregressive VAR process as:

¹ If the time series need to be differenced d times before they become stationary, we can say that these time series are integrated of order d and denoted as $X_t \sim I(d)$.

$$Y_t = A_0 + \sum_{i=1}^p A_i Y_{t-i} + \varepsilon_t \quad (6.2)$$

The VAR equation (6.2) always can be rewritten as follows:

$$\Delta Y_t = A_0 + \Pi Y_{t-p} + \sum_{i=1}^{p-1} \Gamma_i \Delta Y_{t-i} + \varepsilon_t \quad (6.3)$$

where

$$\Pi = \sum_{i=1}^p A_i - I \text{ and } \Gamma_i = \sum_{i=1}^{p-1} A_i - I$$

The matrix Π can be written as a form of the matrix of adjustment parameters α with the matrix of cointegrating vectors β : $\Pi = \alpha\beta'$. The number of cointegrating vectors is identical to the number of stationary relationships in the Π -matrix. The rank of Π matrix equals to the number of independent rows in Π and therefore determines the number of cointegrating vectors. As proposed by Johansen and Juselius (1990), Trace and Maximum Eigenvalue tests are commonly used to identify the existence of cointegrating relationships. The trace test tests the null hypothesis H_0 : r cointegrating vectors against H_1 : n cointegrating vectors whereas the maximum eigenvalue test tests the null hypothesis H_0 : r cointegrating vectors versus the alternative hypothesis H_1 : $r + 1$ cointegrating vectors. The corresponding likelihood ratio statistics are calculated as follows:

$$\text{Trace statistic: } \lambda_{Trace}(r) = -T \sum_{i=r+1}^n \ln(1 - \hat{\lambda}_i)$$

Maximum eigenvalue statistic: $\lambda_{Max}(r) = -T \ln(1 - \hat{\lambda}_{r+1})$, where T is the sample size and $\hat{\lambda}_i$ is the i th largest canonical correlation.

6.5.2 Bayesian Vector Autoregression (BVAR) Model

The Bayesian Vector Autoregression (BVAR) forecasting model is used to analyse the spillover dynamics and market behaviour of these selected Asian countries. Since the seminal paper of Sims (1980), the VAR model has become one of the most popular econometric methods for examining multivariable time series. Our unit root results indicate the non-stationarity of all stock markets indices. A number of dynamic factor models can be used to overcome the stationarity of the data. However, Félix and Nunes (2003) note that “Bayesian models perform better than their non-Bayesian counterparts in terms of forecasting accuracy”. Canova and Ciccarelli (2004) indicate that Bayesian VAR could produce better forecasts than unrestricted VAR. Sims et al. (1990) suggest that the BVAR technique is optimal for analysing non-stationary data since the parameter estimates will not be affected by non-stationarity as required under the unrestrictive Ordinary Least Squares method. Using this approach could also reduce the degrees of freedom problem and address the over-fitting dilemma by introducing relevant prior information. Eventually, it will lead to a substantial improvement in the forecasting performance over the traditional VAR model (Abrego and Österholm, 2010). Early work by Doan et al. (1984) and Litterman (1986) proposes the widely used priors by combining the likelihood function with the informative prior distributions, later called the Minnesota (Litterman) prior. While using the natural logarithm of the Shanghai Stock Exchange Composite Index (SSEC) and each the Asia-Pacific stock market indices at a time, let us define an initial BVAR model as:

$$Y_t = b_0 + B_1 Y_{t-1} + B_2 Y_{t-2} + \dots + B_p Y_{t-p} + \varepsilon_t \quad t=1, \dots, T, \quad (6.4)$$

where Y_t is an $n \times 1$ vector of variables, ε_t is a $n \times 1$ vector of error terms which are independently, identically and normally distributed with variance–covariance matrix Σ ($\varepsilon_t \sim \text{IIN}(0, \Sigma)$), b_0 is a $N \times 1$ vector of intercepts and $B_i (i=1, \dots, p)$ is $n \times n$ matrices of parameters. Following Koop and Korobilis (2010), Y is a $T \times N$ matrix which stacks the T observations on each dependent variable in columns next to each other, while y is an $NT \times 1$ vector y which stacks all T observations on the first dependent variable, then all T observations on the second dependent variable, etc. Given that E and ε are the error terms vectors for Y and y respectively, the equation (6.4) can be presented as:

$$Y = XB + E \quad (6.5)$$

or

$$y = (I_n \otimes X)\beta + \varepsilon$$

where \otimes indicates the matrix Kronecker product, I_n is the identity matrix of dimension n , $x_t = (1, Y'_{t-1}, \dots, Y'_{t-p})$ and $X = (x_1, x_2, \dots, x_T)'$. X is $T \times K$ Matrix, where $K=1+N \times p$ is the number of coefficients in each equation of VAR and $B=(b_0, B_1, B_2, \dots, B_p)'$ and $\beta = \text{vec}(B)$ is an $nK \times 1$ vector which stacks all the VAR coefficients and the intercepts into a vector. The unknown parameters are β and Σ . As outlined by Ciccarelli and Rebucci (2003), we specify the Bayesian VAR model's likelihood function as:

$$L(Y|\beta, \Sigma) \propto |\Sigma|^{-1/2} \exp \left\{ -\frac{1}{2} \sum_t (Y_t - X_t \beta)' \Sigma^{-1} (Y_t - X_t \beta) \right\} \quad (6.6)$$

and the joint posterior distribution on the parameters can be obtained based on the Bayes theorem:

$$\begin{aligned} p(\beta, \Sigma|Y,) &= \frac{p(\beta, \Sigma)L(Y|\beta, \Sigma)}{p(Y)} \\ &\propto p(\beta, \Sigma)L(Y|\beta, \Sigma) \end{aligned} \quad (6.7)$$

According to the definition of the conditional probability, the probability density function (pdf) of the parameters is given in the following form:

$$\begin{aligned} p(\beta, \Sigma, Y) &= p(\beta, \Sigma)L(Y|\beta, \Sigma) \\ &= p(\beta, \Sigma|Y,)p(Y) \end{aligned} \quad (6.8)$$

given that $L()$ denotes the likelihood function, $p()$ denotes the probability density function (pdf) and \propto denotes proportional to.

For the Minnesota (Litterman) prior, let us denote the unknown parameters of interest $\theta=(\beta, \Sigma)$ the Minnesota (Litterman) prior assumes that θ is:

$$\theta \sim N(\mu, V)$$

where $\mu=0$ suggests a zero mean model but the prior covariance $V \neq 0$. We exclude the elements of V which correspond to exogenous variables, because the prior does not contain any information about the exogenous variables. Therefore the remainder of V is a diagonal matrix with the elements v_{ij}^l for $l = 1, \dots, p$:

$$v_{ij}^l = \begin{cases} \left(\frac{\lambda_1}{l\lambda_3}\right)^2 & \text{for } (i = j) \\ \left(\frac{\lambda_1\lambda_2\sigma_i}{l\lambda_3\sigma_j}\right)^2 & \text{for } (i \neq j) \end{cases} \quad (6.9)$$

where σ_i is the i -th diagonal element Σ .

The Minnesota (Litterman) prior simplifies the complicated problem regarding the choice of three coefficients λ_1, λ_2 and λ_3 where λ_1 and λ_2 are overall tightness and λ_3 is the lag delay coefficient¹. Based on Giannone et al. (2015), the expectation (first moment) and covariance (second moment) of matrix B is given by the following equations:

$$E[(B_s)(B_s)_{ij}|\Sigma] = \begin{cases} 1 & \text{if } i = j \text{ and } s = 1 \\ 0 & \text{otherwise} \end{cases} \quad (6.10)$$

$$COV((B_s)_{ij}, (B_r)_{hm}|\Sigma) = \begin{cases} \lambda^2 \frac{1}{s^2} \frac{\Sigma_{ih}}{\psi_j/(d-n-1)} & \text{if } m = j \text{ and } r = s, \\ 0 & \text{otherwise} \end{cases} \quad (6.11)$$

More specifically, the Bayesian VAR in our research is the bivariate VAR which can be rewritten as the following specification:

¹We use EViews to conduct the Bayesian VAR and the default setting of Minnesota (Litterman) prior is applied with $\text{Mu}1:0, \text{Lambda}1:0.1, \text{Lambda}2:0.99$ and $\text{Lambda}3:1$

$$\begin{cases} Y_{ssec,t} = c_1 + \sum_{i=1}^p b_{11,i} Y_{ssec,t-i} + \sum_{i=1}^p b_{21,i} Y_{ap,t-i} + \varepsilon_{1,t} \\ Y_{ap,t} = c_2 + \sum_{i=1}^p b_{12,i} Y_{ssec,t-i} + \sum_{i=1}^p b_{22,i} Y_{ap,t-i} + \varepsilon_{2,t} \end{cases} \quad (6.12)$$

where $Y_{ssec,t}$ denotes the natural logarithms of the closing price of Shanghai Stock Exchange Composite Index, $Y_{ap,t}$ denotes the natural logarithms of the closing price of one of the Asia-Pacific stock market indices. In this context, ap = Australia, India, Indonesia, Malaysia, Singapore, Japan, Hong Kong, Thailand, Taiwan, South Korea, and New Zealand respectively. Table 6.6 provides the estimated results of Bayesian VAR.

6.5.3 BEKK GARCH Model

The Autoregressive Conditional Heteroskedasticity (ARCH) model developed by Engle (1982) and later Generalized Autoregressive Conditional Heteroscedastic (GARCH) model proposed by Bollerslev (1986) are the most popular methodologies used in forecasting market volatility. Symmetric GARCH models are able to characterize the volatility dynamics of high-frequency data including the “volatility clustering effect” which captures the time-varying conditional variance of the financial time series (Slimane et al., 2013). Due to the increasing interdependence of international financial markets, the univariate GARCH specifications have been extended to the multivariate GARCH models which could explain the dynamics of stock market volatility among different financial markets. By specifying the conditional variance and covariance equations, multivariate GARCH models have been widely used to examine how the correlation and covariance between different variables change over time (see Majdoub and Mansour, 2014; Saleem et al., 2014; Li and Giles, 2015). In line with previous literature, we follow the multivariate GARCH approach to examine the volatility transmission relationship between Chinese and Asia-Pacific stock markets and our mean equation is specified as:

$$R_t = \mu + GR_{t-1} + \varepsilon_t, \varepsilon_t | \Omega_{t-1} \sim N(0, H_t) \quad (6.13)$$

where R_t denotes a vector of stock markets returns: $R_t = (R_{ssec,t}, R_{ap,t})'$,

G is a vector of VAR coefficients,

ε_t represents a vector of Gaussian error: $\varepsilon_t = (\varepsilon_{ssec,t}, \varepsilon_{ap,t})'$ and

μ_t is a vector of constants: $\mu_t = (\mu_{ssec,t}, \mu_{ap,t})'$,

ap = Australia, India, Indonesia, Malaysia, Singapore, Japan, Hong Kong, Thailand, Taiwan, South Korea, and New Zealand respectively.

There are many different variations of multivariate GARCH models used in previous literature. To extend the univariate GARCH model, Bollerslev et al. (1988) first proposed a general VECH GARCH which is expressed by:

$$vech(H_t) = A_0 + \sum_{i=1}^q A_i vech(\eta_{t-i}) + \sum_{j=1}^p B_j vech(H_{t-j}) \quad (6.14)$$

where H_t denotes conditional variance-covariance matrix, $\eta_t = (\varepsilon_t, \varepsilon_t')$, $vech(\cdot)$ denotes the operator that stacks the lower triangular part of a symmetric $d \times d$ matrix into $d(d+1)/2$ dimensional vector, A_i and B_j are $d(d+1)/2$ dimensional parameter matrices.

For VECH GARCH, the conditional variance and covariance are a linear function of all lagged squared errors and conditional variance and covariance, but this leads to the difficulty of estimating parameters because the number of parameters is very large and it is hard to guarantee a positive H_t without restrictions on parameters. Engle and Kroner (1995) introduced a more feasible model called the BEKK (Baba-Engle-Kraft-Kroner) GARCH model to overcome such two difficult problems in the above VECH GARCH specification. The BEKK GARCH model uses quadratic forms to release the positive restriction on the conditional variance matrix and further simplify the estimation process by reducing the number of parameters. In addition, the BEKK GARCH model can efficiently capture the spillover effect among international stock markets. The conditional variance and covariance matrix of the BEKK GARCH model can be written as:

$$H_t = C' C + A' \varepsilon_{t-1} \varepsilon_{t-1}' A + B' H_{t-1} B \quad (6.15)$$

where C is a lower triangular matrix of intercept coefficients while A and B are two unrestrictive matrices. To expand the matrices, the conditional variance can be represented as:

$$H_t = \begin{bmatrix} c_{11} & c_{12} \\ 0 & c_{22} \end{bmatrix}' \begin{bmatrix} c_{11} & c_{12} \\ 0 & c_{22} \end{bmatrix} + \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}' \begin{bmatrix} \varepsilon_{1,t-1}^2 & \varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ \varepsilon_{1,t-1}\varepsilon_{2,t-1} & \varepsilon_{2,t-1}^2 \end{bmatrix} \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} + \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}' H_{t-1} \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix} \quad (6.16)$$

More specifically, the conditional variance and volatility transmission are given as:¹

$$h_{11,t} = c_{11}^2 + c_{21}^2 + a_{11}^2 \varepsilon_{1,t-1}^2 + 2a_{11}a_{21}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + a_{21}^2 \varepsilon_{2,t-1}^2 + b_{11}^2 h_{11,t-1} + 2b_{11}b_{21}h_{12,t-1} + b_{21}^2 h_{22,t-1} \quad (6.17)$$

$$h_{22,t} = c_{22}^2 + a_{12}^2 \varepsilon_{1,t-1}^2 + 2a_{22}a_{12}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + a_{22}^2 \varepsilon_{2,t-1}^2 + b_{12}^2 h_{11,t-1} + 2b_{12}b_{22}h_{12,t-1} + b_{22}^2 h_{22,t-1} \quad (6.18)$$

In this regard, the tested hypothesis in the off-diagonal parameters can be given as:

Hypothesis H_0 : $a_{12} = a_{21} = b_{12} = b_{21} = 0$ (no volatility spillovers)

Hypothesis H_1 : $a_{12} \neq a_{21} \neq b_{12} \neq b_{21} \neq 0$ (existence of volatility spillovers)

Assuming the residuals of the BEKK GARCH model are normally distributed, the following logarithm likelihood function should be maximised in order to estimate the BEKK GARCH model:

$$L(\theta) = \sum_{t=1}^T L_t(\theta) \quad (6.19)$$

The logarithm likelihood function of the joint distribution is the sum of all the logarithm likelihood functions of the conditional distributions which can be represented as follow:

$$L_t(\theta) = -\ln(2\pi) - \frac{1}{2} \ln |H_t| - \frac{1}{2} \varepsilon_t' H_t^{-1} \varepsilon_t \quad (6.20)$$

where θ denotes the vector of parameters to be estimated and T is the number of observations. Since the above function is non-linear, here we employ BFGS (Broyden, Fletcher, Goldfarb, Shanno) algorithms as the maximization technique to obtain the initial condition and the final parameter estimates of the variance-covariance matrix. Under our research, the bivariate BEKK GARCH model is employed to estimate the interdependence between the Chinese and Asia-Pacific stock markets for both Bullish and Bearish periods.

¹ In interpreting the coefficients of the conditional variance equation, the sign of our parameter estimates does not matter since their squared values affect the conditional variance as noted by Kim et al. (2015).

6.6 Findings and Results

6.6.1 Results from Unit Root and Cointegration Tests

We commence by performing unit root tests with intercept and deterministic trend in levels and first differences for all stock market indices series. We observe that the null hypothesis of a unit root in the levels cannot be rejected in all cases whereas the null hypothesis of a unit root in the first differences of the series can be rejected at the 1% significance level (see Table 6.4). Similar results are observed in both ADF and PP tests. Thus we can conclude that all the indices are integrated of order one $I(1)$. Further, bivariate Johansen-Juselius cointegration tests are performed between China and one of the Asia-Pacific stock markets. Table 6.5 reports results for both the Trace and Max-Eigen Statistics with their statistical significance (p-value). The results do not reveal any significant evidence of a cointegration relationship since the null hypothesis of no cointegration vector is not rejected based on both Trace and Max-Eigen Statistics. The implication is that there is no specific long-term relationship between the Asia-Pacific stock markets and Chinese stock market.

Thus, despite their geographical proximity, we cannot observe a stable cointegration long-term relationship between China and each Asia-Pacific stock market. This could be explained by the fact that China still maintains some restrictions on its capital markets which could lead to market segmentation. Our results here are consistent with previous studies which report no evidence of a cointegration relationship between Chinese and other stock markets (see Huang et al., 2000; Zhu et al., 2004; Cheng and Glascock, 2005). One important implication of our results is that Chinese investors may enhance their diversification benefits by allocating their portfolio investments across these stock markets to provide downside protection. Also, investors from the Asia-Pacific region may reallocate their investment portfolios in China proportionately to foster greater diversification benefits in the long run.

Table 6. 4: Unit Root Test
 Panel A: Price Level

	ADF with Intercept	Prob.	ADF with Trend and Intercept	Prob.	PP with Intercept	Prob.	PP with Trend and Intercept	Prob.
Y _{China}	-1.555767	0.5039	-1.660201	0.7663	-1.723710	0.4182	-1.728875	0.7360
Y _{Australia}	-1.413083	0.5760	-2.850205	0.1807	-1.301984	0.6294	-2.759925	0.2136
Y _{Hong Kong}	-0.418082	0.9028	-1.637316	0.7759	-0.418082	0.9028	-1.663470	0.7649
Y _{Indonesia}	-1.154478	0.6945	-2.160943	0.5091	-0.980897	0.7606	-2.007740	0.5942
Y _{India}	-1.907380	0.3287	-2.778325	0.2066	-2.013686	0.2809	-2.937568	0.1523
Y _{Japan}	-1.913186	0.3260	-1.773036	0.7154	-1.802936	0.3787	-1.616382	0.7844
Y _{South Korea}	-1.795848	0.3822	-1.888949	0.6577	-1.938461	0.3144	-2.000476	0.5982
Y _{Malaysia}	-1.845762	0.3579	-2.498203	0.3289	-1.704187	0.4281	-2.306813	0.4284
Y _{New Zealand}	-2.167946	0.2187	-2.173542	0.5021	-2.296992	0.1737	-2.317580	0.4226
Y _{Singapore}	0.381739	0.9819	-1.893795	0.6552	0.288355	0.9774	-1.961466	0.6193
Y _{Thailand}	-1.018322	0.7474	-2.640063	0.2629	-0.983120	0.7599	-2.744178	0.2197
Y _{Taiwan}	-0.859066	0.8001	-2.280709	0.4427	-0.891021	0.7903	-2.339172	0.4110

Panel B: First Difference

	ADF with Intercept		ADF with Trend and Intercept		PP with Intercept		PP with Trend and Intercept	
	ADF with Intercept	Prob.	ADF with Trend and Intercept	Prob.	PP with Intercept	Prob.	PP with Trend and Intercept	Prob.
ΔY_{China}	-15.42038	0.0000	-15.61470	0.0000	-15.41049	0.0000	-15.58039	0.0000
$\Delta Y_{\text{Australia}}$	-16.49265	0.0000	-16.52235	0.0000	-16.66763	0.0000	-17.00527	0.0000
$\Delta Y_{\text{Hong Kong}}$	-15.96409	0.0000	-16.04919	0.0000	-15.94624	0.0000	-16.02290	0.0000
$\Delta Y_{\text{Indonesia}}$	-11.24932	0.0000	-11.22872	0.0000	-15.64704	0.0000	-15.60807	0.0000
ΔY_{India}	-15.65830	0.0000	-15.64722	0.0000	-15.62647	0.0000	-15.61293	0.0000
ΔY_{Japan}	-17.18441	0.0000	-17.22174	0.0000	-17.30729	0.0000	-17.44236	0.0000
$\Delta Y_{\text{South Korea}}$	-15.50061	0.0000	-15.50041	0.0000	-15.44521	0.0000	-15.44750	0.0000
$\Delta Y_{\text{Malaysia}}$	-14.07800	0.0000	-14.05029	0.0000	-14.00252	0.0000	-13.97530	0.0000
$\Delta Y_{\text{New Zealand}}$	-15.93093	0.0000	-15.90727	0.0000	-15.92967	0.0000	-15.90610	0.0000
$\Delta Y_{\text{Singapore}}$	-15.25181	0.0000	-15.34121	0.0000	-15.21523	0.0000	-15.25541	0.0000
$\Delta Y_{\text{Thailand}}$	-16.23380	0.0000	-16.20534	0.0000	-16.25921	0.0000	-16.22814	0.0000
ΔY_{Taiwan}	-15.62954	0.0000	-15.63328	0.0000	-15.57559	0.0000	-15.57617	0.0000

Note: The ADF and PP tests test the null hypothesis of non-stationarity of the series (the time series have a unit root). The ADF and PP tests conducted here are with intercept and with both trend and intercept. The lag selection for the ADF test is based on Schwarz Info Criterion (SIC) while the bandwidth selection for PP test is based on Newey-West Bandwidth.

Table 6. 5: Johansen- Juselius Cointegration Tests

	Hypothesis	Trace Statistic	Prob.	Max-Eigen Statistic	Prob.	No. of CE(s)
China	None	5.640417	0.4812	5.555438	0.4030	0
Australia	At most 1	0.084979	0.8108	0.084979	0.8108	
China	None	8.369987	0.2094	7.543351	0.2059	0
Hong Kong	At most 1	0.826636	0.4190	0.826636	0.4190	
China	None	8.300733	0.2143	7.982161	0.1755	0
Indonesia	At most 1	0.318572	0.6345	0.318572	0.6345	
China	None	3.697210	0.7541	3.500779	0.7085	0
India	At most 1	0.196431	0.7129	0.196431	0.7129	
China	None	3.810139	0.7381	3.807666	0.6592	0
Japan	At most 1	0.002473	0.9681	0.002473	0.9681	
China	None	4.919161	0.5789	4.882167	0.4940	0
South Korea	At most 1	0.036994	0.8749	0.036994	0.8749	
China	None	7.426813	0.2846	7.257430	0.2280	0
Malaysia	At most 1	0.169382	0.7334	0.169382	0.7334	
China	None	3.674362	0.7573	3.141491	0.7657	0
New Zealand	At most 1	0.532871	0.5279	0.532871	0.5279	
China	None	10.113210	0.1140	7.596279	0.2020	0
Singapore	At most 1	2.516932	0.1331	2.516932	0.1331	
China	None	8.149082	0.2253	6.479181	0.2984	0
Thailand	At most 1	1.669900	0.2305	1.669900	0.2305	
China	None	10.263150	0.1080	9.928459	0.0838	0
Taiwan	At most 1	0.334687	0.6254	0.334687	0.6254	

Note: The lag selection is based on Schwarz Information Criterion (SIC). We use one lag to conduct the Johansen-Juselius Cointegration test for all the groups. The tests assume no deterministic trend in data, no intercept or trend in cointegration equation.

6.6.2 Bayesian VAR Results

We employ a bivariate Bayesian VAR model to estimate the interdependence among China and Asia-Pacific stock markets for bullish and bearish periods. Table 6.6 provides parameter estimates of our Bayesian VAR specification to examine the financial market behaviours and transmission of price volatility. During both bullish and bearish periods, all stock markets display a dependence on their own past values, since the coefficients $b_{11,1}$ and $b_{22,1}$ are statistically significant at the 1% level for all indices, indicating an autoregressive (AR) feature for all stock markets. In terms of cross-market impact, we analyse the observed results market by market by examining the significance level of the coefficients $b_{12,1}$ and $b_{21,1}$. Explicitly, the coefficients $b_{12,1}$ and $b_{21,1}$, from the conditional mean equation, reflect the price changes transmission from country 1 to country 2, and from country 2 to country 1, respectively. For the bullish period, we observe a bi-directional feedback relationship between the Chinese stock market and some Asia-Pacific stock markets such as Hong Kong, Japan and South Korea on account of the corresponding coefficients $b_{12,1}$ and $b_{21,1}$ being all statistically significant at the 1% level. We also find uni-directional price spillover from China to India, Indonesia, Thailand and Taiwan as the corresponding coefficients $b_{12,1}$ are statistically significant, at least at the 10% level. However, there seems to be no evidence of a price spillover effect between China and Australia, Malaysia, New Zealand and Singapore, as both coefficients $b_{12,1}$ and $b_{21,1}$ are statistically insignificant.

Nevertheless, our results indicate that China has a much bigger influence on most of the Asia-Pacific stock markets (Hong Kong, Indonesia, India, Japan, South Korea, Thailand and Taiwan). On the other hand, only a few markets (Hong Kong, Japan and South Korea) seem to influence the information transmission related to the prices of the Chinese stock market in the stable period, suggesting a bigger impact of ‘good news’ from China to Asia-Pacific stock markets during a bullish period. Our results show that innovations emerging from more advanced Asian stock markets (Hong Kong, Japan and South Korea) have some influential power on the less developed Chinese stock market. Looking at the nature of interdependence between these markets, we see that the Chinese stock market adjusts to the information flow from these advanced markets in an efficient manner. It seems that our result supports the conventional expectation that the spillover is usually from the more developed markets to the less developed markets.

In contrast, we find that most of the Asia-Pacific stock markets influence price and return of the Chinese stock market during the turmoil period. To be specific, and with the exception of New Zealand, we observe significant price spillovers from the Asia-Pacific markets to the Chinese stock market, as the coefficients $b_{21,1}$ are statistically significant at the 1% level. For example, in the case of Japan, the coefficient $b_{21,1}$ is determined as 0.2712, which implies that about 27.12% of the Japanese market innovation can be transferred to the Chinese stock market during the crisis period. In the opposite direction, we observe that the market influence and price movement of the Chinese stock market on five Asia-Pacific stock markets (Australia, Hong Kong, Indonesia, India and Japan) is much stronger and remains significant during the crisis period. For example, about 8.51% of the price volatility of the Japanese market is explained by the price volatility of the Chinese stock market in the crisis (bearish) period as compared to only 3.01% in the non-crisis (bullish) period.

Our results emphasise China's rising influence and regional integration and these have significant implications for financial markets in the Asia-Pacific, especially during the turbulent period. These findings show significant interrelationship in information transmission between Asia-Pacific markets and China. This observation is in line with Shu et al. (2015) who report that China's financial market explains about 50% of the short-run variation in equity returns in Asian markets during the European debt crisis as compared to about 33% before the crisis period. Because China has a close geographical and trading relationship with Asia-Pacific economies, market information is instantaneously transmitted across the region. Our findings suggest that China and Asia-Pacific stock markets have been integrated to share such information. The results show that although China's influence on the Asia-Pacific financial markets has been rising, these regional stock markets in turn strongly impact on the Chinese financial markets in stress periods through the price channel (i.e. the variance of prices). The spillover effects of the market prices from the Asia-Pacific region possibly reflect the adverse impact of the Chinese economy's slowdown on those markets which, in turn, influences the Chinese stock market. Our results here are consistent with Samarakoon (2011) who finds evidence of contagion from emerging markets to the US during the GFC. Lack of evidence of a price spillover effect between China and New Zealand in both periods implies better diversification benefits between these two markets.

Table 6. 6: Bayesian VAR Results: Bullish Period

	b_{11,1}	b_{12,1}	c₁	b_{21,1}	b_{22,1}	c₂
Australia	0.983669*** [86.3354]	-0.001814 [-0.36233]	0.031567 [0.08905]	0.012426 [0.28076]	0.937677*** [48.2046]	0.553844*** [3.55481]
Hong Kong	0.938967*** [38.7607]	0.044641*** [3.68437]	-0.765509* [-1.76604]	0.125364*** [2.10279]	0.871747*** [29.2266]	0.935323*** [4.31266]
Indonesia	0.985089*** [94.7863]	-0.009678*** [-2.36086]	-0.391565 [-0.68732]	0.060530 [0.92269]	0.912243*** [35.2260]	0.831234*** [3.69619]
India	0.984355*** [93.8337]	-0.009042* [-1.71723]	0.358703 [0.67063]	-0.025482 [-0.43657]	0.866676*** [29.5530]	1.253054*** [4.66289]
Japan	0.910000*** [44.8288]	0.030131*** [2.93649]	-1.534801*** [-3.87552]	0.231567*** [4.29993]	0.902790*** [33.1540]	0.710279*** [3.54690]
South Korea	0.927280*** [47.6656]	0.017583*** [2.74403]	-1.549279*** [-3.19019]	0.282688*** [3.50858]	0.905102*** [34.0948]	0.578126*** [3.61292]
Malaysia	0.983136*** [90.1008]	0.000725 [0.21074]	-0.175947 [-0.31706]	0.042633 [0.55461]	0.916477*** [37.7864]	0.619310*** [3.53704]
New Zealand	0.984344*** [91.0132]	-0.000469 [-0.20196]	-0.023973 [-0.03323]	0.019680 [0.21241]	0.918510*** [46.1621]	0.655860*** [4.23370]
Singapore	0.980034*** [81.5156]	0.004135 [1.18876]	-0.485709 [-0.64327]	0.080486 [0.81825]	0.877947*** [30.8249]	0.958626*** [4.38461]
Thailand	0.978616*** [85.1737]	-0.007799* [-1.66747]	0.914070 [1.49584]	-0.099985 [-1.29878]	0.837711*** [26.7063]	1.254457*** [5.03843]
Taiwan	0.980196*** [75.5326]	0.008573* [1.77979]	-0.292111 [-0.42453]	0.050191 [0.61555]	0.864659*** [28.5474]	1.168954*** [4.57340]

Note: Based on Schwarz Information Criterion (SIC) and Hannan-Quinn information criterion (HQ), one lag is the most appropriate for all the Asia-Pacific stock markets. Figures in parentheses indicate the T statistics. *, **, *** indicate statistical significance level at 10%, 5%, and 1% respectively.

Table 6.6: Bayesian VAR Results: Bearish Period (Continued)

	b_{11,1}	b_{12,1}	c₁	b_{21,1}	b_{22,1}	c₂
Australia	0.850097*** [31.5983]	0.039574*** [3.37173]	-1.119171** [-2.19971]	0.273019*** [3.61162]	0.827575*** [25.0724]	1.153418*** [5.19140]
Hong Kong	0.737640*** [19.5175]	0.037306* [1.72365]	-0.846090*** [-2.76554]	0.297509*** [5.55486]	0.908509*** [29.6036]	0.610974*** [3.48354]
Indonesia	0.868305*** [33.9416]	0.022824** [1.97348]	-0.705714 [-1.48003]	0.210817*** [2.96609]	0.851688*** [26.4826]	1.063258*** [4.92766]
India	0.886899*** [39.6958]	0.026021*** [3.14355]	-0.766101 [-1.40885]	0.191273*** [2.68436]	0.875061*** [33.1206]	0.888226*** [4.40507]
Japan	0.809638*** [25.8250]	0.085155*** [4.49263]	-1.123576*** [-2.62375]	0.271225*** [4.38750]	0.781175*** [20.8843]	1.460920*** [5.63708]
South Korea	0.845789*** [34.6171]	0.012994 [1.56359]	-2.062533*** [-3.44893]	0.436863*** [4.66249]	0.866197*** [27.1557]	0.909547*** [4.46731]
Malaysia	0.879689*** [40.5760]	0.001778 [0.26958]	-1.536451*** [-2.45439]	0.338983*** [3.57592]	0.883144*** [30.6020]	0.852092*** [4.47097]
New Zealand	0.922074*** [50.3773]	-0.001797 [-0.46891]	1.053042 [1.55673]	-0.052633 [-0.62972]	0.950740*** [54.2985]	0.408782*** [2.88478]
Singapore	0.804161*** [26.5262]	0.003303 [0.28553]	-0.403524 [-1.54297]	0.249743*** [4.84707]	0.971936*** [49.4053]	0.196023** [1.96237]
Thailand	0.860591*** [35.3098]	-0.005263 [-0.60596]	-0.344866 [-1.14868]	0.204591*** [3.77091]	0.965330*** [49.9044]	0.292647*** [2.73359]
Taiwan	0.826994*** [29.9305]	0.007872 [0.68285]	-1.255464*** [-2.84352]	0.294662*** [4.55555]	0.920286*** [34.0791]	0.655475*** [3.55535]

Note: Based on Schwarz Information Criterion (SIC) and Hannan-Quinn information criterion (HQ), one lag is the most appropriate for all the Asia-Pacific stock markets. Figures in parentheses indicate the T statistics. *, **, *** indicate statistical significance level at 10%, 5%, and 1% respectively.

6.6.3 Results from the VAR BEKK GARCH Estimation Model

Table 6.7 reports parameter estimates based on the BEKK-GARCH model which is known to capture well the conditional volatility of stock market returns and volatility interactions. The mean equation captures the return relationships between China and each Asia-Pacific market. The results show that the relationships in the conditional mean are not statistically significant for most of the pairs considered, implying that there is little evidence of return spillovers between China and the Asia-Pacific region. Moving to the conditional variance equations, the diagonal parameters of the matrix A illustrate the effect of a market's past shocks on its own conditional variance while the diagonal elements of the matrix B measure the effect of the market's past volatility on its own conditional variance. Specifically, $A(1,1)$ and $B(1,1)$ measure the effects of the Chinese stock market's past shocks and volatility on its own conditional variance respectively, while $A(2,2)$ and $B(2,2)$ capture the impact of each Asia-Pacific stock market's past shock and volatility on its own conditional variance. As shown in Table 6.7, the estimated parameters $A(1,1)$ are statistically significant at the 5% level for some pairs and $B(1,1)$ are statistically significant at the 5% level for most pairs in both bullish and stress periods.

These findings indicate that the Chinese stock market has moderate ARCH and strong GARCH effect as captured by the coefficients of $A(1,1)$ and $B(1,1)$ respectively. For the Asia-Pacific stock markets, $A(2,2)$ which captures the ARCH effect for Hong Kong, Taiwan, Singapore, Thailand, Malaysia, Japan and Australia are statistically significant at the 10% level in the bullish period. Meanwhile, in the bearish (crisis) period, we observe ARCH effects in most stock markets in the region but not in the case of South Korea, New Zealand and India. In terms of the GARCH effect, captured by $B(2,2)$, only Hong Kong, Taiwan, Thailand, Japan, South Korea and Australia show strong GARCH effects in the bullish period, while there exists a GARCH effect in most stock markets during the bearish period with the exception of Malaysia, South Korea and India. Our results are consistent with Beirne et al. (2013) who observe that most emerging markets have significant ARCH and GARCH effects.

We next examine the shock and volatility transmission across the stock markets. The off-diagonal elements of matrices A and B capture the shock and volatility spillover effect respectively. Focusing on matrix A, coefficient $A(1,2)$ indicates the overall shock spillover effect from China to each Asia-Pacific stock market. These coefficients are statistically significant for most pairs except for Hong Kong in the stable period, but shock spillover

effects from China are not significant for Hong Kong, Taiwan, Thailand and New Zealand during the crisis period. In the opposite channel, the coefficient $A(2,1)$ measures the shock spillover effect from the Asia-Pacific stock markets to China. We find this effect has strengthened, since this coefficient is significant at the 10% level for *four* markets (Malaysia, South Korea, Indonesia and New Zealand) in the stable period compared to *eight* markets (Hong Kong, Taiwan, Singapore, Thailand, Malaysia, Japan, Indonesia and India) during the turmoil period. Since the shock spillover effect measures the short-term influence of the innovation from the last period (yesterday), we can observe that the Chinese stock market is largely influenced by the previous period's markets results in the Asia-Pacific region during the crash period. This result is consistent with our Bayesian VAR result which also shows the significant impact from outside China during the crisis.

We conjecture that because market behaviour in China is strongly correlated with the investors' sentiment, Chinese investors who are not mature investors may overreact to the bad news originating externally, and further sell shares in panic, driving asset prices down significantly in the short-run and leading to significant increases of market volatility. This is similar to the overreaction of the over-optimistic investor sentiment when the Chinese stock market rises (He et al., 2014). At the same time, we can see that China has strong shock spillovers to the Asia-Pacific markets since the corresponding coefficients are statistically significant for most pairs. This evidence reinforces our finding that China's impact on the regional financial markets has risen during the recent volatile period.

Moving to the volatility spillover effect, which is captured by the off-diagonal parameters of matrix B , we see that the volatility spillover effect from China to the Asia-Pacific stock markets that is captured by the coefficient $B(1,2)$ indicates that transmissions are stronger during the bearish period. This is because the number of pairs whose $B(1,2)$ coefficients are statistically significant dramatically increases from six in the bullish period to ten in the bearish period. For example, about 28.87%, 19.91%, 20.69% and 22.70% of Hong Kong, Taiwan, Thailand and Malaysia market volatilities are affected by the Chinese market in a crisis period, respectively. This suggests that volatility originating in China can be easily transmitted to most Asia-Pacific stock markets, so important market signalling occurs when there is a crisis. The results are consistent with Lam and Qiao (2009) who find that the Chinese stock markets play a leading role among the stock markets in the Greater China region. This result is also in line with the argument that China is now becoming a global

financial hub, playing a major role in information transmission in line with the global centre hypothesis (Li, 2007). Turning to cross-effects in the opposite direction, the off-diagonal coefficients $B(2,1)$ are statistically significant for all countries during the bullish period. Referring to the bearish period, with the exception of Hong Kong, Singapore, South Korea and Indonesia, all other markets have significant volatility spillovers with the Chinese stock market. These results show that the Asia-Pacific stock markets also exert influence on China through the volatility channel. Thus, we can see that China has become integrated with the Asia-Pacific region during both stable and stress periods, indicating efficient information transmission regionally.

Overall, we observe that strengthened shock spillovers from most Asia-Pacific stock markets and enhanced volatility spillovers from China during the crisis period, which is consistent with the 'global centre hypothesis'. Meanwhile, we find that China is more integrated within the region because most stock markets are responsive to the shocks and volatility from China and most Asia-Pacific markets also exert volatility spillover impacts to markets in China, showing evidence of strengthened regional linkages. Given the recent market-based currency reforms, Chinese influence in the region is rising and financial shocks emanating from the country will come into play over the short-run and long-run. It should be noted that our results are contrary to Wang (2014) who indicates that the Chinese stock market with higher idiosyncratic risk is still less correlated with the world due to its low level of market sensitivity to global factors.

To further analyse the level of stock market connectivity, Table 6.8 analyses the direction of volatility spillover effects between China and the selected Asia-Pacific stock markets using joint Wald tests. We test the significance of cross-market coefficient estimates $A(1,2)$, $A(2,1)$ and $B(1,2)$, $B(2,1)$ under the null hypothesis H_0 : no spillovers in variance from China to one of the Asia-Pacific markets or vice versa. With the exception of Hong Kong in the bullish period, we observe bi-directional volatility spillover effects between China and Asia-Pacific markets in both periods. While these results highlight spillover effects regarding China's financial turmoil, it also provides strong evidence of increasing volatility linkages, significant market co-movement and strong regional integration. As a result of stronger financial market integration, the region now has a diverse spectrum of market information transmission and higher correlation of stock market prices, which may potentially reduce any gains in investors' portfolio diversification.

Table 6. 7: VAR BEKK GARCH Model (Bullish Period)

$$H_t = C'C + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'H_{t-1}B$$

	Hong Kong	Taiwan	Singapore	Thailand	Malaysia
μ_1	0.004941*** (0.0040)	0.003992** (0.0227)	0.004744*** (0.0025)	0.005003*** (0.0032)	0.004198*** (0.0098)
g_{11}	0.000108 (0.9991)	-0.050349 (0.5483)	0.015994 (0.8382)	0.014208 (0.8789)	0.081262 (0.3891)
g_{21}	0.102508 (0.5857)	0.417847* (0.0659)	0.401512 (0.2073)	0.144961 (0.5115)	0.038888 (0.8844)
μ_2	0.001151 (0.1645)	-0.000162 (0.8097)	-0.000333 (0.3677)	0.000121 (0.8574)	-0.000202 (0.7049)
g_{12}	-0.033350 (0.4858)	0.005688 (0.8700)	-0.052735** (0.0120)	-0.072155** (0.0450)	0.012719 (0.6663)
g_{22}	0.108554 (0.3010)	0.095529 (0.3036)	0.050534 (0.5743)	0.119637 (0.1449)	0.113964 (0.2077)
C(1,1)	0.003046* (0.0862)	0.001944 (0.6288)	0.001555 (0.6915)	0.001119 (0.8244)	-0.004227 (0.3669)
C(2,1)	-0.002223** (0.0491)	0.001311 (0.2992)	0.003464*** (0.0000)	0.001157 (0.4242)	-0.001629 (0.2592)
C(2,2)	0.000000 (1.0000)	0.000000 (1.0000)	0.000001 (1.0000)	0.000000 (1.0000)	0.000005 (0.9996)
A(1,1)	-0.095456 (0.2595)	0.183377** (0.0216)	-0.161854 (0.1058)	-0.133285 (0.2459)	-0.290533*** (0.0013)
A(1,2)	-0.086429 (0.1240)	-0.088417*** (0.0049)	-0.110719*** (0.0000)	-0.095663*** (0.0005)	-0.085804*** (0.0038)
A(2,1)	-0.020014 (0.8927)	-0.240407 (0.2089)	0.730821 (0.1132)	0.266106 (0.1448)	0.790228*** (0.0090)
A(2,2)	0.296778*** (0.0011)	-0.275603*** (0.0002)	-0.773604*** (0.0000)	-0.178373** (0.0288)	-0.220551** (0.0333)
B(1,1)	0.933568*** (0.0000)	0.765068*** (0.0000)	0.659833*** (0.0001)	0.686783*** (0.0000)	-0.016071 (0.9515)
B(1,2)	-0.008193 (0.6371)	0.239508*** (0.0000)	0.046138 (0.5235)	-0.260567*** (0.0000)	0.280443*** (0.0000)
B(2,1)	0.207726* (0.0697)	-1.645418*** (0.0000)	2.453538*** (0.0000)	1.765470*** (0.0000)	2.824921*** (0.0000)
B(2,2)	0.938167*** (0.0000)	0.651008*** (0.0000)	-0.192037 (0.2057)	0.675745*** (0.0000)	-0.094695 (0.7362)

Table 6.7: VAR BEKK GARCH Model (Bullish Period Continued)

$$H_t = C'C + A'\varepsilon_{t-1}\varepsilon_{t-1}'A + B'H_{t-1}B$$

	Japan	South Korea	Australia	Indonesia	New Zealand	India
μ_1	0.005890*** (0.0004)	0.002809* (0.0546)	0.004631*** (0.0019)	0.005624*** (0.0019)	0.004525*** (0.0079)	0.004423*** (0.0072)
g_{11}	0.028581 (0.7267)	0.004068 (0.9513)	-0.010104 (0.9014)	0.015850 (0.8398)	-0.004719 (0.9569)	-0.009558 (0.9025)
g_{21}	0.204257 (0.1904)	0.539779** (0.0240)	-0.016199 (0.9221)	0.123560 (0.6730)	0.830384* (0.0562)	0.079712 (0.6385)
μ_2	0.001403 (0.1185)	0.000527 (0.3715)	0.000368 (0.6354)	-0.000001 (0.9984)	0.000524 (0.1944)	0.000022 (0.9806)
g_{12}	-0.007956 (0.8502)	0.019206 (0.6233)	0.009201 (0.8251)	0.026890 (0.5062)	0.002212 (0.9178)	-0.024684 (0.6534)
g_{22}	0.078665 (0.3790)	0.067092 (0.4008)	0.056229 (0.4929)	0.035080 (0.6310)	-0.092749 (0.2908)	0.142975* (0.0921)
C(1,1)	0.000001 (0.9998)	-0.000702 (0.8935)	-0.003054 (0.3711)	-0.000340 (0.9162)	0.008419* (0.0869)	0.002775 (0.6566)
C(2,1)	0.000001 (0.9996)	0.001873** (0.0497)	0.006877*** (0.0000)	-0.006096*** (0.0000)	-0.003731*** (0.0000)	0.008625*** (0.0000)
C(2,2)	0.000000 (0.9998)	0.000000 (1.0000)	0.000000 (1.0000)	0.000019 (0.9998)	0.000000 (1.0000)	0.000000 (1.0000)
A(1,1)	-0.060240 (0.2716)	0.108225 (0.2613)	-0.212147 (0.1170)	-0.254715* (0.0549)	-0.094776 (0.5893)	-0.116239 (0.4555)
A(1,2)	0.115079*** (0.0005)	0.178465*** (0.0000)	-0.227861*** (0.0001)	-0.119242*** (0.0096)	0.074391*** (0.0078)	-0.257854*** (0.0073)
A(2,1)	-0.130249 (0.2534)	0.682233* (0.0521)	-0.165269 (0.6323)	1.482094*** (0.0007)	1.449407* (0.0525)	0.115391 (0.7830)
A(2,2)	0.224598*** (0.0004)	-0.082871 (0.2078)	-0.216808* (0.0665)	0.033723 (0.7888)	0.075549 (0.6607)	-0.162195 (0.1881)
B(1,1)	0.673452*** (0.0000)	0.262167*** (0.0098)	-0.561724** (0.0113)	-0.037556 (0.8344)	0.238066 (0.5051)	-0.162654 (0.8851)
B(1,2)	0.387521*** (0.0000)	0.279521*** (0.0000)	0.088342 (0.2447)	0.230288** (0.0130)	0.020861 (0.7884)	0.013021 (0.9850)
B(2,1)	-1.552884*** (0.0000)	-2.604614*** (0.0000)	-1.519064*** (0.0002)	1.943084*** (0.0000)	-3.445546*** (0.0003)	1.876443*** (0.0000)
B(2,2)	0.496643*** (0.0000)	0.258192*** (0.0033)	-0.348926* (0.0565)	-0.114907 (0.5469)	-0.390650 (0.1133)	-0.078978 (0.7057)

Table 6.7: VAR BEKK GARCH Model (Bearish Period Continued)

$$H_t = C'C + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'H_{t-1}B$$

	Hong Kong	Taiwan	Singapore	Thailand	Malaysia
μ_1	-0.002594 (0.2170)	-0.001096 (0.5142)	-0.002421 (0.2266)	-0.002186 (0.3305)	-0.002743 (0.1987)
g_{11}	-0.046251 (0.6666)	0.140198 (0.1137)	-0.030063 (0.7518)	0.033376 (0.7048)	-0.042654 (0.5794)
g_{21}	0.408231** (0.0271)	-0.354251* (0.0711)	0.449110** (0.0430)	0.112208 (0.6806)	0.139963 (0.5986)
μ_2	-0.001779 (0.1166)	-0.000772 (0.3871)	-0.001286 (0.1242)	-0.000798 (0.3013)	-0.000756 (0.2107)
g_{12}	-0.075827 (0.1866)	0.051395 (0.1470)	-0.023004 (0.4805)	0.004959 (0.8734)	-0.007673 (0.7257)
g_{22}	0.273560*** (0.0076)	0.039897 (0.6375)	0.148819 (0.1430)	0.037805 (0.6812)	0.184603** (0.0235)
C(1,1)	0.012661*** (0.0000)	0.003367 (0.6239)	0.005641*** (0.0013)	0.021718*** (0.0000)	0.015451*** (0.0000)
C(2,1)	-0.002324 (0.2026)	0.005268*** (0.0000)	0.002218*** (0.0028)	0.001392 (0.5141)	-0.001166 (0.1784)
C(2,2)	0.000000 (1.0000)	0.000000 (1.0000)	0.000000 (1.0000)	0.000000 (1.0000)	0.000000 (1.0000)
A(1,1)	-0.668885*** (0.0000)	-0.629012*** (0.0000)	-0.338671*** (0.0000)	0.257023* (0.0590)	0.135633 (0.1250)
A(1,2)	-0.099892 (0.1787)	0.013738 (0.7880)	-0.082636*** (0.0057)	0.031361 (0.4883)	0.071889** (0.0175)
A(2,1)	0.785402*** (0.0002)	0.888520*** (0.0009)	0.434486** (0.0148)	0.559886* (0.0688)	0.812224* (0.0539)
A(2,2)	0.628307*** (0.0000)	0.211625* (0.0506)	0.329024*** (0.0001)	-0.214461** (0.0280)	-0.730320*** (0.0000)
B(1,1)	0.771218*** (0.0000)	0.878164*** (0.0000)	0.922615*** (0.0000)	0.214587 (0.2216)	0.189934 (0.3205)
B(1,2)	0.288730*** (0.0000)	0.199062*** (0.0000)	-0.028966*** (0.0034)	-0.206871*** (0.0000)	0.227037*** (0.0000)
B(2,1)	-0.087721 (0.6432)	-1.193839*** (0.0000)	0.049131 (0.3100)	1.182201*** (0.0060)	2.325361*** (0.0000)
B(2,2)	0.432418*** (0.0027)	0.507767*** (0.0000)	0.969557*** (0.0000)	1.009335*** (0.0000)	0.162437 (0.3387)

Table 6 7: VAR BEKK GARCH Model (Bearish Period Continued)

$$H_t = C'C + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'H_{t-1}B$$

	Japan	South Korea	Australia	Indonesia	New Zealand	India
μ_1	-0.003573* (0.0835)	-0.001782 (0.4015)	-0.001198 (0.5992)	-0.002543 (0.1962)	-0.001444 (0.4853)	-0.001431 (0.4794)
g_{11}	0.014554 (0.8650)	0.058548 (0.4771)	0.103021 (0.2456)	0.032693 (0.6915)	0.166906** (0.0448)	0.055208 (0.5224)
g_{21}	0.227448 (0.1023)	0.293342 (0.2098)	0.012176 (0.9484)	0.135209 (0.4179)	0.029072 (0.9416)	-0.394666* (0.0854)
μ_2	-0.000407 (0.7005)	-0.000462 (0.5558)	0.000062 (0.9471)	0.000078 (0.9332)	0.000683 (0.1450)	-0.000015 (0.9826)
g_{12}	0.071296* (0.0727)	-0.017023 (0.6360)	0.016704 (0.6281)	0.000978 (0.9775)	0.028185 (0.1432)	-0.025724 (0.4994)
g_{22}	-0.101246 (0.2813)	0.093439 (0.2793)	0.047409 (0.5872)	0.144355 (0.1447)	0.149727* (0.0695)	0.060589 (0.5258)
C(1,1)	-0.006371** (0.0145)	0.001901 (0.7030)	0.010757 (0.1437)	0.018481*** (0.0000)	0.006906 (0.6271)	0.015970*** (0.0000)
C(2,1)	-0.003941* (0.0576)	0.007766*** (0.0000)	-0.003859 (0.2069)	-0.000379 (0.8311)	-0.001291 (0.6036)	-0.004412*** (0.0002)
C(2,2)	-0.003694*** (0.0044)	0.000035 (0.9998)	0.000000 (1.0000)	0.000000 (1.0000)	0.000000 (1.0000)	0.000000 (1.0000)
A(1,1)	-0.111578* (0.0938)	-0.117746 (0.2286)	0.182683 (0.1380)	-0.388910*** (0.0018)	-0.273648 (0.1204)	-0.208970 (0.2120)
A(1,2)	0.139707*** (0.0015)	0.165229*** (0.0001)	-0.089889* (0.0833)	0.159287*** (0.0004)	0.042713 (0.2097)	-0.219834*** (0.0000)
A(2,1)	-0.433197*** (0.0061)	-0.346332 (0.1965)	0.361863 (0.3357)	-0.604157** (0.0158)	-0.454300 (0.3513)	0.946407*** (0.0038)
A(2,2)	-0.656055*** (0.0000)	-0.244574 (0.2523)	-0.194610* (0.0604)	-0.479481*** (0.0000)	-0.010155 (0.9456)	0.123848 (0.3042)
B(1,1)	0.967275*** (0.0000)	1.038147*** (0.0000)	0.118485 (0.5155)	0.600026*** (0.0004)	0.885448*** (0.0000)	0.374524 (0.1234)
B(1,2)	0.018974 (0.5348)	0.115324** (0.0284)	-0.295815*** (0.0002)	0.206436*** (0.0001)	0.131461*** (0.0000)	0.191833*** (0.0035)
B(2,1)	-0.230027** (0.0174)	-0.890338 (0.1249)	1.911202*** (0.0000)	-0.228891 (0.5001)	-2.475540*** (0.0057)	1.483094*** (0.0038)
B(2,2)	0.738418*** (0.0000)	0.082101 (0.7927)	0.808169*** (0.0000)	0.616241*** (0.0000)	0.576509*** (0.0001)	0.340303 (0.1952)

Note: 1 and 2 denote Shanghai Stock Exchange Composite Index and one of the Asia-Pacific stock markets indices; Figures in parentheses indicate the P value;

*, **, *** indicate statistical significance level at 10%, 5%, and 1% respectively

Table 6. 8: Joint Wald tests for Spillover Effects

	Bullish Period			Bearish Period		
	Wald ₁	Wald ₂	Wald ₃	Wald ₁	Wald ₂	Wald ₃
Hong Kong	3.083756 (0.2140)	4.700532 (0.0953)	6.165305 (0.1871)	32.113091* (0.0000)	13.634043* (0.0011)	33.749641* (0.0000)
Taiwan	106.622995* (0.0000)	79.419670* (0.0000)	320.626241* (0.0000)	37.531811* (0.0000)	105.150032* (0.0000)	165.801145* (0.0000)
Singapore	21.592896* (0.0000)	21.546309* (0.0000)	59.843426* (0.0000)	10.287484* (0.0058)	10.594857* (0.0050)	14.495786* (0.0059)
Thailand	102.369595* (0.0000)	78.572890* (0.0000)	413.338671* (0.0000)	23.093954* (0.0000)	10.215324* (0.0061)	45.757074* (0.0000)
Malaysia	54.022913* (0.0000)	81.230886* (0.0000)	637.202714* (0.0000)	75.951660* (0.0000)	29.925968* (0.0000)	286.794064* (0.0000)
Japan	159.479230* (0.0000)	154.07227* (0.0000)	7301.56358* (0.0000)	10.131818* (0.0063)	7.758537* (0.0207)	13.519233* (0.0090)
South Korea	100.05732* (0.0000)	136.10611* (0.0000)	1519.04618* (0.0000)	19.795907* (0.0001)	3.782238 (0.1509)	30.656252* (0.0000)
Australia	17.104304* (0.0002)	15.066922* (0.0005)	36.005632* (0.0000)	21.773363* (0.0000)	62.934271* (0.0000)	132.289569* (0.0000)
Indonesia	13.052045* (0.0015)	145.52435* (0.0000)	266.03475* (0.0000)	17.534087* (0.0002)	6.115199* (0.0470)	21.518277* (0.0002)
New Zealand	7.446385* (0.0242)	18.301347* (0.0001)	29.939206* (0.0000)	78.196660* (0.0000)	8.228500* (0.0163)	139.60658* (0.0000)
India	15.68379* (0.0004)	84.750526* (0.0000)	171.62964* (0.0000)	45.913960* (0.0000)	22.575138* (0.0000)	108.23909* (0.0000)

Note: Under the following null hypotheses H_0^i , Wald_i are Chi-Square distributed (for i=1, 2, 3). H_0^1 : A(1,2)=B(1,2)=0 (no spillover in variance from China to one of the Asia-Pacific markets); H_0^2 : A(2,1)=B(2,1)=0 (no spillover in conditional variance from one of the Asia-Pacific markets to China); H_0^3 : A(1,2)=A(2,1)=B(1,2)=B(2,1)=0 (no spillover in variance between China and one of the Asia-Pacific markets). P-values are in brackets to indicate the significance level. * denotes significance at the 5% level.

6.7 Concluding Remarks and Policy Implementation

This chapter examines the relative importance of the Chinese stock market in the Asia-Pacific region. We investigate daily price and volatility transmissions across alternative types of markets during the Chinese financial market crisis in 2015. We utilise different forecasting techniques - including Bayesian VAR and BEKK GARCH models - to investigate volatility spillovers and financial linkages between Asia-Pacific stock markets.

We find no evidence of a long-term cointegration relationship between Chinese and Asia-Pacific stock markets, providing the potential for international investors to enhance their diversification benefits over the long run. Looking at spillovers of asset prices, all stock market indices are significantly affected by their own past shocks with a strong autoregressive feature. The results indicate that price behaviours in the Chinese stock market are different during crisis and non-crisis periods. Specifically, price spillover transmitted from the Chinese stock market to other regional markets was more important during the bullish period as foreign prices are significantly influenced by the changes in China's domestic prices in seven Asia-Pacific stock markets. However, the price dynamics differ when the Chinese stock market declines. These results indicate that the Asia-Pacific financial markets are significantly affected by 'good news' emanating from the Chinese stock market during the bullish period. We also observe that the Chinese stock market adjusts to the information flow from Asia-Pacific markets during the crash period, implying significant evidence of shock transmission from these markets to China. Importantly, these price spillovers show robustness in the turbulent period when compared to the stable period.

Examining the transmission of shocks and volatility spillovers, we observe strong evidence of the shock and volatility spillover effects between China and Asia-Pacific stock markets for both stable and turbulent periods. Looking at the estimated results from the pairs in our BEKK model, volatility transmission from China is statistically significant in ten Asia-Pacific markets in the bearish period, confirming strong interdependencies among these markets during the stress period. We observe that about 28.87%, 19.91%, 20.69% and 22.70% of Hong Kong, Taiwan, Thailand and Malaysia market volatilities are affected by the Chinese market during the crisis period respectively. Thus the volatility transmission from China to these markets is captured as 28.87%, 19.91%, 20.69% and 22.70% change, respectively for the above markets for every 1% change in Chinese market volatility.

In the opposite direction, we cannot ignore the impacts from the Asia-Pacific region in influencing volatility in the Chinese market. The enhanced shock spillovers from the former to the latter are observed, indicating the reality of significant influence from outside China. We see a persistent and robust effect on shock and volatility between Chinese and Asia-Pacific stock markets both during bullish and crisis periods. Thus, Asia-Pacific markets are deeply interrelated with the outcomes of the Chinese market. Surprisingly, our results show that the stock market of New Zealand reveals no evidence of price and shock spillovers with China during the bearish period. This absence of interdependence between New Zealand and China during the turmoil period is important because it provides significant benefits of portfolio diversification opportunities to investors during these stressful times.

Overall, there is a significant difference in the pattern of price and volatility spillovers between the two sample periods and it can be seen that the Chinese stock market behaves differently during bullish and bearish periods. We conclude that Asia-Pacific stock markets are responsive to market volatility from China during the crisis, showing the importance of China as a strategic financial centre in this region. As a majority of pairs of $A(1,2)$ and $B(1,2)$ are statically significant, the implication is that shocks in one market have considerable influence on other emerging markets' volatility. We see that the Chinese stock market is becoming more integrated with regional financial markets and that the regional factors also matter. However, China's rising regional influence and increasing regional integration may reduce diversification opportunities in both China and the Asia-Pacific neighbours.

Our results imply that the China and Asia-Pacific region now are more financially integrated and highlight the influential role of China. It is not surprising that China's geographical position, strong economic linkage and greater trade and financial relations with Asia-Pacific countries and regions are fostering regional success and connectivity. There are important policy implications that can be drawn from our analyses. Based on our results, both Chinese and Asia-Pacific markets can forecast each other at different stages, providing important market trading signals.

Following the implementation of broad-based market reforms to support liberalisation of investments, regional policy-makers should explore complementarities and diversity to support new growth opportunities. As argued by OECD (2009), China needs to broaden efforts to reduce regulatory complexity and improve its financial institution's standards to align with international expectations and best practices. To reduce future risk of crisis and

minimise market uncertainties, capital account liberalisation should carefully be approached and progressively eased to ensure macroeconomic stability. While streamlining public institutions and strengthening governance structures will promote competitive and efficient market operations, this will also inspire international investors' confidence and foster flows of savings and investment.

Our evidence indicates that, given the increased interdependencies among the Asia-Pacific economies, Chinese financial crisis increases the risk exposure and vulnerabilities of financial institutions in the region. In a crisis, it seems to be the case that these economies may experience a sudden acceleration of systemic risk through deteriorations in both the capital flow and foreign market activities. Thus co-volatility among these markets seems to be high during episodes of financial stress. This calls for a need to put in place a financial stabilisation mechanism against contagion originating from regional markets and international partners (Kim et al., 2015). Given the increasing importance of China, policy-makers are suggested to monitor Chinese financial and economic conditions carefully and establish warning systems to forecast potential financial crises. Further financial liberalisation reforms need to be introduced to improve the market's efficiency in China. These may include improving information disclosure and bringing accounting and reporting standards up to the international standards, putting in place clear insolvency procedures and moving towards market-driven interest rates. The Chinese government and securities regulatory authority should welcome policies that will improve the transparency of stock markets, promote harmonisation of financial rules, strengthen regulations and supervision and enhance better corporate governance. It is also necessary to promote a stronger and friendlier relationship with countries in the Asia-Pacific region so that economic and financial cooperation is promoted with more economic and trading agreements between China and Asia-Pacific region.

Chapter 7: Dynamic Relationship between Chinese Stock Market and its Index Futures Market: the Influence from Qualified Foreign Institutional Investors (QFII)

7.1 Introduction

The stock index futures market plays an important role in the financial market sector. Economic influences of the futures market include: fostering the price discovery process; helping to hedge against investment risks; reducing risk, affecting stock market volatility and supporting timely information transmission. If the markets are perfectly efficient, a new set of information is transmitted into cash (or spot) and futures markets simultaneously. As a result, prices in the two markets adjust to the new equilibrium immediately. In reality, however, futures markets are more efficient and lead the spot market because of lower transaction cost, fewer restrictions imposed on trading, higher transaction efficiency and a greater degree of leverage effects and benefits.

Many studies have attempted to examine the joint behaviour of spot and futures markets in order to investigate the spot and futures pricing dynamics, understand the structure of information flows between the two markets and examine whether price changes in future markets provide efficient forecasts of the price of the spot market. Following the introduction of the first stock index futures (S&P 500 Index futures) in the US in 1982, stock index futures contracts quickly grow to be one of the most important investments and risk management tools in the financial markets (CME, 2014). Studies also reveal that the stock index futures market plays a primary role in price discovery process on the spot market (Kawaller et al., 1987; Harris, 1989; Stoll and Whaley, 1990).

As Chinese financial markets develop in a way, similar to other developed nations, additional financial instruments are introduced to provide investors with more choices for investment and risk management. One important financial instrument introduced in recent years is the CSI 300 index futures contract which was launched on 16 April 2010. This instrument provides a mechanism by which investors are able to short sell as a means of managing a risky portfolio. Since the introduction of CSI 300 index futures, the volatility of the underlying stock market has generally decreased (Fang and Chen, 2011; Zhang et al.,

2011; Wu, 2011; Chen et al., 2013; Hou and Li, 2014). However, research on the joint behaviours of CSI 300 futures and spot markets as well as volatility spillover is inevitably limited in a newly established stock index futures market. Nonetheless, Yang et al. (2012) find no evidence of price discovery in the CSI 300 futures market at its initial stage but report a strong bi-directional dependence in the intraday volatility of the futures and spot markets. Contrary to the previous findings, Hou and Li (2013) find evidence of price discovery of CSI 300 futures market one year after its introduction.

The Chinese stock index futures market has continued to grow with the China Securities Regulatory Commission (CSRC) in its mission to expand the market allowing Qualified Foreign Institutional Investors (QFII) to trade on CSI 300 index futures from 4 May 2011. This provides an opportunity for foreign capital flows to participate in the Chinese stock index futures market. Several studies argue that foreign institutional investors may be classified as informed traders and may have significant predictive power in the option and futures markets (Lee et al., 2013; Chang et al., 2009). So far, there has been no empirical research on the impact of QFII to the Chinese stock index futures market, including the price discovery role, volatility estimation and the spillover effect between CSI 300 futures and spot markets. This research attempts to fill this gap in the literature by examining the impact of the introduction of QFII on the Chinese stock index futures markets. This analysis of the joint behaviour relationship between Chinese stock index futures market and its spot market aims to enhance the understanding of the dynamic relationship between the two markets. In particular, the research will assess the effect of QFII on the price discovery function, the volatility of the Chinese stock index futures market and the volatility spillover effects between the futures and spot markets. All of the above is critical to understanding the efficiency of CSI 300 futures and spot markets and the mechanism of information transmission which is also crucial for investors and regulators to make financial decisions.

To examine the joint behaviours relationship between CSI 300 futures and spot markets, this study undertakes the following. Firstly, the research contributes to the existing literature by examining the price discovery dynamics between the two markets with reference to the level of openness to foreign institutional investors on the local stock index futures market. Most of the existing studies on the price discovery role of futures markets look at developed countries and only a few of them use data from emerging markets. To date, Yang et al. (2012) and Hou and Li (2013) are the only studies examining the price discovery role of

CSI 300 futures market using data from China. However, their work is subject to different time intervals, different research methods with the diverging empirical results. It is noted that the allowance for QFII to trade on CSI 300 futures market was an important and significant event. It is therefore timely to examine the impact of the openness to foreign institutional investors on the price discovery role of CSI 300 futures.

Secondly, this chapter will investigate the influence of QFII on the volatility of the CSI 300 futures market. The existing literature only concentrates on the impact of the Chinese stock index futures market on the spot market (Fang and Chen, 2011; Zhang et al., 2011; Chen et al., 2013), but not on the impact of the QFII on the Chinese stock index futures market. In this regard, our study will be among the first to examine the influence of QFII on both price discovery and volatility behaviour of the Chinese stock index futures market and will contribute to understanding volatility transmission, risk level and efficiency after the introduction of QFII. We use dynamic GARCH models and intraday data to capture the volatility of the two markets and their spillover effects because high-frequency data contains much more important information about market behaviours. This study will provide important insights into the mechanism of information transmission between these two markets. Additionally, our findings provide important implications for policy-makers.

The rest of this chapter is organised as follows. Section 7.2 discusses the background of the Chinese economy, Chinese financial markets and the Qualified Foreign Institutional Investor (QFII) scheme. Section 7.3 discusses the preliminary literature on the price discovery role of the futures markets and spillover effect between the futures and spot markets. Section 7.4 provides detail information about the data used in this study. Section 7.5 describes the methodological framework. Section 7.6 presents the empirical results. Finally, this chapter outlines the policy implementation and conclusion in section 7.7.

7.2 Background of the Chinese Economy and Financial Markets

7.2.1 The Development of the Chinese Stock Markets

The fast growth of the Chinese economy in recent years has contributed to the development of Chinese capital markets, especially the stock market. This is emphasised by the establishment of two stock markets (Shanghai and Shenzhen) which was a milestone event.

The 3rd plenary session of the 11th Party Congress in 1978 launched “Gai Ge Kai Fang” or the “opening China” policy which paved the way for the emergence of the Chinese capital markets. The Shanghai Stock Exchange (SSE) was established on 26 November 1990 with the Shanghai Composite Index launched on 15 July 1991, and the Shenzhen Stock Exchange (SZSE) was established on 1 December 1990 with the Shenzhen Composite Index launched on 4 April 1991. At the end of 1991, the Shanghai Stock Exchange had 8 listed stocks and 25 members, while the Shenzhen Stock Exchange had 6 listed stocks and 15 members (SSE, 2014; SZSE, 2014; CSRC, 2008). With the establishment of the national trading platforms in Shanghai and Shenzhen Stock Exchanges, a centralised regulatory framework and a formal legal system were put in place. Several other significant reforms were implemented to raise the number of listed companies and securities and increase total market capitalisation. By 31 December 2014, there were 3758 listed securities in the Shanghai Stock Exchange, among which there were 1039 listed stocks on SSE with a total market capitalisation of RMB 2,439,740,200 million (SSE, 2015b). On the same date, there were 2523 securities listed on the Shenzhen Stock Exchange, among which there were 1657 listed stocks on SZSE with a total market capitalisation of RMB 12,857,293,600 million (SZSE, 2015). Table 7.1 Panel A and B summarise the information about listed securities on both stock exchanges. In terms of market capitalisation, the Chinese stock market has become the second largest one in the world just behind the US stock market since it surpassed Japan at the end of 2007.

7.2.2 The Historical Development of the Chinese Index Futures Markets

On 8 April 2005, the China Securities Index Co. Ltd introduced the CSI 300 index, which is a capitalisation-weighted stock market index designed to replicate the performance of the most representative 300 stocks traded in the Shanghai Stock Exchange and Shenzhen Stock Exchanges. The value of the CSI 300 is normalised relative to a base of 1000 on December 31, 2004. This index represents about 60% of capitalisation in the Shanghai and Shenzhen Stock Exchanges and aims to reflect the price fluctuation and performance of the Chinese A-Share markets (CSI, 2014). Based on the CSI 300 index, the CSI 300 index futures contracts were introduced on 16 April 2010 by the China Financial Futures Exchange (CFFEX). The introduction of the CSI 300 index futures contracts provided an opportunity for domestic investors in the market to short sell and hedge risks. As a new financial instrument, the average daily trading turnover of the CSI 300 futures contracts for the first three months hit

RMB230.8 billion, but the open interests were quite low, suggesting that the trading was mainly driven by speculative purpose. The CSI 300 futures contracts attracted a good deal of attention from domestic investors initially and became one of the most actively traded financial instruments in China since its introduction (Yang et al., 2012). However, CSI 300 futures trading is relatively restrictive compared to other developed markets, as the domestic retail and institutional investors are required to fulfil several tough conditions in order to open an account²⁴. The tough entry barriers to the CSI 300 futures market lead to the institutional investors rather than individual investors dominating the CSI 300 futures market. To enable the foreign investors to trade CSI 300 futures, CSRC promulgated “The Guidelines on the Participation of Qualified Foreign Institutional Investors in Stock Index Futures Trading” which regulates the participation of Qualified Foreign Institutional Investors (QFII) since 4 May 2011(CSRC, 2011). As a result, the Chinese stock index futures market is open to foreign investors. The margin requirements for the current and following month contracts were set at 15%, and for the next two calendar quarters contracts, the margin is increased to 18% (Yang et al., 2012). On 29 June 2012, two years after the introduction of the CSI 300 futures contracts, the margin requirements were reduced to 12% for all futures contracts in order to promote more trading.²⁵ Detailed information about the CSI 300 index futures contract is shown in Table 7.2.

²⁴ Retail investors must satisfy the following conditions to open an account:

1. The money available in the margin account must be not less than RMB500000
2. Have basic knowledge of stock index futures and pass the relevant test
3. Must have prior trading experience on mock index futures trading (more than 20 transaction records within at least 10 days) or commodities futures trading (more than 10 commodity future transaction records within the past three years)
4. No bad credit record and the circumstances that laws and rules ban for index future trading

Institutional investors must satisfy the following conditions to open an account:

1. The net asset of the institution must be not less than RMB1000000
2. The money available in margin account must be not less than RMB500000
3. Have relevant decision-making mechanism and operation procedure
4. The relevant people have basic knowledge on stock index futures and pass the relevant test
5. Must have prior trading experience on mock index futures trading (more than 20 transaction records within at least 10 days) or commodities futures trading (more than 10 commodity future transaction records within the past three years)
6. No bad credit record and the circumstances that laws and rules ban for index future trading

²⁵ http://www.cffex.com.cn/flfg/jysgz/xgywtz/201211/t20121114_16794.html

7.2.3 The Introduction of QFII

Before the introduction of the QFII scheme, investments in A shares (RMB-denominated shares listed on the Shanghai and Shenzhen stock exchanges) were only available to domestic Chinese individual and institutional investors and prohibited to foreign investors. Foreign investors were only permitted to invest locally in the US and Hong Kong-Dollar-denominated B shares. Early in 2001, both academic think tanks and practitioners suggested that the Chinese government introduce the QFII scheme (which is a temporary institutional arrangement) that would allow licensed foreign institutional participants to invest in Chinese securities market as soon as possible, in order to compensate for the absence of foreign institutional investors. Since China became a member of the World Trade Organization (WTO) in December 2001, several measures had been implemented to liberalise the Chinese economy. One of the most important changes was the Provisional Measures on Administration of Domestic Securities Investments by Qualified Foreign Institutional Investors. The provisional measures allowed some of the largest overseas institutions to invest in the Chinese local stock markets. In 2002, China launched the QFII arrangement. Following this, the China Securities Regulatory Commission (CSRC) and the People's Bank of China (PBOC) jointly took a significant step in the development of the Chinese securities markets by issuing the Provisional Measures on Administration of Domestic Securities Investments by Qualified Foreign Institutional Investors (the QFII Provisional Measures) on 5 November 2002. This came into force on 1 December 2002 allowing foreign investors to enter China's capital market directly. The QFII scheme has had some positive impacts on the Chinese capital market. In particular, this policy introduction improved corporate governance of listed companies, enhanced a value investing approach and long-term investment philosophy and enriched investor structure within these markets. The QFII scheme represents a notable departure from China's strict adherence to capital controls (Yeo, 2003; SSE, 2015a; Fergusson and McGuinness, 2004; Liu et al., 2012). Table 7.3 summarises some important milestones of the QFII scheme. However, the QFII scheme is only a temporary institutional arrangement that allows licensed foreign institutional investors to invest in Chinese stock markets.

With the continuous development and improvement of the QFII scheme, foreign institutional investors have gradually become important institutional investors in the Chinese stock markets. According to the data released by China's State Administration of Foreign

Exchange, as at 31 December 2012, China has awarded a combined \$37.443billion of QFII quotas to 169 foreign institutions (Wang et al., 2014). The active participation of QFII in Chinese securities markets can facilitate the reform on the interest rate and RMB exchange rate, promote the opening of Chinese capital markets and globalisation of RMB, improve the governance and performance of listed companies and improve the markets' efficiency. As CSRC introduced the stock index futures markets in 2010, experts and practitioners also suggested that QFII should be permitted to invest in the stock index futures markets. CSRC promulgated "The Guidelines on the Participation of Qualified Foreign Institutional Investors in Stock Index Futures Trading" which regulates the participation of Qualified Foreign Institutional Investors (QFII) on 4 May 2011 (CSRC, 2011). Accordingly, these investors can only trade the stock index futures for hedging purposes. Several studies show that foreign investors may have an information edge because they are equipped with better investment experience and expertise. In this case, the foreign institutional investors may be informed traders and have significant predictive power in option and futures markets (Lee et al., 2013; Chang et al., 2009). This chapter will examine the important role of the QFII on the price discovery function of the Chinese stock index futures markets.

Table 7. 1: Information about Listed Securities and Companies
 Panel A: Information about Listed Securities and Companies in Shanghai Stock Exchange

Year	No. of Listed Companies	No. of New Listed Companies	No. of Listed Securities	No. of Listed Stocks	Market Capitalisation (RMB 100 million)
1999	484	46	574	525	14580.47
2000	572	88	657	614	26930.86
2001	646	75	744	690	27590.56
2002	715	70	826	759	25363.72
2003	780	67	914	824	29804.92
2004	837	61	996	881	26041.34
2005	834	3	1069	878	23096.13
2006	842	13	1126	886	71612.38
2007	860	25	1125	904	269838.87
2008	864	6	1184	908	97251.91
2009	870	9	1351	914	184655.21
2010	894	26	1500	938	179007.24
2011	931	39	1691	975	148376.22
2012	954	26	2098	998	158698.44
2013	953	1	2786	997	151165.27
2014	995	43	3758	1039	243974.02

Source: The fact books of Shanghai Stock Exchange (SSE), various issues

Panel B: Information about Listed Securities and Companies in Shenzhen Stock Exchange

Year	No. of Listed Companies	No. of Listed Securities	No. of Listed Stocks	Market Capitalisation (RMB 100 million)
1999	463	540	504	1189070.42
2000	514	596	557	2116008.44
2001	508	598	550	1593163.91
2002	508	615	551	1296540.62
2003	505	627	548	1265279.40
2004	536	673	578	1104122.72
2005	544	708	586	933414.96
2006	579	768	621	1779151.76
2007	670	868	712	5730201.98
2008	740	964	782	2411453.09
2009	830	1165	872	5928389.28
2010	1169	1590	1211	8641535.43
2011	1411	1938	1453	6638187.21
2012	1540	2190	1581	7165918.18
2013	1536	2328	1577	8791192.44
2014	1618	2523	1657	12857293.60

Source: The fact books of Shenzhen Stock Exchange (SZSE), various issues

Table 7. 2: Specifications of CSI 300 Index Futures

Contract Elements	Specifications
Underlying Index	CSI 300 Index
Contract Multiplier	CNY 300
Unit	Index point
Tick Size	0.2 point
Contract Months	Monthly: current month, next month, next two calendar quarters (four total)
Trading Hours	09:15 am - 11:30 am, 01:00 pm - 03:15 pm
Trading Hours on Last Trading Day	09:15 am - 11:30 am, 01:00 pm - 03:00 pm
Limit Up/Down	+/-10% of settlement price on the previous trading day
Margin Requirement	12% of the contract value
Last Trading Day	Third Friday of the contract month, postponed to the next business day if it falls on a public holiday
Delivery Day	Third Friday, same as "Last Trading Day"
Settlement Method	Cash Settlement
Transaction Code	IF
Exchange	China Financial Futures Exchange (CFFEX)

Source: China Financial Future Exchange, http://www.cffex.com.cn/en_new/sspz/hs300zs/.

Table 7. 3: Milestones of the Qualified Foreign Institutional Investors (QFII) Scheme

Year	Events
2002	QFII scheme began pilot run
2005	Total QFII quota increased from US\$4 billion to US\$10 billion
2006	Formalised QFII rules and lowered qualification requirements
2007	Total QFII quota increased to US\$30 billion
2009	Regulations on foreign exchange regarding QFII revised: 1. Increased upper limit for single QFII's quota 2. Loosened restrictions on capital transfer
2011	1. QFII allowed to invest in stock index futures 2. RMB QFII scheme launched
2012	1. Total QFII quota increased to US\$80 billion 2. RQFII quota increased to RMB 270 billion 3. QFII rules revised again: a) Lowered qualification requirements substantially b) Raised shareholding upper limit c) Offered more investment options 4. Regulations on foreign exchange regarding QFII revised again: a) Increased upper limit for single QFII's quota b) Increased frequency of capital remittance c) Loosened restrictions on accounts d) Allowed QFII to open futures accounts
2013	1. Revised RMB QFII rules: a) Diverse the types of institutions involved in the pilot scheme b) Relaxed restrictions on investment scope 2. Total QFII quota and number of QFII keep increasing

Source: http://www.szse.cn/main/en/QFII/include/About_QFII.html

7.3 Review of Recent Literature

The stock index futures market plays an important role for investors because it helps the price discovery process and enhances information transmission mechanisms. Futures contracts can also reduce the cost of trading and facilitate the transfer of risks associated with the underlying market (Puttonen, 1993). Price discovery in futures markets is commonly defined as the use of futures prices to determine expectations of cash market prices (Yang et al., 2012). So the price discovery function implies that there is a relationship (short run or long run) between the futures and spot markets. If the market is perfectly efficient, the information will spread to the spot and futures markets simultaneously. However, due to many other factors which contribute to the market's inefficiency, it is not possible for the information to arrive simultaneously, and hence a lead-lag relationship exists between the two markets in reality. The existing literature on price discovery mechanism mainly focuses on developed markets such as the US, the UK and Germany. There is substantial evidence to suggest that the stock index futures market can contribute to price discovery and thus to the efficiency of the spot market. Focusing on the US market, Kawaller et al. (1987) found that the S&P 500 futures market can lead the spot market by 20 to 45 minutes while the lead from cash prices to futures prices rarely extends beyond 1 minute. Harris (1989) observes that the S&P 500 futures market led the spot market during a ten-day period surrounding the October 1987 stock market crash. Stoll and Whaley (1990) provide evidence suggesting that S&P 500 and MMI futures returns tend to lead stock market returns by about 5 minutes on average, and lagged stock index returns also have a mild positive predictive impact on futures returns. In an earlier study, Wahab and Lashgari (1993) report evidence suggesting that the lead from S&P 500 and FT-SE100 futures to spot is more than the lead from spot to futures market, whereas Fleming et al. (1996) highlight that S&P 500 index futures lead the S&P 500 cash index, supporting the trading cost hypothesis.

For European markets, Martikainen and Puttonen (1994) point out that the Finnish stock index futures returns show significant Granger causality with Finnish stock market returns where the stock market is the lagging indicator. They further observe short selling restrictions to be the significant factor leading to a delay in the pricing process of securities in the Finnish stock market. Abhyankar (1995) reports empirical evidence suggesting that FT-SE 100 futures led the cash market in all three subperiods the study covers, but the cash market only has weak predictive power for the futures market in period 2 which is after the

big bang to the 1987 crash. In another empirical analysis, Kavussanos et al. (2008) point out that in FTSE/ATHEX-20 and FTSE/ATHEX Mid-40 markets, the futures returns lead is stronger than the cash index returns, as the futures market responds more rapidly to economic events than stock prices do. More recently, Bohl et al. (2011) find that price discovery is related to changes in the investor structure of the futures market and change in the composition of investors from individual to institutional investors lead to an increased price discovery contribution in the Polish blue-chip index WIG20 futures market.

For emerging markets, Zhong et al. (2004) suggest that volatility spillover effect is running from futures to spot in the Mexican futures market. Lee et al. (2013) observe results indicating that the Taiwan Stock Exchange Capitalisation Weighted Stock Index (TAIEX) futures market leads the spot market and that informed traders choose to trade in the futures market. Choy and Zhang (2010) argue that the regular Hang Seng index futures contract plays a dominant and leading role in price discovery, while the mini-futures contracts and cash index play minor roles. Similarly, Tao and Song (2010) indicate that the Mini Hang Seng Index futures contribute about 16.8% to price discovery, the Hang Seng Index Futures (HSIF) market still has the largest information share (about 71.0%), whereas the HSIF spot market has a 12.2% share. However, only Choi et al. (2015) examine the influence of the foreign trading on the bond futures market showing that foreign trading in the South Korean treasury bond futures market leads the price discovery process for the underlying bonds. For Chinese stock index futures markets, some research focuses on the impact of CSI 300 futures on the underlying spot market after the introduction of CSI 300 futures contracts. These studies (Fang and Chen, 2011; Zhang et al., 2011; Wu, 2011; Chen et al., 2013; Hou and Li, 2014) report evidence supporting the view that the introduction of futures decreased volatility in the stock market. There are a few other studies on the relationship between Chinese stock index futures and spot markets but only two research papers emphasise the price discovery role of CSI 300 futures. Thus Yang et al. (2012) find that the Chinese stock index futures market does not function well in its price discovery role at its initial stage and show strong bi-directional dependence in the intraday volatility of the futures and spot markets. In contrast, Hou and Li (2013) use high-frequency data to point out that the CSI 300 futures market has price discovery function 1 year after its introduction using 5 minutes intraday data for one month. However, the results of these two studies are contradictive and indicate the complex nature of the Chinese stock index futures markets, supporting the need for more detailed empirical analysis.

Apart from the information that is contained in prices, volatility is also an important source of information. Understanding the volatility spillover between the futures and spot markets is very important for predicting future volatility in both markets. This crucial information can help portfolio managers manage risks and enable policy-makers to assess the impact of market stability. The volatility spillover is related to the risk spillover effect between two markets and helps to visualize the risks relationships. Existing research evidence shows the possibility of bi-directional volatility spillovers between the futures and spot markets. Chan et al. (1991) report evidence of bi-directional intraday volatility spillovers between the S&P 500 futures and spot markets. Tse (1999) uses bivariate EGARCH to examine bi-directional volatility spillover effect between Dow Jones Industrial Average (DJIA) futures and spot markets, pointing out that the futures market volatility spillovers to the stock market are more prominent. Kang et al. (2013) use three high-frequency intraday data sets (10 minutes, 30 minutes, and 1 hour intervals) to investigate the existence of bi-directional volatility spillovers between KOSPI200 futures and spot markets and show that new information is filtered and reflected in futures and spot markets simultaneously. However, some studies only observe volatility spillover running from the futures market to the spot market (see Koutmos and Tucker (1996)).

In terms of the influence of foreign investors on the spillover effect, we find only one study exploring the impact of foreign capital inflows on the volatility spillover effect between the futures and spot markets (Kuo et al., 2008). These authors show that volatility spillovers from the futures to spot markets are stronger than the opposite direction after the opening up of Taiwan's futures markets to foreign investments. Their analysis suggests that the futures market leads the spot market in order to incorporate the arrival of new information after the adoption of liberalisation and deregulation policies in the Taiwan futures markets. Increased participation of foreign investments in Taiwan's futures market may have enhanced the rate of information flow and improved the quality and reliability of information transmissions of the local futures market, supporting the view that deregulation policies were more appropriate. On the other hand, there are fewer studies on the influence of the foreign investment in the relationship between the futures and spot markets that incorporate price discovery and volatility spillover. One concentrates on the price discovery (Choi et al., 2015) and another one examines the volatility spillover (Kuo et al., 2008). In this regard, our study aims to fill this gap in the literature and shed light on the influence of QFII on the relationship between Chinese stock index futures and spot markets.

7.4 Data and Descriptive Statistics

This study uses the CSI 300 futures prices and CSI 300 index data recorded at 5 minutes interval obtained from SIRCA and Thomson Reuters Tick History (TRTH). This chapter uses high-frequency data because it is believed that low-frequency data may not fully reflect the information transmission process within a short horizon when the speed of the information transmission is much faster.

The sample period is from 1 February 2011 to 29 July 2011. The chapter initially depicts the log price movements of the CSI 300 futures and CSI 300 index for the sample period. It is observed that the log prices of the futures and spot follow a similar trend, indicating that the two markets have strong co-movement and are more likely to be cointegrated. The sample is further divided into two sub-periods in order to investigate how the introduction of QFII impacts on the price discovery role of the futures market. The first subsample which is referred to as the Pre-QFII period, is from 1 February 2011 to 3 May 2011. The second sub-period is called the Post-QFII period, is from 4 May 2011 to 29 July 2011. To construct the continuous price series, the study uses the prices for the contract with the nearest expiration time until the last trading day and rolls over to the nearest contract given that the nearby futures contract is expected to be highly liquid and the most active.

Usually the trading of CSI 300 index futures is open from 09:15 am - 11:30 am and 01:00 pm - 03:15 pm (Beijing time) every weekday except the holidays, and the trading hours on the last trading day are 09:15 am - 11:30 am and 01:00 pm - 03:00 pm. However, both the Shanghai and Shenzhen Stock Exchanges start trading from 09:30 am to 11:30 am and then from 01:00 pm to 03:00 pm. To get reliable data, futures and spot prices recorded before either the stock or futures exchange market opens or after either of them closes are excluded from the sample. Thus the research only uses the data from 09:30 am to 11:30 am and from 01:00 pm to 03:00 pm on a trading day. If there is no observation in the interval, then the previous period's price is used. After eliminating weekends and holidays, our final data includes 6000 5-minute price observations for the full sample period (2900 observations for the Pre-QFII period and 3100 observations for the Post-QFII period).

The brief descriptive statistics for the intraday 5-minute log closing price of the CSI 300 futures and spot markets are provided in Table 7.4. The statistics reported include the mean, the standard deviation, the measure of skewness, the maximum value, the minimum

value, the measure of kurtosis (excess) and the Jarque-Bera (JB) statistics. The mean and standard deviation for the log futures and spot prices are very similar. The log futures and spot price series are both negatively skewed and exhibit a negative kurtosis (excess). Based on the Jarque-Bera statistics, which tests for normality and goodness of fit, the log futures and spot prices appear to be non-normally distributed (reject the null hypothesis for the normal distribution).

Figure 7. 1: The price movement of the CSI 300 futures and spot index

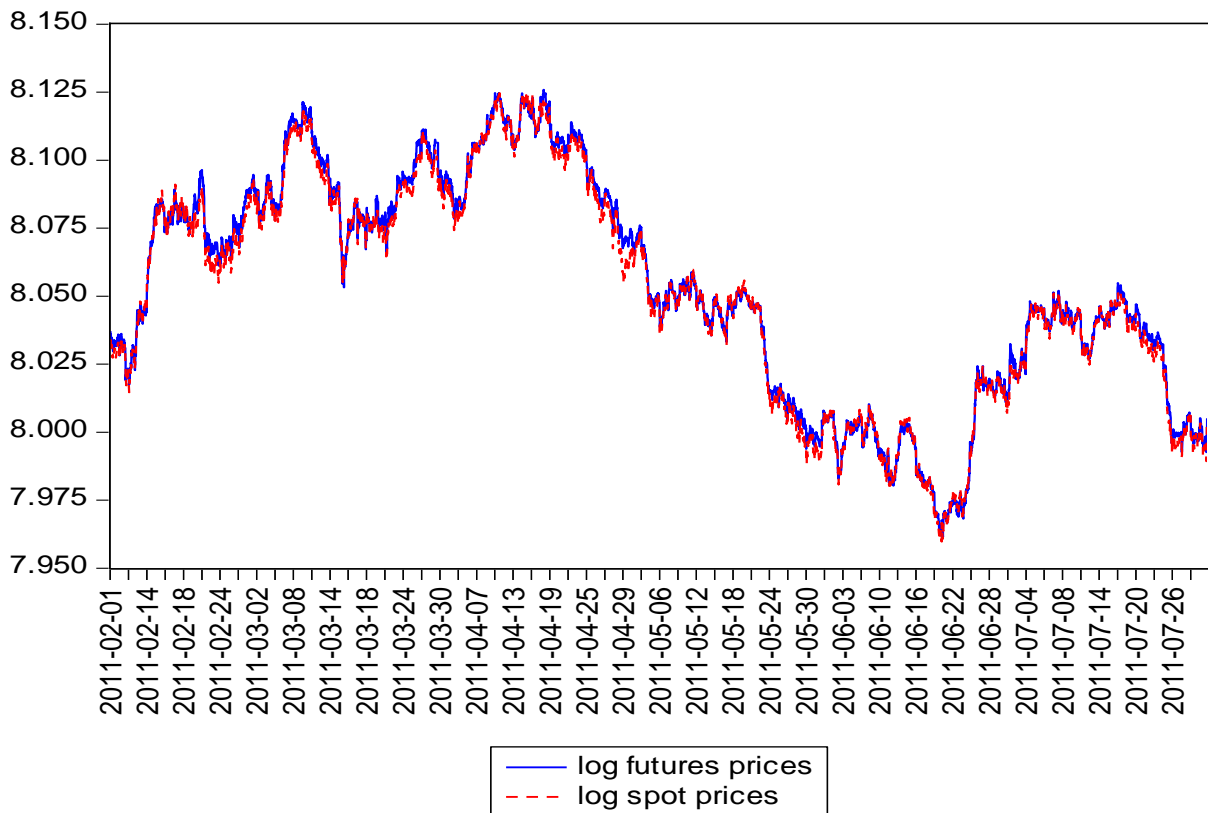


Table 7. 4: Summarised Descriptive Statistics

	Mean	Standard Deviation	Maximum	Minimum	Skewness	Kurtosis (excess)	Jarque-Bera
Futures prices	8.053055	0.041232	8.125927	7.961301	-0.174194	-1.025684	293.350071
Spot prices	8.051322	0.040693	8.125252	7.959612	-0.164462	-1.004363	279.234162

Note: Futures prices are the natural logarithms of the CSI 300 futures prices. Spot prices are the natural logarithms of the underlying CSI 300 index prices. It should be noted that the terms cash rate and spot rate are used interchangeably because they indicate the same thing in this context.

7.5. Research Methodology and Framework

7.5.1 Vector Error Correction Model (VECM)

This study initially explores the possibility of cointegration among our series. It is expected that the log closing futures price, F_t , and the log closing underlying cash price, S_t , are cointegrated. The research determines the order of integration of F_t and S_t using Augmented Dickey-Fuller test (Dickey and Fuller, 1981), PP test (Phillips and Perron, 1988) and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test (Kwiatkowski et al., 1992) to conduct our unit root tests. Table 7.5 presents the results of the unit root tests on the log prices of futures and spot markets and their first difference series for the sample period. Our null hypothesis is that the unit root (random walk) cannot be rejected for the log prices of the futures and spot markets, F_t and S_t series at the 5% level.

In order to address the potential problem of serial correlation, the study includes lagged difference terms of the dependent variable in the error term while conducting our unit root tests. From the results provided, the null hypothesis of unit roots cannot be rejected at the 5% level of statistical significance for both our series in the levels indicating that they are integrated of order one. However, the null is rejected and the estimated values are less than the critical values when the first difference of these variables is taken. Hence, it is concluded that F_t and S_t are non-stationary and integrated of order one $I(1)$. In order to examine the causality relationship, Granger test is applied and the result is shown in Table 7.6. It is observed that there is a bi-directional Granger causality relationship between the futures and spot prices.

The research next applies a Johansen-Juselius test (Johansen and Juselius, 1990) to conduct a cointegration analysis so as to determine whether F_t and S_t have a long-run relationship. The study starts with Vector Autoregressive (VAR) and considers the following equation:

$$Y_t = A_0 + \sum_{i=1}^p A_i Y_{t-i} + \varepsilon_t \quad (7.1)$$

$$\text{where } Y_t = \begin{pmatrix} F_t \\ S_t \end{pmatrix}$$

This VAR can be rewritten as:

$$\Delta Y_t = A_0 + \Pi Y_{t-p} + \sum_{i=1}^{p-1} \Gamma_i Y_{t-i} + \varepsilon_t \quad (7.2)$$

where $\Pi = \sum_{i=1}^p A_i - I$ and $\Gamma_i = \sum_{i=1}^{p-1} A_i - I$

The existence of a cointegrating relationship can be confirmed by examining the rank of the coefficient matrix Π . The number of cointegrating vectors (r) equals the rank of the coefficient matrix Π . The matrix Π can be written as a vector of adjustment parameters and cointegrating vectors $\Pi = \alpha\beta'$, where α is the matrix which represents the speed of adjustment parameters and β represents the matrix of cointegrating parameters. In order to determine the number of cointegrating vectors, the following two likelihood ratio statistics – trace statistic and maximum eigenvalue statistic – are represented as:

$$\text{Trace statistic: } \lambda_{\text{Trace}}(r) = -T \sum_{i=r_0+1}^n \ln(1 - \hat{\lambda}_i)$$

$$\text{Maximum eigenvalue statistic: } \lambda_{\text{Max}}(r) = -T \ln(1 - \hat{\lambda}_{r_0+1})$$

where T is the sample size and $\hat{\lambda}_i$ is the i th largest canonical correlation. The trace test assumes the null hypothesis of at most r_0 cointegrating vectors against the alternative hypothesis that $r_0 < \text{rank}(\Pi) \leq n$ where n represents is the possible cointegrating vectors. The maximum eigenvalue test is a test where the null hypothesis is that $\text{rank}(\Pi) = r_0$ against the alternative hypothesis of $r + 1$ cointegrating vectors. Our result is reported in Table 7.7. Both the trace and maximum eigenvalue statistics suggest that there is only one cointegrating relationship within the system. Therefore, F_t and S_t are cointegrated.

Using the multivariate cointegration framework (Johansen, 1991; Johansen, 1988), we assume that the long run relationship between the futures and spot markets can be represented as:

$$F_t = \alpha + \beta S_t + \varepsilon_t \quad (7.3)$$

The VECM is then represented as follows:

$$\Delta Y_t = \Phi + \Gamma Y_{t-1} + \sum_{i=1}^p \Pi_i \Delta Y_{t-i} + \varepsilon_t \quad (7.4)$$

$$\Delta Y_t = \begin{pmatrix} \Delta F_t \\ \Delta S_t \end{pmatrix}, Y_t = \begin{pmatrix} F_t \\ S_t \end{pmatrix}$$

where Δ is the first difference operator, $\Delta F_t = F_t - F_{t-1}$ and $\Delta S_t = S_t - S_{t-1}$, Φ is the constant term $\Gamma = \begin{pmatrix} \alpha_f, -\alpha_f \beta \\ \alpha_s, -\alpha_s \beta \end{pmatrix}$, $\Pi_i = \begin{pmatrix} \alpha_{f,i}, \beta_{f,i} \\ \alpha_{s,i}, \beta_{s,i} \end{pmatrix}$, $\varepsilon_t = \begin{pmatrix} \varepsilon_{f,t} \\ \varepsilon_{s,t} \end{pmatrix}$ is iid.

While expanding the above equation, the VECM representation can be written as:

$$\Delta F_t = \alpha_{f,0} + \alpha_f \mu_{t-1} + \sum_{i=1}^p \alpha_{f,i} \Delta S_{t-i} + \sum_{i=1}^p \beta_{f,i} \Delta F_{t-i} + \varepsilon_{f,t} \quad (7.5)$$

$$\Delta S_t = \alpha_{s,0} + \alpha_s \mu_{t-1} + \sum_{i=1}^p \alpha_{s,i} \Delta S_{t-i} + \sum_{i=1}^p \beta_{s,i} \Delta F_{t-i} + \varepsilon_{s,t} \quad (7.6)$$

where $\mu_{t-1} = F_{t-1} - \alpha - \beta S_{t-1}$ is the lagged error correction term ECT_{t-1} that can be interpreted as the speed of short-term adjustment factors. The term measures how fast the two markets react to the deviation from the long-term equilibrium. If the futures and spot prices are not at their equilibrium, a negative price change on the futures market and/or a positive price change on the spot market will correct the mispricing. Therefore, α_f is expected to be negative and α_s is expected to be positive. At the same time, the coefficients $\alpha_{s,i}, \beta_{s,i}, \alpha_{f,i}, \beta_{f,i}$ measure the short-term adjustment of the lagged price changes on the current price changes. The reaction of the futures price changes to its own lagged price changes and the lagged spot price changes are measured by $\alpha_{f,i}, \beta_{f,i}$, and the adjustment of the spot price changes to its own lagged price changes and the lagged futures price changes are measured by $\alpha_{s,i}, \beta_{s,i}$. The terms $\alpha_{s,0}$ and $\alpha_{f,0}$ are constant terms, and $\varepsilon_{s,t}$ and $\varepsilon_{f,t}$ are error terms which follow a bivariate independent identically distribution with mean zero.

In order to investigate how the openness to QFII affects the price discovery role of CSI 300 futures market, our VECM system with the modified version becomes:

$$\Delta S_t = \alpha_{s,0} + \alpha_s \mu_{t-1} + \sum_{i=1}^p \alpha_{s,i} \Delta S_{t-i} + \sum_{i=1}^p \beta_{s,i} \Delta F_{t-i} + \sum_{i=1}^p d_{s,i} D_i \Delta F_{t-i} + \varepsilon_{s,t} \quad (7.7)$$

$$\Delta F_t = \alpha_{f,0} + \alpha_f \mu_{t-1} + \sum_{i=1}^p \alpha_{f,i} \Delta S_{t-i} + \sum_{i=1}^p \beta_{f,i} \Delta F_{t-i} + \sum_{i=1}^p d_{f,i} D_i \Delta F_{t-i} + \varepsilon_{s,t} \quad (7.8)$$

where $D_i = 1$ if F_{t-i} is observed after 4 May 2011 when QFII were allowed to trade in the Chinese index futures market, 0 otherwise. The coefficients $d_{s,i}$ and $d_{f,i}$ capture the incremental impact of QFII on price discovery of futures market. If they are significant, the lead of the futures market strengthens. The lag selection is based on the AIC and SIC information criterion. AIC shows that the lag structure of 3 is appropriate, while SIC shows that the lag length of 6 is appropriate.

Table 7. 5: Unit Root Test Results

	ADF without Trend	ADF with Trend	PP without Trend	PP with Trend	KPSS
Ft	-1.037207	-2.374951	-1.026466	-2.366951	5.901382*
St	-1.110797	-2.465235	-1.085902	-2.446625	5.866126*
ΔFt	-79.77598*	-79.78663*	-79.74379*	-79.75485*	0.205927
ΔSt	-56.87908*	-56.89207*	-76.76557*	-76.77539*	0.199988

Note: The ADF and PP test the null hypothesis of non-stationarity of the series (the time series have a unit root), whereas the KPSS technique tests the null hypothesis: the time series are stationary. * indicates rejection of the null hypothesis at the 1% level of significance.

Table 7. 6: Granger causality Test

Null hypothesis	F-statistic	P value
Futures price does not Granger Cause spot price	68.9428	6.E-92
Spot price does not Granger Cause futures price	2.37025	0.0203

Note: Following the Akaike Information Criterion (AIC), seven lags have been selected as an optimal lag length. This is realistic given the high-frequency nature of our data.

Table 7. 7: Johansen-Juselius Cointegration Tests

Panel A: Trace test

Hypothesised No. of CE(s)	<u>7 lags based on AIC specification</u>			<u>4 lags based on SIC specification</u>		
	Eigenvalue	Trace statistic	P value	Eigenvalue	Trace statistic	P value
None	0.011412	70.11067	0.0000	0.014133	86.56301	0.0000
At most 1*	0.000208	1.245286	0.2645	0.000194	1.162507	0.2809

Panel B: Maximum eigenvalue test

Hypothesised No. of CE(s)	<u>7 lags based on AIC specification</u>			<u>4 lags based on SIC specification</u>		
	Eigenvalue	Max-Eigen statistic	P value	Eigenvalue	Max-Eigen statistic	P value
None	0.011412	68.86539	0.0000	0.014133	85.40050	0.0000
At most 1*	0.000208	1.245286	0.2645	0.000194	1.162507	0.2809

Note: AIC is Akaike Information Criterion and SIC is Schwarz Information Criterion. Our lag length selections are based on these two information criteria.

*indicate the stopping point based on the test results.

7.5.2 Univariate GARCH Approach

In order to examine volatility transmissions, both univariate and multivariate Generalized Autoregressive Conditional Heteroscedastic (GARCH) models are utilised to estimate the conditional variance of the futures and spot markets and investigate spillover effects. To examine the impact of QFII on the volatility of the Chinese stock index futures market, this study uses a modified univariate GARCH model. GARCH models were first suggested by Bollerslev (Bollerslev, 1986) in order to overcome the ARCH model's long lag structure (overparametrisation) and the negative coefficient problems. Empirical research shows that GARCH-based models not only provide a robust and reliable method of estimating volatility, but also fit time-varying volatility fairly well and are more parsimonious compared with ARCH models (Poon and Granger, 2003). GARCH models here therefore have become an important and popular econometric time series model for volatility forecasting. GARCH (1,1) is the simplest and one of the most popular models for volatility forecasting with conditional variance $\sigma_t^2 = a_0 + a_1\varepsilon_{t-1}^2 + b_1\sigma_{t-1}^2$.

In 1993, Glosten, Jagannathan and Runkle (Glosten et al., 1993) introduced the GJR GARCH (henceforth) which allows for asymmetric effects in the response (leverage effect). This allows for positive and negative shocks, which represent good news and bad news, to have different impacts on volatility forecasting. Under a GJR GARCH framework, the conditional variance equation is given as: $\sigma_t^2 = a_0 + a_1\varepsilon_{t-1}^2 + \varphi_1\varepsilon_{t-1}^2d_1 + b_1\sigma_{t-1}^2$, where d_1 is a dummy variable, when $\varepsilon_{t-1} < 0$, $d_1=1$, when $\varepsilon_{t-1} > 0$, $d_1=0$. Based on the GJR GARCH model, this research introduces a modified GJR GARCH model with the dummy variable. Initially, the study runs the following mean equation $F_t = c + \lambda F_{t-1} + \varepsilon_t$ and uses a Lagrange Multiplier Test to examine time-varying volatility (ARCH effect). It is observed that the LM statistics reject the null hypothesis of no ARCH effect in the residual term, indicating the presence of time-varying volatility in the Chinese stock index futures market. The research then estimates the modified GARCH model which is presented as follows:

The mean equation of GJR GARCH model is:

$$F_t = c + \lambda F_{t-1} + \varepsilon_t \quad \varepsilon_t \Big| \Omega_{t-1} \sim N(0, \sigma_t^2) \quad (7.9)$$

The conditional variance equation is:

$$\sigma_t^2 = a_0 + a_1 \varepsilon_{t-1}^2 + \varphi_1 \varepsilon_{t-1}^2 d_1 + b_1 \sigma_{t-1}^2 \quad (7.10)$$

The modified conditional variance equation is:

$$\sigma_t^2 = a_0 + a_1 \varepsilon_{t-1}^2 + b_1 \sigma_{t-1}^2 + \varphi_1 \varepsilon_{t-1}^2 d_1 + d * DUMMY_t \quad (7.11)$$

where Ω_{t-1} is the information set available at time $t - 1$, $DUMMY_t = 1$ if F_t is observed after 4 May 2011 when QFII were allowed to trade in the Chinese index futures market, otherwise 0. c is the intercept of the mean equation $a_0 \geq 0, a_1 \geq 0$ and $b_1 \geq 0$ to ensure a positive conditional variance. The ARCH effect is captured by the parameter a_1 , while b_1 captures the GARCH effect, and $a_1 + b_1$ measures the persistence of the impact of shocks to price to long-run persistence. A GARCH (1,1) process is weakly stationary if $a_1 + b_1 < 1$. The coefficient d captures the incremental influence of QFII on the volatility of the Chinese stock index futures market. Firstly, this chapter uses the GJR GARCH model to estimate the futures market volatility for the Pre-QFII and Post-QFII periods to observe changes in the coefficient of volatility parameters. Our results are detailed in Table 7.9. The study then applies the modified GARCH model with a dummy variable to estimate the futures market volatility for the whole sample period where the results are provided in Table 7.10.

7.5.3 Bivariate GARCH Approach Using BEKK GARCH

To examine the volatility spillovers between the futures and spot markets, the research further uses the GARCH (1, 1) model with Baba, Engle, Kraft and Kroner (BEKK) parameterisation assuming a conditional normal bivariate distribution for the vector of error distribution for the Pre-QFII and Post-QFII periods respectively. Engle and Kroner (1995) introduced the BEKK model to simplify the estimation process by reducing the number of parameters. The bivariate GARCH process can provide information on properties such as volatility spillover between markets, autoregressive tendencies, volatility persistence, and volatility clustering. Also, the BEKK model can economise on the parameters by imposing restrictions both within and across equations. The bivariate BEKK GARCH model is generally represented as:

$$Y_t = c_0 + \varepsilon_t \quad \varepsilon_t | \Omega_{t-1} \sim N(0, H_t)$$

$$H_t = C' C + A' \varepsilon_{t-1} \varepsilon_{t-1}' A + B' H_{t-1} B$$

$$H_t = \begin{bmatrix} c_{11} & 0 \\ c_{21} & c_{22} \end{bmatrix}' \begin{bmatrix} c_{11} & 0 \\ c_{21} & c_{22} \end{bmatrix} + \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}' \begin{bmatrix} \varepsilon_{1,t-1}^2 & \varepsilon_{1,t-1} \varepsilon_{2,t-1} \\ \varepsilon_{2,t-1} \varepsilon_{1,t-1} & \varepsilon_{2,t-1}^2 \end{bmatrix} \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} + \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}' H_{t-1} \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix} \quad (12)$$

Y_t is a vector of log prices for futures and spot $Y_t = \begin{bmatrix} F_t \\ S_t \end{bmatrix}$

ε_t is a vector of Gaussian error. $\varepsilon_t = \begin{bmatrix} \varepsilon_{f,t} \\ \varepsilon_{s,t} \end{bmatrix}$

c_0 is a vector of constants. $c_0 = \begin{bmatrix} c_f \\ c_s \end{bmatrix}$

The conditional variance of the bivariate GARCH (1,1) model can be alternatively represented as an expanded form:

$$h_{11,t} = c_{11}^2 + c_{21}^2 + a_{11}^2 \varepsilon_{1,t-1}^2 + 2a_{11} a_{21} \varepsilon_{1,t-1} \varepsilon_{2,t-1} + a_{21}^2 \varepsilon_{2,t-1}^2 + b_{11}^2 h_{11,t-1} + 2b_{11} b_{21} h_{12,t-1} + b_{21}^2 h_{22,t-1} \quad (7.13)$$

$$h_{22,t} = c_{22}^2 + a_{12}^2 \varepsilon_{1,t-1}^2 + 2a_{22} a_{12} \varepsilon_{1,t-1} \varepsilon_{2,t-1} + a_{22}^2 \varepsilon_{2,t-1}^2 + b_{12}^2 h_{11,t-1} + 2b_{12} b_{22} h_{12,t-1} + b_{22}^2 h_{22,t-1} \quad (7.14)$$

where H_t denotes conditional variance-covariance matrix, C is the matrix of intercept coefficients, A measures the effect of previous period shocks or news (ARCH effect), B measures the effect of previous conditional volatility (GARCH effect). In this model, the diagonal elements of matrices $A(a_{11}$ and $a_{22})$ and $B(b_{11}$ and $b_{22})$ capture the effect of own previous shocks and historical volatility to the current conditional variance, respectively. On the other hand, the off-diagonal elements of matrices $A(a_{12}$ and $a_{21})$ and $B(b_{12}$ and $b_{21})$ measure the cross-market effects of shocks and volatility (the volatility spillovers). The estimation aims to maximise the conditional log-likelihood function based on the Broyden, Fletcher, Goldfarb, and Shanno (BFGS) algorithm.

7.5.4 Bivariate GARCH Approach Using DCC GARCH

Bollerslev (1990) introduced a bivariate GARCH where the conditional correlation is constant. This model proposed a constant conditional correlation matrix which can simplify the estimation and inference. The conditional variance matrix is:

$$H_t = \begin{bmatrix} h_{11,t} & h_{12,t} \\ h_{21,t} & h_{22,t} \end{bmatrix} = \begin{bmatrix} \sigma_{11,t}^2 & \sigma_{12,t}^2 \\ \sigma_{21,t}^2 & \sigma_{22,t}^2 \end{bmatrix} \quad (7.15)$$

where $h_{ii,t} = \alpha_{i0} + \alpha_{i1}\varepsilon_{i,t-1}^2 + \beta_{i1}h_{i,t-1}$ and $h_{12,t} = \rho\sqrt{h_{11,t}}\sqrt{h_{22,t}}$

The model assumes the conditional correlation is constant over time. As a result, the variation in the conditional covariance is based on changes in each individual corresponding conditional variance. The model is therefore referred to as the Constant Conditional Correlation GARCH (CCC GARCH). However, in the real world, the conditional correlation may be time variant, because the business activities change over time and further affect the shocks in the financial markets. Engle (2002) proposed a time-varying correlation model: Dynamic Conditional Correlation GARCH (DCC GARCH) which can capture correlation dynamics among different time series. Engle's model can provide more sensitive results compared to the CCC GARCH model. Engle (2002) indicates that the specification of the dynamic conditional correlation (DCC) structure presents no obstacle to model estimation. The DCC model is based on univariate GARCH. The GARCH parameters are estimated from the GARCH(1,1) as:

The mean equation of GARCH model for futures is:

$$F_t = c_f + \varepsilon_t \quad \varepsilon_t \mid \Omega_{t-1} \sim N(0, \sigma_t^2) \quad (7.16)$$

The conditional variance equation is:

$$\sigma_t^2 = a_f + a_{1f}\varepsilon_{t-1}^2 + b_{1f}\sigma_{t-1}^2 \quad (7.17)$$

The mean equation of GARCH model for spot is:

$$S_t = c_s + \varepsilon_t \quad \varepsilon_t \mid \Omega_{t-1} \sim N(0, \sigma_t^2) \quad (7.18)$$

The conditional variance equation is:

$$\sigma_t^2 = a_s + a_{1s} \varepsilon_{t-1}^2 + b_{1s} \sigma_{t-1}^2 \quad (7.19)$$

The correlations are estimated as follow:

$$H_t = D_t R_t D_t \quad (7.20)$$

where D_t denotes $N \times N$ diagonal matrix with $\sigma_{1t}, \dots, \sigma_{Nt}$ and R_t is an $N \times N$ time variant matrix

$$R_t = \text{diag}(\sqrt{q_{11,t}}, \sqrt{q_{22,t}} \dots \sqrt{q_{nn,t}})^{-1} Q_t \text{diag}(\sqrt{q_{11,t}}, \sqrt{q_{22,t}} \dots \sqrt{q_{nn,t}})^{-1}$$

where $Q_t = \bar{Q}(1 - \alpha - \beta) + \alpha(\varepsilon_{t-1} \varepsilon_{t-1}') + \beta Q_{t-1}$ and \bar{Q} is the unconditional correlation matrix of the standardised residuals. The conditional correlation can be written as:

$$\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t} q_{jj,t}}} \quad (7.21)$$

where $q_{ij,t} = \bar{\rho}_{ij} + \alpha(\varepsilon_{i,t-1} \varepsilon_{j,t-1} - \bar{\rho}_{ij}) + \beta(q_{ij,t-1} - \bar{\rho}_{ij}) = (1 - \alpha - \beta)\bar{\rho}_{ij} + \alpha\varepsilon_{i,t-1} \varepsilon_{j,t-1} + \beta q_{ij,t-1}$

The model can be estimated by employing the Quasi-Maximum Likelihood Estimation (QMLE) suggested by Engle (2002) and the log-likelihood function can be written as the sum of a volatility component and a correlation component:

$$L(\theta, \phi) = L_v(\theta) + L_c(\theta, \phi) \quad (7.22)$$

The volatility component is

$$L_v(\theta) = -\frac{1}{2} \sum_{t=1}^T (n \log(2\pi) + \log |D_t| + r_t' D_t^{-2} r_t) \quad (7.23)$$

and the correlation term is

$$L_c(\theta, \phi) = -\frac{1}{2} \sum_{t=1}^T (\log |R_t| + \varepsilon_t' R_t^{-1} \varepsilon_t - \varepsilon_t' \varepsilon_t) \quad (7.24)$$

where θ denotes the parameters in D, ϕ denotes the additional parameters in R, T denotes the number of observations, n denotes the number of equations. Based on the estimated output, we can retrieve the dynamic correlation coefficients between the futures and spot markets from the DCC GARCH results. We then divide the sample into two sub-samples Pre-QFII and Post-QFII periods and use t-statistics to test the consistency of dynamic correlation coefficients between the futures and spot markets in these two periods. We define the null hypothesis as:

H₀: the means of the dynamic correlation coefficients between the futures and spot markets are the same for the periods of Pre-QFII and Post-QFII periods, $\mu_{DCC}^{pre-QFII} = \mu_{DCC}^{post-QFII}$.

The alternative hypothesis is:

H₁: the means of the dynamic correlation coefficients between the futures and spot markets are different for the periods of Pre-QFII and Post-QFII periods, $\mu_{DCC}^{pre-QFII} \neq \mu_{DCC}^{post-QFII}$.

The t-statistics will be calculated as follow:

$$t = \frac{\bar{\mu}_{DCC}^{pre-QFII} - \bar{\mu}_{DCC}^{post-QFII}}{\sqrt{\frac{s_{pre-QFII}^2}{n_{pre-QFII}} + \frac{s_{post-QFII}^2}{n_{post-QFII}}}} \quad (7.25)$$

where $\mu_{DCC}^{pre-QFII}$ and $\mu_{DCC}^{post-QFII}$ are the means of dynamic conditional correlation coefficients of the population for the Pre-QFII and Post-QFII periods. $\bar{\mu}_{DCC}^{pre-QFII}$ and $\bar{\mu}_{DCC}^{post-QFII}$ are the means of dynamic conditional correlation coefficients of the samples for the two periods. $n_{pre-QFII}$ and $n_{post-QFII}$ are the sample sizes, $s_{pre-QFII}^2$ and $s_{post-QFII}^2$ are the variances of dynamic conditional correlation coefficients of the samples for the two periods. The degree of freedom df is:

$$df = \frac{\left(\frac{s_{pre-QFII}^2}{n_{pre-QFII}} + \frac{s_{post-QFII}^2}{n_{post-QFII}} \right)^2}{\frac{\left(s_{pre-QFII}^2 / n_{pre-QFII} \right)^2}{n_{pre-QFII} - 1} + \frac{\left(s_{post-QFII}^2 / n_{post-QFII} \right)^2}{n_{post-QFII} - 1}} \quad (7.26)$$

If the t-statistics are significantly greater than the critical value, then H_0 , which supports the contention there is no impact of the QFII on the correlation between the futures and spot markets, will be rejected.

7.6 Major Findings and Results Analysis

7.6.1 Results on price discovery based on VECM

We first examine the price discovery role of the Chinese stock index futures market based on our VECM model. Table 7.8 displays the full sample parameters estimate using the VECM technique. The long-run coefficients (α and β) in the cointegrating vector are all significantly different from zero, implying that the Chinese stock index futures and spot markets are cointegrated in the long-term. The coefficients of the error-correction terms α_f are statistically significant and negative, implying that the short-run deviations of the futures prices would be adjusted in a downward direction towards long-term equilibrium if ECT is positive. The coefficients of the error-correction terms α_s are statistically significant and positive, implying that the short-run deviations of the spot prices would be adjusted in an upward direction towards the long-term equilibrium if ECT is positive. This result is consistent with previous literature like Zhong et al. (2004) but different from Bohl et al. (2011) and Hou and Li (2013). Zhong et al. (2004) point out that the sign of error correction term in the spot equation is the net outcome of two opposing effects, i.e. arbitrage effect and momentum effect.

The arbitrage effect supports the sign of error correction term for the spot market is positive. If the error correction term is positive, the spot index is under-priced, so arbitragers may buy the component stocks in the index. This action could cause the spot index to increase. However, the spot index is not a traded asset. On the other hand, the underlying stocks may also have a momentum effect and become more under-priced following a positive disequilibrium, leading to a negative sign for the spot market. Based on our finding, the arbitrage effect dominates Chinese stock index futures markets. The statistical significance of the error correction coefficients implies that both futures and spot markets do respond to the error of the previous period equilibrium to correct a shock in order to reach the long run equilibrium and participate in the price discovery in the long-term. For the spot equation, the

significant short-run adjustment coefficients of the lagged changes in the spot price (own price) confirm an autoregressive relationship in the spot market. All the coefficients of the lagged changes in the futures price are also significant, indicating that the futures market has a price discovery role on the spot market. For the futures equation, the coefficients of the lagged changes in the futures price are statistically insignificant, suggesting that the futures price does not exhibit a strong autoregressive relationship. The one lag coefficient ($\alpha_{s,1}$) of the changes in the spot price is statistically significant while other lags coefficients are not statistically significant. Hence the price discovery role of the spot market on the futures market is small and last only for short periods of time.

In terms of the absolute value, the cross-market coefficients ($\beta_{s,1}$) from futures to spot coefficients of the price discovery role of futures market are much larger than the opposite direction ($\alpha_{s,1}$). This implies that the lagged futures prices have stronger predictive power and the direction of causality is stronger from futures to spot markets in the short run. As well, the price discovery of the futures market can last much longer than the spot market, since all the coefficients (from $\beta_{s,1}$ to $\beta_{s,6}$) of the lagged futures price changes are significant for the cash equation, but only the first lagged spot price changes coefficient ($\alpha_{s,1}$) is significant for the futures equation.

The research observes a bi-directional asymmetric causality relationship (price discovery) between the futures and cash markets. The price discovery role of the futures market is much stronger than the underlying cash market, suggesting that news is first aggregated in the futures market and then transferred to the stock market. This is confirmed by the Granger causality test which is outlined in Table 7.6 where the results reveal that the causality from futures to spot is more prominent than from spot to futures. The null hypothesis whereby futures price does not Granger Cause spot price is significantly rejected at the 1% level while we can only reject the null hypothesis that spot price does not Granger Cause futures price at the 10% level. Therefore, the futures market dominates the cash market in the price discovery role.

Moving to the coefficients on dummy variables, only the coefficient of the lagged one futures price on the spot is statistically significant while all other coefficients are reportedly insignificant. Since the lagged-one coefficient $d_{s,1}$ is positive and statistically significant, this

evidence suggests that we can reject the null hypothesis that the introduction of QFII to invest in the Chinese stock index futures market has no impact on the price discovery role of the futures market. Given that the coefficient is positive, we believe the introduction of QFII to invest in the Chinese stock index futures market has increased the predictive power of the futures market with the outcome that the price changes of the spot market respond more to the price changes of the futures market after the introduction of QFII. Thus the price discovery role of the futures market could be enhanced after the introduction of the QFII. However, the magnitude of the coefficient is only 1/8 of the original price discovery coefficient and the enhancement can only exist for a short period of time (5 minutes under our model). Our results here therefore suggest that foreign institutional investors are better informed, and that opening of Chinese financial markets can improve local markets' efficiency. Overall, our results show that QFII does make a significant contribution to the price discovery role of the Chinese stock index futures market.

Table 7. 8: VECM Model Estimation Results
 Panel A: VECM Model based on SIC

<u>Cointegration Equation</u>			
β	-1.014592*	α	0.115752*
Cash Equation		Futures Equation	
$\alpha_{s,0}$	-4.05E-06	$\alpha_{f,0}$	-5.37E-06
α_s	0.019867*	α_f	-0.023761*
$\alpha_{s,1}$	-0.351708*	$\alpha_{f,1}$	-0.058081*
$\alpha_{s,2}$	-0.162628*	$\alpha_{f,2}$	-0.024105
$\alpha_{s,3}$	-0.087546*	$\alpha_{s,3}$	0.031325
$\alpha_{s,4}$	-0.065550*	$\alpha_{f,4}$	0.007740
$\alpha_{s,5}$	-0.065965*	$\alpha_{f,5}$	-0.019351
$\alpha_{s,6}$	-0.066324*	$\alpha_{f,6}$	-0.012138
$\beta_{s,1}$	0.422035*	$\beta_{f,1}$	0.000268
$\beta_{s,2}$	0.147205*	$\beta_{f,2}$	0.013100
$\beta_{s,3}$	0.126946*	$\beta_{f,3}$	-0.002044
$\beta_{s,4}$	0.072837*	$\beta_{f,4}$	0.012328
$\beta_{s,5}$	0.064689*	$\beta_{f,5}$	0.018075
$\beta_{s,6}$	0.052548*	$\beta_{f,6}$	0.007553
$d_{s,1}$	0.059527*	$d_{f,1}$	0.042946
$d_{s,2}$	0.038497	$d_{f,2}$	0.028441
$d_{s,3}$	-0.019762	$d_{f,3}$	-0.008655
$d_{s,4}$	-0.020936	$d_{f,4}$	-0.042211
$d_{s,5}$	0.026280	$d_{f,5}$	0.012486
$d_{s,6}$	0.010635	$d_{f,6}$	-0.001361

Note: SIC indicates that the optimal lag structure selection is 6. * indicates rejection of the null hypothesis at the 5% level of significance.

Panel B: VECM Model based on AIC

<u>Cointegration Equation</u>			
β	-1.014591*	α	0.115747*
Cash Equation		Futures Equation	
$\alpha_{s,0}$	-4.19E-06	$\alpha_{f,0}$	-5.08E-06
α_s	0.026337*	α_f	-0.023225*
$\alpha_{s,1}$	-0.337298*	$\alpha_{f,1}$	-0.057355*
$\alpha_{s,2}$	-0.142767*	$\alpha_{f,2}$	-0.023264
$\alpha_{s,3}$	-0.055328*	$\alpha_{f,3}$	0.029610
$\beta_{s,1}$	0.408957*	$\beta_{f,1}$	0.000592
$\beta_{s,2}$	0.127186*	$\beta_{f,2}$	0.011379
$\beta_{s,3}$	0.095683*	$\beta_{f,3}$	-0.002609
$d_{s,1}$	0.059537*	$d_{f,1}$	0.040848
$d_{s,2}$	0.040136	$d_{f,2}$	0.029190
$d_{s,3}$	-0.015928	$d_{f,3}$	-0.006169

Note: AIC indicates that the optimal lag structure selection is 3. * indicates rejection of the null hypothesis at the 5% level of significance.

7.6.2 Result on the univariate GARCH

Table 7.9 presents the volatility estimates for the Chinese stock index futures market based on the univariate GARCH model for the Pre-QFII and Post-QFII periods. All the coefficients except the intercept term for the Pre-QFII period are statistically significant at the 5% level. Firstly, the magnitude of the coefficient a_1 has increased while that of coefficient b_1 has decreased from the Pre-QFII period to the Post-QFII period. The coefficient a_1 increases from 0.0256 in the pre-QFII period to 0.0475 in the Post-QFII period, implying that the recent information (news in the previous period) becomes more influential in terms of the information transmission after the introduction of QFII. An increase in a_1 is expected to decrease b_1 since the improvement in the rate of flow of recent news would cause the old information to have less influence on current conditional volatility. This is confirmed by the decrease in coefficient b_1 from 0.6742 in the Pre-QFII to 0.5929 in the Post-QFII period. Thus the recent news may be having more impact on the current conditional than the old news volatility following the introduction of QFII, suggesting an improvement of the market efficiency. The sum of a_1 and b_1 measures the persistence of the conditional volatility,

whereby if the sum is higher and closer to unity, it implies more persistence. In other words, the volatility is more integrated (or permanent).

We observe that the sum of a_1 and b_1 slightly decreases from 0.6998 in the Pre-QFII to 0.6405 in the Post-QFII period, suggesting a decrease in the persistence of the shocks after the introduction of QFII. Less persistence means the price can adjust more quickly based on more available information, indicating that the market can absorb more information and become more efficient after QFII. If the sum of a_1 and b_1 is less than 1, the GARCH model is mean reverting and conditionally heteroskedastic, but has a constant unconditional variance (Engle, 2001). The unconditional variance, given by $1/(1 - a_1 - b_1)$, is 3.3322 in the Pre-QFII period and 2.7818 in the Post-QFII period. This demonstrates that the Chinese stock index futures market becomes less volatile after the introduction of QFII. This is expected since the participation of foreign investors is more likely to improve market competitiveness, enhance allocative efficiency and increase liquidity level. The market is also more likely to be less volatile when the participants are better informed and smarter because the impact of noise traders may be reduced. In addition, the asymmetric coefficient is significantly positive in the Pre-QFII period, but significantly negative in the Post-QFII period, implying that the foreign investors may influence the market asymmetric effect. However, this influence does not seem to last for a long period of time as the asymmetric coefficient becomes positive when we expand the Post-QFII sample period.

Table 7.10 reports the parameter estimates of our modified univariate GARCH model with the dummy variable. All the coefficients (except the intercept term) are statistically significant. The coefficient λ is significant suggesting that the futures price is autoregressive. The coefficient a_1 measures the impact of the lagged square error term in the mean equation which relates to the impact of price changes of the previous period on current volatility. A higher a_1 implies that the recent news has a greater impact on conditional volatility. The coefficient b_1 captures the impact of the lagged conditional volatility on the current volatility and therefore shows the effect of the old news (already available news) on the current conditional volatility. Generally, we do observe evidence of significant ARCH and GARCH effects in the conditional volatility of the futures prices in China. The coefficient ϕ_1 capturing the asymmetric effect is positive and significant. This result denotes that the conditional volatility of the Chinese stock index futures market intensifies in response to the bad news in the previous period. Coefficient d represents the impact of the introduction of

QFII on the conditional volatility. This term is negative and statistically significant, thus implying that the conditional volatility of the Chinese stock index futures market had reduced after the introduction of QFII. This finding is consistent with the results in Table 7.9. It means that the Chinese stock index futures market is less volatile (or risky) and may become more efficient after allowing QFII to trade in that market. Overall, we see evidence whereby the introduction of QFII does influence conditional volatility, risk level and market efficiency of the Chinese futures market

Table 7. 9: Estimation Results using GJR GARCH Model for Pre-QFII and Post-QFII

Parameters	Pre-QFII		Post-QFII	
	Estimate	P Value	Estimate	P Value
Mean Equation				
C	0.022065*	0.0605	0.018546**	0.0208
λ	0.997276***	0.0000	0.997681***	0.0000
Variance Equation				
a_0	6.74E-07***	0.0000	6.64E-07***	0.0000
a_1	0.025686***	0.0001	0.047590***	0.0000
φ_1	0.112285***	0.0000	-0.034481**	0.0358
b_1	0.674212***	0.0000	0.592937***	0.0000
$a_1 + b_1$	0.699898		0.640527	
$1/(1-a_1-b_1)$	3.332200		2.781850	

Note: *, **, *** indicate statistical significance level at 10%, 5%, and 1% respectively

Table 7. 10: GJR GARCH Model Results with Dummy Variable

Parameters	Estimates	P Value
Mean Equation		
c	0.001291	0.7374
λ	0.999839***	0.0000
Variance Equation		
a_0	7.26E-07***	0.0000
a_1	0.033799***	0.0000
φ_1	0.020348**	0.0169
b_1	0.630056***	0.0000
d	-1.71E-07***	0.0000

Note: *, **, *** indicate statistical significance level at 10%, 5%, and 1% respectively

7.6.3 Estimation Result from BEKK GARCH

Table 7.11 outlines the spillover effects of intraday volatilities between the Chinese stock index futures and spot markets for the Pre-QFII and Post-QFII periods on the basis of the BEKK GARCH model conditional variance-covariance equation. The diagonal parameters (i.e., a_{11} and a_{22}) of the matrix A capture past shock effects of each market on the current volatility (the dependence of the volatility in one market on its own lagged innovations). These coefficients are statistically significant for both periods, implying that there are ARCH effects in both futures and spot markets. The diagonal parameters (b_{11} and b_{22}) of the matrix B measure past volatility effects on the current volatility in each market and are found to be statistically significant for both periods. This indicates that there are strong GARCH effects in both markets. Based on this result, we see that the current conditional variances of both futures and spot prices are considerably influenced by their own past shocks and past conditional variance, respectively. This is consistent with previous studies, as ARCH and GARCH effects in both spot and futures markets have been observed in many markets (Pati and Rajib, 2011; Kang et al., 2013). We see that for the futures market, a_{11} increases from 0.723 in the Pre-QFII period to 0.905 in the Post-QFII period. Accordingly, b_{11} decreases from 0.672 in the Pre-QFII period to 0.406 in the Post-QFII period.

Since matrix A measures the effect of recent news, while matrix B captures the effect of old news, our finding suggests that recent news has more impact on the conditional volatility of the futures market than old news and can be channelled to the futures market more quickly after the introduction of QFII. This finding confirms the influence of the QFII on the volatility of the futures market. However, the result for the spot market is contrary to that for the futures market. We find that the spot market coefficient, a_{22} decreases from 0.792 in the Pre-QFII period to 0.573 in the Post-QFII period. The magnitude of the coefficient b_{22} increases from 0.548 in the Pre-QFII period to about 0.868 in the Post-QFII period. Contrary to the results of the futures market, this implies that the old news in the market wields more influence on the conditional volatility of the spot market. These results show that the capital from foreign institutional investors seems to move from the spot market to the futures market after the introduction of QFII.

Looking at the volatility spillover effect, the off-diagonal parameters of the matrices A and B measure cross-market impacts, capturing shock spillovers and volatility spillovers between futures and spot markets, respectively. The coefficient a_{12} captures the cross-market

effect from the lagged spot market error to the futures conditional variance, while a_{21} captures the cross-market effect in the opposite direction. The variable b_{12} measures the cross-market effect from the lagged conditional variance of the spot market to the conditional variance of the futures market, while b_{21} indicates the cross-market effect in the opposite direction. All the coefficients in matrices A and B (except a_{12} and b_{12}) are statistically significant for the Pre-QFII period and all the coefficients in matrices A and B are statistically significant for the Post-QFII period. We observe that the parameters a_{12} and b_{12} are not statistically significant in the Pre-QFII period, indicating that the lagged shocks and historical conditional volatility in the futures market do not affect the current conditional volatility of the spot market. We see that there is a spillover effect from the spot market to the futures market, but none from the futures market to the spot market before the introduction of QFII. This finding is very interesting, because we have not seen previous evidence showing that the spot volatility can lead the futures volatility (Pati and Rajib, 2011).

We believe this could be explained by the fact that high entry barriers in the futures market decrease the information gathering and sharing, since many individual investors and foreign participants are prohibited from trading in the futures market (Yang et al., 2012). However, a_{12} and b_{12} become statistically significant in the Post-QFII period. Thus we see spillover effect from the futures market to the spot market in terms of both the lagged shocks and the historical conditional volatility after the introduction of QFII. We believe that the introduction of QFII could have improved the information transmission running from the futures to spot markets in terms of volatility spillovers. Moving to the spillover effect from the spot to the futures markets, a_{21} and b_{21} are statistically significant at the 5% level for the Post-QFII period. So we see a bi-directional spillover effect between the spot market and the futures market for the Post-QFII period. Our result here is in line with Yang et al. (2012) who also report a strong bi-directional intraday volatility spillover effect between Chinese stock and futures markets. In addition, the magnitude of the spillover effect from the spot market to the futures market increases, as a_{21} and b_{21} improve from 0.0765 to -0.1585 and -0.10117 to 0.2428 in absolute value.

These results confirm that the spillover effect from the spot market to the futures market is stronger after the introduction of the QFII. The explanation could be that improvement in the information absorbing capacity for the futures market can transfer new information to the spot market more quickly and efficiently. This makes the spot market more

sensitive to innovations originating in futures market after the introduction of foreign institutional investments in the futures market. Under the impact of the futures market, the spot market also becomes more efficient and absorb the information more quickly than ever before, so the spot market has been more powerful, and therefore the spot market can influence more on the futures market. Therefore the openness to foreign institutional investments for the futures market could improve the market efficiency of both futures and spot markets since both markets become more interactive and more influential in terms of the market volatility after QFII.

Table 7. 11: Estimation Results from the BEKK GARCH for Pre-QFII and Post-QFII

Parameters	Pre-QFII		Post-QFII	
	Estimate	P Value	Estimate	P Value
Mean equation				
c_f	8.085962	0.0000	8.015408	0.0000
c_s	8.082976	0.0000	8.014019	0.0000
Variance equation				
c_{11}	-0.001324	0.0000	0.000910	0.0000
c_{21}	-0.001263	0.0000	0.000767	0.0000
c_{22}	0.000568	0.0000	-0.000484	0.0000
a_{11}	0.723047	0.0000	0.905869	0.0000
a_{12}	0.008211	0.7814	0.176832	0.0000
a_{21}	0.076551	0.0085	-0.158596	0.0003
a_{22}	0.792532	0.0000	0.573523	0.0000
b_{11}	0.672902	0.0000	0.406317	0.0000
b_{12}	0.021928	0.6073	-0.222614	0.0000
b_{21}	-0.101170	0.0102	0.242878	0.0000
b_{22}	0.548431	0.0000	0.868532	0.0000

Note: This table shows the estimates of the multivariate BEKK GARCH(1,1) model. The parameters c_{ij} , a_{ij} , and b_{ij} are the elements of the matrices C, A and B, as presented in the methodology section.

7.6.4 DCC GARCH Modelling Estimation Results

Table 7.12 presents the results of our DCC GARCH technique while Figure 7.1 shows the time-varying conditional correlations calculated from DCC GARCH model. All the coefficients are statistically significant and this suggests that DCC GARCH is a fitting dynamic model. The coefficients a_{1f} , b_{1f} , a_{1s} and b_{1s} are statistically significant at the 1% level, hinting that both futures and spot markets have ARCH and GARCH effects. The parameter α which captures the past shocks on current conditional correlation and β that reflects the impact from the past correlation are statistically significant. Results imply that the conditional

correlations are not constant and support our expectation that there exist dynamic correlations and that the DCC GARCH model is preferred to the CCC GARCH model. Since the sum of α and β is less than the unity, the dynamic conditional correlations are mean reverting (Engle, 2002). This means that after a shock, the conditional correlation will return to the long run equilibrium (unconditional level). From Figure 7.2, we observe the strong correlation between the two markets, since the correlation coefficients are very near to 1. Notice that the dynamic conditional correlation decreases and becomes more volatile in the month of May (Figure 7.2). This could be due to the introduction of QFII, since foreign investors who are more professional, more informed and seemingly smarter can influence the market efficiency to further change the dynamic conditional correlation between the futures and spot markets. There are more obvious spikes in Figure 7.2 in the Post-QFII periods. This shows that arbitrageurs become less active after the introduction of QFII, resulting in more periodic loosening of the link between the two markets (Tao and Green, 2012). This may be because the Chinese authority only allows foreign institutional investors to trade on the futures market for hedging purposes so that foreign arbitrageurs are prohibited in the market. From the Table 7.13, the mean of the DCC coefficients appears to decrease slightly and the variance (standard deviation) of the DCC coefficients significantly increases. The t-test results which are consistent with those in Figure 7.2 show that the dynamic conditional correlation between the futures and spot market decreases and becomes more volatile after the introduction of QFII. From the t-test result, we can reject the null hypothesis that the means of the dynamic correlation coefficients remain the same for the periods of Pre-QFII and Post-QFII. Thus, the futures and spot markets become less correlated after the introduction of QFII.

We believe there could be three possible scenarios in terms of the volatility changes to explain our findings here. Firstly, the futures market experiences some variation given that the spot market remains unchanged; secondly, the spot market experiences changes given that the futures market remains stable; and thirdly, both futures and spot markets become more dynamic following the introduction of QFII. Based on our analysis, the third scenario is more likely to be the case here where both futures and spot markets have operational improvement. However, since when foreign institutional investment in the Chinese stock index futures market was introduced for the first time, we expect that the volatility of the futures market should change more significantly than the spot market. Consequently, the correlation between the two markets should reduce. This reduction in the dynamic conditional correlation may affect the hedging strategies adopted. In fact, we believe the optimal hedge ratio may slightly

decrease after the introduction of QFII. Under the DCC approach, this reduction is minimal because the mean of the DCC coefficients (0.977651) is still very near to 1. Also, since the dynamic conditional correlation becomes more volatile, this may lead to frequent trading in order to get the perfect hedging based on the DCC method. As a result, the transaction cost could greatly increase, which may affect the hedging performance.

Table 7. 12: The Result on DCC GARCH

GARCH Equation	Estimate	P value
c_f	8.046267	0.0000
a_f	0.000002	0.0000
a_{1f}	0.612005	0.0000
b_{1f}	0.453024	0.0000
c_s	8.046287	0.0000
a_s	0.000003	0.0000
a_{1s}	0.703729	0.0000
b_{1s}	0.370782	0.0000
Correlation Equation		
α	0.196720	0.0000
β	0.802946	0.0000

Figure 7. 2: DCC Coefficients between the Futures and Spot Markets

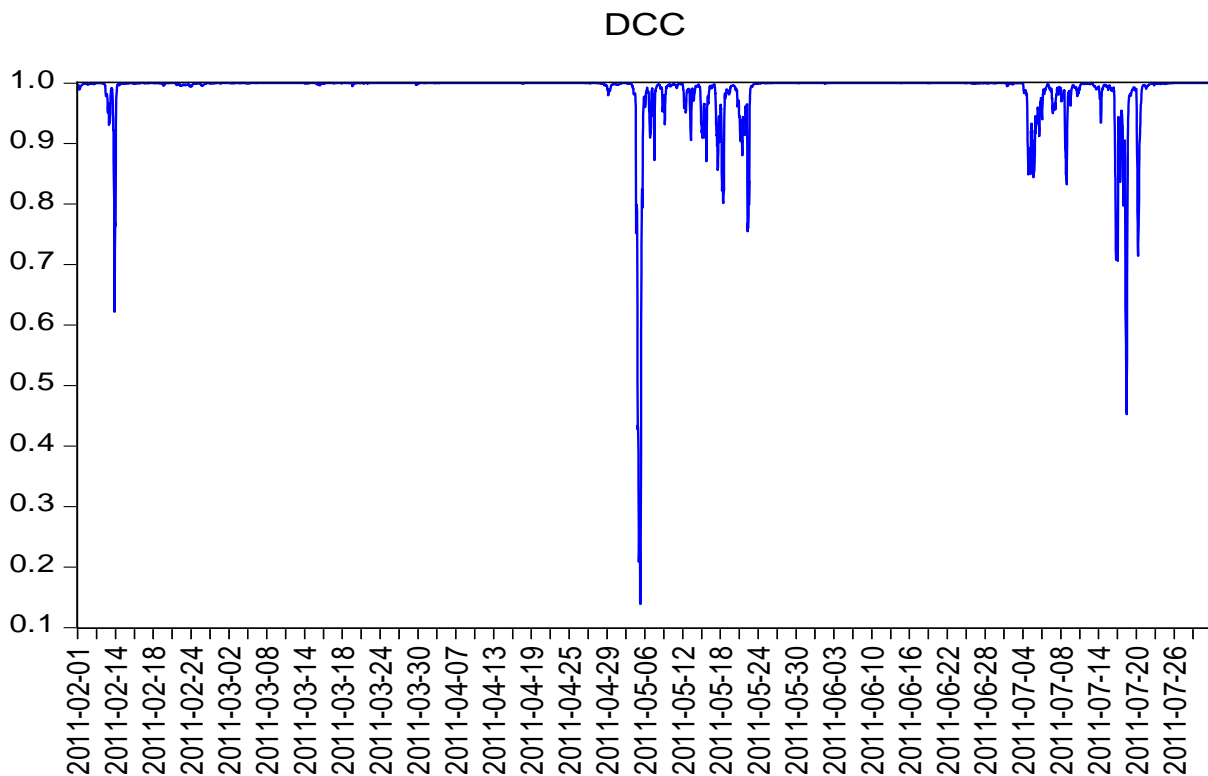


Table 7. 13: t-Test Results of Pre-QFII and Post-QFII Periods

	Pre-QFII	Post-QFII
Mean	0.997798	0.977651
Sample size	2900	3100
Standard deviation	0.016870	0.072774
Variance	0.000285	0.005296
t	14.98994 (0.0000)	
df	3453	

Note: df is degree of freedom

7.7 Conclusion and Policy Implications

This study aims to examine the impact of QFII on the dynamic relationship between the Chinese stock index futures and its underlying markets. Our empirical research using VECM models provides a detailed analysis of the price discovery role of the Chinese stock index futures market and the impact of the QFII on the price discovery role of the futures market.

We also look at the volatility of the futures market, the spillover effect and the dynamic conditional correlation between the Chinese stock index futures and spot markets.

Both univariate and multivariate GARCH models including GJR GARCH, BEKK GARCH and DCC GARCH are used to estimate the volatility. A high-frequency data (5 minutes intervals) of the Chinese stock index futures market and its underlying index (CSI 300 index) is utilized to analyse the market dynamic behaviours. The dataset is from 01/02/2011 to 29/07/2011 which is 3 months before and after the QFII can trade in the Chinese stock index futures market. For the price discovery role, our empirical results indicate evidence of a bi-directional asymmetric lead-lag relationship between the Chinese stock index futures and spot markets. The relationship is a strong lead from the futures market to the spot market but a weak lead vice versa. It is reported that not only the magnitude of the price discovery role of the futures market is greater than for the spot to futures direction, but also the price discovery role of the futures market can last much longer than that from the spot to futures direction. The findings here suggest that the Chinese stock index futures market plays an important price discovery role for the Chinese stock market.

In terms of the influence of the QFII, the introduction of the QFII seems to have enhanced the price discovery role of the futures market and increased the predictive power of the futures market. Price changes in the spot market respond more to price changes in the futures market after the QFII reforms. We see that foreign institutional investors could be more informed. Our analysis indicates that foreign institutional investors' participation in the Chinese stock index futures market could be useful for the price discovery role and improve information gathering and sharing. After the introduction of QFII to the CSI 300 futures market, recent news has a stronger impact than the old news on the current conditional volatility. The persistence of the conditional volatility, the conditional and unconditional volatilities of the futures market decreases after the introduction of QFII. It is observed that the Chinese stock index futures market is less volatile (or risky) and may be more efficient after allowing QFII to trade in that market.

Our results also show that foreign capital inflows can influence the market asymmetric effect in the short-term. In addition, the introduction of QFII enhances the spillover effect from the futures market to the spot market, since we find uni-directional spillover effect from spot to futures market before QFII, but bi-directional spillover effect between the two markets after QFII. The results suggest an improvement of the information transmission running from the futures to spot markets in terms of volatility spillovers. The research also finds that the mean of dynamic conditional correlation between the futures and

spot market decreases and conditional correlation becomes more volatile after the introduction of QFII.

A number of important policy implications arise from our empirical analysis. We find that the openness of the Chinese stock index futures market to foreign institutional investors may reduce the risk level, enhance the rate of information flow and improve the quality of information and further market efficiency. The liberalisation of the Chinese stock index futures market makes a positive contribution to the development of the Chinese financial system. Consequently, China should continue opening its financial markets to the world so that its financial markets become more innovative and competitive. Given the recent growth in financial globalisation and the country's accession to the WTO, it is critical that China continues to develop its financial markets so that the risk associated with large capital inflows can be better managed. The gradual move towards a market-based financial system and China's transition towards a market-oriented banking sector should also be supported by required changes in legal and institutional frameworks. Consistently, Chen et al. (2009) suggest that enhanced financial openness and a more independent market-based monetary and exchange rate policy in China will improve the efficiency of investment and provide better access for households to both credit and saving facilities. QFII reform only allows foreign institutional investors to trade on the stock index futures market, but many foreign individual investors are still prohibited from participating in that market. China should consider establishing several policies which allow qualified individual investors to participate in the trading of the stock index futures market. Both foreign and local investors will benefit from information sharing and risk management strategies and become more active in their participation once China's capital market is more open. However, the adopted financial liberalisation should follow a proper sequential process in order to avoid greater risk exposure and crisis. Finally, the Chinese authority needs to set up better regulations to limit local and foreign arbitrage trading and encourage trading with a hedging purpose to guarantee a safe, reliable, efficient financial system.

Chapter 8: Return and Volatility Transmissions across the International Oil Market, China's Stock and Commodity Markets with Implications for Portfolio Management

8.1 Introduction

The fast development in commodity markets has led to the rapid growth of investments over the past two decades, despite commodity prices experiencing substantial fluctuations. The global booming demand has been driving force behind the observed upwards swings in commodity prices in recent decades. However, the GFC which pushed many economies into recession dramatically affected commodity markets. The observed turbulence in stock markets across developed and developing countries has changed financial investors to consider alternative investment asset classes to diversify their portfolios potentially. This has also increased research interest in commodity markets to re-examine direct and indirect market dynamics amongst global asset markets. As investors have to make important choices in the asset allocation process and enhance access to information systems, the rapid growth of investment in commodities via commodity futures markets is observed in recent years. Differently, it is well known that crude oil, agricultural markets, metal commodities and stock markets are characterized by periods of sharp fluctuations and noisy signals. Given these more volatile dynamic properties, it is very crucial that portfolio managers and policy-makers understand these dynamic interdependencies amongst the widely traded commodities, energy prices and stock markets. This therefore calls for a deeper analysis of spillover effects among these markets.

From a theoretical perspective, the economic and financial factors that drive commodity and equity markets are different. Returns of these two asset classes are expected to be less or even negatively correlated, which may potentially lead to portfolio diversification benefits (Daskalaki and Skiadopoulos, 2011; Gorton and Rouwenhorst, 2006). Empirically, some existing studies highlight that by including commodities into the stock portfolio, investors can be better off and hedge some risk (Jensen et al., 2000). With time and as awareness of this beneficial effect increases, more investors may reallocate portions of their investment into commodity markets, enhancing the commodity markets' liquidity and efficiency and fostering capital inflows. This may then further lead to market co-movements

of some sort (Belousova and Dorfleitner, 2012). Recent empirical studies indicate that interdependencies between commodity and equity may have become stronger and prices more volatile since the GFC (Delatte and Lopez, 2013; Creti et al., 2013; Silvennoinen and Thorp, 2013). The more recent and rapid growth of index investment in commodities markets may have contributed to these markets being integrated with the equity and bond markets (Tang and Xiong, 2012).

Within the commodity markets, the interaction between the crude oil market and other commodity has increasingly caught the attention of financial analysts. Commodity traders (particularly oil traders) concurrently pay close attention to both commodity and stock market movements in order to infer the directions as they optimise their investment portfolios (Choi and Hammoudeh, 2010). Some empirical studies have pointed out the existence of interdependencies between oil and non-energy commodities (including both metals and agriculture). Commodity prices may tend to move together as some of the common macroeconomic factors such as interest rates, inflation rates and industrial production are able to influence different commodities simultaneously (Hammoudeh and Yuan, 2008). Ji and Fan (2012) indicate that the substitution of fossil fuels with biofuel along with some hedging strategies against inflation is caused by high oil prices. This has also influenced the dynamic linkages between oil and other commodities in recent years. Increases in oil price could possibly create shortfalls in power supply in some countries so that the production of precious metal commodities may be affected (Sari et al., 2010).

However, the existing literature in this area focuses on global commodity markets and developed equity markets, whereas studies on spillover dynamics with regards to emerging market remain limited. While Chinese investors are becoming more important in terms of investment choices and influencing the global trading, the commodity futures market is taking off within and beyond China. To our knowledge, not many studies examine the contagion effects between oil price and Chinese non-energy commodity markets. Understanding the dynamic linkages between commodity and equity markets in emerging countries is important since volatility spillovers and its transmission are the central issues that affect asset allocations and asset substitutions strategies. Thus the existing literature gap motivates us to investigate the spillover effects between these three markets, providing a deeper and rigorous analysis of interdependence structure.

Our research focuses on the context of China because its increasing financial integration and economic transformation policies will attract more foreign capital and provide access to equity markets. While China's future markets are definitely becoming more actively traded by the day, the country has been launching more innovative financial instruments which assist investors to mitigate the risks of price volatilities. Secondly, the role of China in global commodity markets is also changing after years of an unprecedented economic growth rate. Due to continuous urbanisation, industrialisation and openness to world trade, the demand for raw materials in China has rocketed. China is now the world's largest consumer of several commodities and its share of global trade in commodities is substantial. In 2014, China, the main driving force behind global growth, consumed more than half of the world's iron ore, about half of the world's refined copper, primary aluminium and smelted and refined nickel, representing roughly half of global demand for major base metals. As the largest producer of iron ore and aluminium, the second largest producer of copper, China is also the centre of metal production indicating its importance in the world industrial production (IMF, 2015). In terms of oil consumption, China overtook Japan to become the world's second largest oil consumer and largest net oil-importing country since 2003 (Zhang and Qu, 2015). Greater dependence on imported crude oil will result in close linkage between global oil price and Chinese economy, and thus further affect Chinese local financial markets. On the other hand, due to the increasing demand for energy and non-energy commodities simultaneously, the interlinkages between Chinese equity market, commodity markets and international oil price movements are expected to be enhanced.

The study will contribute to the emerging empirical research work on the dynamic relationship between key financial and commodity markets, especially in the post-GFC period. Through applying the VAR-BEKK-GARCH models, we provide a deeper examination of the degree of the spillover and other time-varying effects across the Chinese equity market, commodity markets and international oil markets. We investigate the extent to which commodity market are able to provide diversification benefits for investors holding positions in equity and oil markets. We report significant uni-directional return and volatility spillover effects from both the Chinese stock market and international oil market to the Chinese commodity markets, providing important practical implications for investors and regulators. From the empirical literature, the dynamic cross-effects between oil and commodity market remain unclear. Few studies take oil or stock markets into consideration when examining volatility spillover effects on the commodities market. In this analysis, we

account for both oil and stock markets in considering volatility transmission to the commodity market. Secondly, in addition to the bivariate GARCH models that are very popular in measuring the conditional volatilities, we use the trivariate GARCH structure in order to capture dynamic volatilities for the three financial markets more accurately. Thirdly, our analysis on the price interactions and volatility spillovers is aimed to examine portfolio diversification implications, to understand the spillover directions and magnitude of volatility transfers. The findings give a more comprehensive blueprint on financial markets dynamics, meriting particular attention from investors and regulators. Overall, this study provides new insights on the dynamic information transmission among those financial markets and informs investor's efficient trading strategies to improve investment decisions.

The remainder of the chapter is structured as follows. Section 8.2 briefly reviews the current literature. Section 8.3 presents the data used and the methodological framework. After that, Section 8.4 discusses the methodological framework and results, findings and their implications are then analysed in Section 8.5. Finally, Section 8.6 concludes this chapter.

8.2 Brief Literature Review

Theoretically, the correlation between equity and commodity futures markets are expected to be low or negative because they are driven by different financial and economic factors. In this aspect, commodities may have the capacity to bring diversification benefit when added into investors' portfolios (Hammoudeh et al., 2014). Several studies have attempted to explore the dynamic interactions between commodity and stock markets, looking at whether commodity futures in the traditional assets do actually have diversification and hedging benefits. While examining the relationship between commodity, equity and bond assets over 1959–2004, Gorton and Rouwenhorst (2006) find that commodity futures are negatively correlated with stocks and bonds. As a result, investors may be able to choose these commodities to diversify their portfolios and generate risk reduction benefits. This finding could possibly explain the better performance of commodity futures market during the unexpected inflation periods and risk management opportunities generated by commodity market in the periods where cyclical variation of stocks and bonds are observed. Büyüksahin et al. (2010) report that the return co-movement between commodity futures and S&P500 index is weak, as both cross-correlations and dynamic conditional correlations (DCCs) are almost zero during much of the sample time.

Even during the year 2008 when financial turbulence was rife, the DCCs remain at a low level despite the increase in the cross-correlations. They find little statistical evidence of a cointegration relationship in the long-run. Similar findings are documented in Chong and Miffre (2010) who also use the DCC GARCH approach. Their results reveal that the conditional correlations between 11 commodity futures and S&P500 returns tend to fall when traditional market risks rise. Lagesh et al. (2014) perform a similar empirical analysis in Indian, confirming low dynamic conditional correlations between commodity futures returns and traditional asset indices (stock index, long-term bond index and Treasury bill index). Belousova and Dorfleitner (2012) highlight that, because of such low correlation, investors have diversification opportunities through commodity instruments, confirming commodities are valuable investment tools.

This potential diversification opportunity, through commodity futures investment, has led to an increase of capital inflows into the commodity markets. Büyükşahin and Robe (2014) note that co-movements between commodity and equity markets are positively related to commodity market participation by speculators and hedge funds. The increased financialisation of commodity markets together with other reforms may have led to the integration between the commodity markets and traditional assets markets. However, this may eliminate diversification and inflation protection through commodities. This contradictory empirical evidence favours market integration between commodity and conventional assets. Daskalaki and Skiadopoulos (2011) could not find the publicised diversification benefits in their studies which considered the higher order moments of the portfolio returns distribution into the optimal portfolio, challenging the common view of commodities being a diversifying asset class. Silvennoinen and Thorp (2013) report evidence of decreased diversification benefits for portfolio investors holding commodities, equities and bonds, highlighting some degree of integration across these markets.

Crude oil prices have huge impacts on stock prices directly by influencing the future cash flow and influencing corporations' production costs. Thus, an increase in oil price has negative impacts on the real output and stock market returns (Huang et al., 1996). Empirical research on the linkage between stock markets and oil price movements has only been investigated recently. Early studies focusing on the US are able to find evidence of a significant relationship between oil prices and stock markets (Hamilton, 1983; Kling, 1985). Then the research has been extended to other countries. Jones and Kaul (1996) show that the

changes in oil prices have a significant impact on the output and real stock returns in the United States, Canada, Japan, and the United Kingdom during the post-war period, but the theoretical prediction of the negative relationship can be confirmed only in the US and Canadian markets. Sadorsky (1999) highlights that oil price movements are important in explaining movements in stock returns and that positive shock to oil prices depress real stock returns. Ciner (2001) provides evidence of bi-directional nonlinear Granger causality between oil futures returns (both crude and heating oil) and stock index returns.

In the case of emerging markets, Basher and Sadorsky (2006) examine the impact of oil price changes on 21 emerging stock market returns over the period 1992–2005. They show that oil price risk plays a significant role in emerging stock markets returns using both unconditional and conditional risk analysis. Similar evidence in developing markets is reported by elsewhere (Park and Ratti, 2008; Mohanty et al., 2010; Arouri et al., 2011b; Arouri et al., 2011a; Fayyad and Daly, 2011; Cunado and Perez de Gracia, 2014). Oil prices have been found to influence not only equity prices but also other commodities markets and there are some preliminary findings suggesting co-movement between oil and non-energy commodities. The increased linkage could possibly be explained by the substitution of fossil fuels with biofuels and the hedging strategies against high oil prices (Ji and Fan, 2012).

In more recent years, researchers and analysts have been paying attention to the possible linkage between crude oil prices and agricultural markets following simultaneous surges and significant swings in both oil and foods prices. As mentioned by Mensi et al. (2014), these kinds of market co-movements between energy and agricultural markets are likely driven by macroeconomic uncertainty and global warming related regulations. Taking another perspective, the rapid economic growth in emerging markets may trigger increases in the demand and consumptions of these commodities. As the most important driving force of the emerging market economies, oil price shocks will affect demand for biofuels and lead to rising demand for commodities such as corn and soybeans. Higher oil prices also lead to rising production costs for agricultural commodities which drive up food price levels (Mensi et al., 2014; Ahmadi et al., 2016).

In terms of empirical studies, many researchers use different econometric methodologies to investigate return and volatility transmissions between various agricultural commodities and oil markets and find significant linkage between them (see a summary of the literature in Nazlioglu et al. (2013)). For example, Nazlioglu and Soytas (2012) examine

the relationship between global oil prices and 24 world agricultural commodities and provide strong empirical evidence that changes in world oil prices profoundly affect agricultural commodity prices. Due to the growth in productions of the corn-based ethanol and soybean-based bio-diesel which are substitutes for petroleum-based fuels, the prices of corn together with other grains and soybeans approached its highest level in the last decade. Some studies are starting to focus on the important agricultural inputs for biofuels. Chen et al. (2010) indicate that higher oil price leads to higher prices of corn and soybeans because it would induce a higher demand for ethanol or bio-diesel and the changes in crude oil price and other grain prices have significant impacts on the price of a single grain. Trujillo-Barrera et al. (2012) and Mensi et al. (2014) find strong volatility spillovers from crude oil to corns due to their connections with ethanol extractions, suggesting a strong linkage between traditional energy and agricultural inputs for renewable energy. Nicola et al. (2016) report empirical evidence that the overall market co-movements between energy and agricultural commodities increased in recent years and that their returns are highly correlated, especially for commodities such as maize and soybean oil.

From the empirical literature, there is some evidence pointing metal commodities are increasingly being used for hedging and portfolio management purposes, especially by investors who hold oil assets in their investments. Narayan et al. (2010) point out that a higher oil price would create inflationary pressures, thus encouraging investments in gold as a hedging instrument against inflation. While modelling the volatility behaviour of gold, silver and copper, Hammoudeh and Yuan (2008) find that past positive oil shocks have a cooling effect on current gold and silver volatilities but no impact on copper volatility. Sari et al. (2010) detect a weak relationship between oil price and metal commodities but significant linkages among commodities and between precious metals and exchange rates. Ji and Fan (2012) suggest that oil price has significant volatility spillovers on non-energy commodities, indicating oil's significant influence on commodity markets. In fact, they observe a significant bi-directional price and volatility spillover effects between the crude oil and metal commodities before and after the GFC.

Focusing on the Turkish gold and silver markets, Soytaş et al. (2009) could not find the predictive power of the global oil market on precious metal markets in Turkey, suggesting safe haven position of gold when the Turkish lira is devaluated. By decomposing the oil price shock into oil supply shocks, global demand shocks and speculative oil demand shocks,

Ahmadi et al. (2016) note significant differences for gold, silver and copper's responses to oil price shocks. Before the GFC, they observe positive impacts from the global demand shock to the volatilities of gold and silver, while the volatilities of all three metals are negatively affected by the global demand shocks after the crisis. However, after the crisis, it is reported that speculative demand shocks become effective, somehow depressing the volatility of silver and enhancing the volatility of copper. In contrast, Dutta et al. (2017) find strong volatility transmission from the world oil market to metal and aggregate non-energy commodity indices. Fernandez-Perez et al. (2017) also demonstrate a significant causal effect from crude oil to platinum and palladium, highlighting the important role of crude oil on these commodities. However, Kang et al. (2017) find that both gold and silver were net information transmitters to the other commodity markets including the crude oil market. It confirms that gold and silver serve as origins of information transmissions over the other commodities.

The above literature clearly demonstrates that there are many alternative channels existing through which the stock market, crude oil and non-energy commodities can influence each other directly and indirectly. These interrelations need to be considered when studying the dynamic interactions among these assets. Although various studies examine impacts of equity and crude oil separately, our study here investigates the dynamic interactions between stock market, crude oil and non-energy commodities jointly. The aim is to analyse all alternative channels through which they can influence each other.

8.3 Data

We investigate the return and volatility transmissions among global oil price, equity and commodity markets in China. To avoid aggregation bias of commodity prices, we use individual commodity futures including agriculture, industrial metals, and precious metals. All data are compiled from SIRCA. The sample period starts from 2 July 2012 and goes to 30 June 2017, which covers several episodes of wide instabilities for both stock and commodity markets. We consider using the CSI 300 index to represent the Chinese stock market, because it is a capitalisation-weighted index covering the 300 largest and most liquid stocks traded on the Shanghai and Shenzhen stock exchanges, and representing about 60% of the total market capitalisation. Commodities are classified into three categories: precious metals refer to gold and silver, industrial metals comprise copper and aluminium, and agriculture commodities

include soy bean and wheat. Since commodity markets show heterogeneous characteristics, our selection here generates deeper insights into the dynamics among various commodities.

In terms of global oil price,²⁶ we use the Brent oil price to represent the international crude oil market since it is widely viewed as the benchmark of the global oil market to price (El Hedi Arouri et al., 2011). Following the literature, our commodity futures continuous price series are constructed using the closing price of the nearest to maturity contract until the last trading day and then rolling over to the next nearest-to-maturity contract. This is because the nearest contract is often expected to be the most liquid and actively traded. We take the natural logarithms of the prices and returns are calculated as $R_t = 100 * \ln(P_t/P_{t-1})$, where P_t is the futures price at time t . Figure 8.1 demonstrates the price trend for the markets under review. We see that the Chinese stock market increases dramatically from 2014 and reaches the peak in mid-2015. It then undergoes a significant downward swing from then and stabilises after 2016. In contrast, the global oil price shows a downward spiral in 2014 and bottom-up in early 2016. The Chinese commodity markets follow the same trend except for wheat.

Table 8.1 provides descriptive statistics of log prices and returns for the global oil market, Chinese stock and commodity markets. We see that the average returns for most commodity markets are negative with exceptions of the wheat market. The Chinese stock market has a positive average return which is much higher than those in commodity markets. In terms of the standard deviation which measures the unconditional volatility, we observe the highest value in the oil market (2.00) with the second highest in the stock market (1.59) while the aluminium market has the lowest risk with a standard deviation of 0.82. It suggests that the oil and stock markets are more volatile over time compared to other commodity markets. Also, all the market returns except oil and copper are negatively skewed, confirming that the return data are distributed asymmetrically. The large value of kurtosis ranging from the lowest of 6.01 for oil to the highest of 59.05 for wheat indicates the return is highly leptokurtic with fat tails compared to a normal distribution. The non-normality is also confirmed by the Jarque–Bera test statistics which reject the null hypothesis of normality for all the market returns under study at the 1% level significance level. These preliminary descriptive statistics demonstrate significant asymmetry and excess kurtosis. Thus our use of GARCH family models to measure the volatility of returns is justified and appropriate.

²⁶ We decide to use global oil price because the crude oil futures in China were recently launched in 2017.

The Ljung-Box Q test residual autocorrelation is significant at the 10% significance level for all returns series except wheat. Conclusively, market returns exhibit serial correlation and the VAR modelling framework is suitable. We employ Augmented Dickey-Fuller (ADF) together with a nonparametric Phillips-Perron (PP) tests to examine trend stationarity. As noted in Table 8.1, both ADF and PP tests indicate that price level data display a non-stationary feature with the exception of wheat. Table 8.2 provides the unconditional correlation matrix among market returns. The low correlation between indicators means that there are potential portfolio diversification benefits and hedging opportunities. Despite this, the correlations between gold and silver and between copper and aluminium are higher compared with other commodity pairs.

Table 8. 1: Descriptive Statistics for Market Returns

	CSI	OIL	GOLD	SLVR	COP	ALU	SB	WHT
Mean	0.033	-0.058	-0.014	-0.033	-0.013	-0.010	-0.009	0.007
Median	0.056	-0.063	0.000	-0.025	0.000	0.000	0.000	0.000
Maximum	6.499	9.561	5.396	6.414	6.709	3.833	6.973	12.319
Minimum	-9.154	-8.811	-13.399	-8.846	-5.266	-6.942	-10.736	-16.606
Std. Dev.	1.590	2.000	1.070	1.489	1.101	0.823	1.256	1.341
Skewness	-0.899	0.314	-2.010	-0.259	0.096	-0.292	-0.542	-1.656
Kurtosis	8.897	6.013	28.344	7.700	7.369	10.023	13.836	59.049
JB	1927	480	33390	1134	970	2519	6014	159857
Q(20)	99.443	40.925	44.925	31.766	27.912	64.269	28.773	17.753
Unit Root Tests								
ADF ^L	-1.110	-0.739	-1.909	-1.736	-1.562	-1.948	-1.921	-4.046
PP ^L	-1.153	-0.758	-1.905	-1.729	-1.531	-1.879	-1.660	-4.200
ADF ^R	-33.037	-37.104	-39.074	-37.476	-35.950	-32.240	-37.673	-34.671
PP ^R	-33.049	-37.033	-39.215	-37.387	-35.964	-32.164	-38.019	-34.671

Note: CSI stands for Chinese stock market, SLVR means silver, COP stands for copper, ALU for aluminium, SB for Soy Beans and WHT for Wheat; When conducting ADF and PP tests, we include an intercept in the test equation. ADF^L and PP^L are for level data while ADF^R and PP^R represent the first difference of the level data which are the return series. ADF^R and PP^R are all significant at the 1% level whereas ADF^L and PP^L are not significant except for wheat.

Table 8. 2: Correlations Matrix

	CSI	OIL	GOLD	SLVR	COP	ALU	SB	WHT
CSI	1.000							
OIL	0.083	1.000						
GOLD	0.040	-0.068	1.000					
SLVR	0.115	-0.006	0.372	1.000				
COP	0.195	0.055	0.168	0.372	1.000			
ALU	0.159	0.080	0.071	0.147	0.413	1.000		
SB	0.038	0.015	-0.012	-0.016	0.059	0.065	1.000	
WHT	0.046	0.036	-0.035	-0.009	-0.038	-0.039	0.037	1.000

Note: CSI stands for Chinese stock market, SLVR means silver, COP stands for copper, ALU for aluminium, SB for Soy Beans and WHT for Wheat.

Table 8. 3: Cointegration Test Results

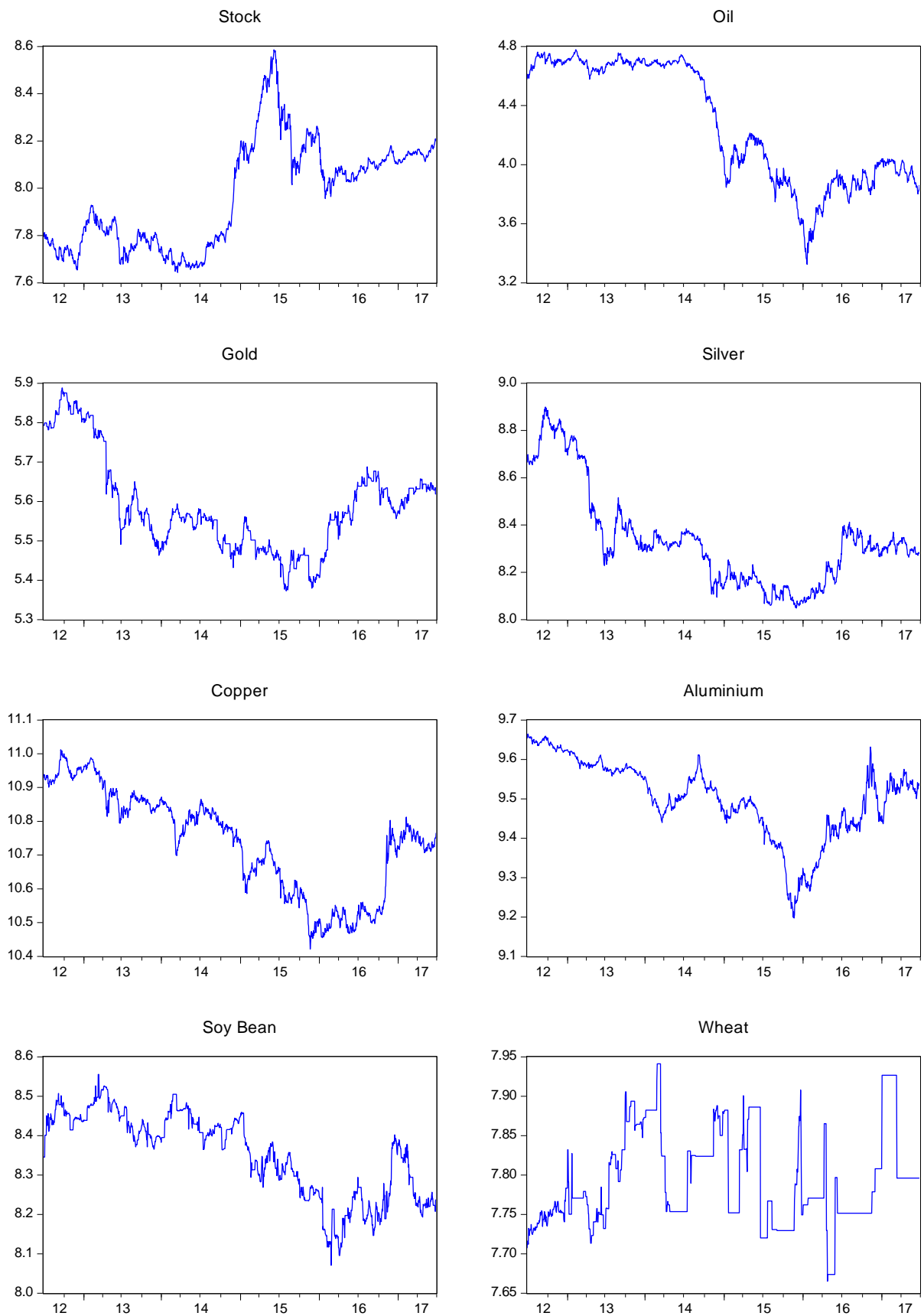
Johansen and Juselius Cointegration Test Results												
H ₀	Gold		Silver		Copper		Aluminium		Soy Bean		Wheat	
	Tr	Max	Tr	Max	Tr	Max	Tr	Max	Tr	Max	Tr	Max
None	21.13	12.91	17.36	10.26	17.05	10.41	20.77	13.97	30.14*	22.03*	NA	
At most 1	8.23	7.25	7.10	5.94	6.63	6.32	6.80	6.47	8.11	7.50	NA	
At most 2	0.98	0.98	1.16	1.16	0.32	0.32	0.32	0.32	0.61	0.61	NA	

ARDL Bounds Test Results

F-statistic	0.65	0.71	0.79	0.70	0.57	1.91
Significance	10%	5%	2.5%	1%		
I(0) Bound	2.63	3.1	3.55	4.13		
I(1) Bound	3.35	3.87	4.38	5		

Note: We allow for linear deterministic trend and intercept in cointegration equation when conducting the Johansen and Juselius cointegration test and the lag selection is based on AIC. Since the wheat prices are stationary according to both ADF and PP tests, it is inappropriate to use the Johansen and Juselius Cointegration Test. Tr and Max refer to Trace statistic and Max-Eigen statistic respectively. * represents rejection of the null hypothesis at the 5% level of significance.

Figure 8. 1: Price Movement of Stock, Oil and Commodity Markets



8.4 Estimation Framework

We use both Johansen and Juselius (1990) and Pesaran et al. (2001) bounds tests to check for a cointegration relationship among the series of P_t^{st} , P_t^{oil} and P_t^{cm} . Thus we initially assume the following VAR:

$$P_t = A_0 + \sum_{i=1}^p A_i P_{t-i} + \varepsilon_i \quad (8.1)$$

where $P_t = (P_t^{st}, P_t^{oil}, P_t^{cm})'$

Equation (8.1) can be rewritten as:

$$\Delta P_t = A_0 + \Pi P_{t-p} + \sum_{i=1}^{p-1} \Gamma_i \Delta P_{t-i} + \varepsilon_i \quad (8.2)$$

where $\Pi = \sum_{i=1}^p A_i - I$ and $\Gamma_i = \sum_{i=1}^{p-1} A_i - I$

The corresponding likelihood ratio statistics for Trace and Maximum Eigenvalue tests are calculated as:

$$\text{Trace statistic: } \lambda_{Trace}(r) = -T \sum_{i=r+1}^n \ln(1 - \hat{\lambda}_i)$$

$$\text{Maximum eigenvalue statistic: } \lambda_{Max}(r) = -T \ln(1 - \hat{\lambda}_{r+1}),$$

where T is the sample size and $\hat{\lambda}_i$ is the i th largest canonical correlation.

The bounds testing procedure requires employing the Autoregressive Distributed Lag (ARDL) technique which is introduced by Pesaran and Shin (1999) and Pesaran et al. (2001). Unlike the other commonly used cointegrating approaches, the ARDL approach does not necessarily require one to test for the orders of integration. Therefore we can specify our equation as:

$$\Delta P_t^{st} = a_i + \sum_{i=1}^{q_1} b_i \Delta P_{t-i}^{st} + \sum_{i=1}^{q_2} c_i \Delta P_{t-i}^{oil} + \sum_{i=1}^{q_3} d_i \Delta P_{t-i}^{cm} + \lambda_1 P_{t-1}^{st} + \lambda_2 P_{t-1}^{oil} + \lambda_3 P_{t-1}^{cm} + \varepsilon_t \quad (8.3)$$

where Δ denotes the first difference operator, q_1 , q_2 and q_3 are the lag lengths, b_i , c_i , d_i are the short-term coefficients whereas λ_1 , λ_2 and λ_3 are the long-run coefficients.

In order to determine the existence of a cointegrating relationship among P_t^{st} , P_t^{oil} and P_t^{cm} , we test the null hypothesis which asserts there is no cointegration relationship: $\lambda_1=\lambda_2=\lambda_3=0$ against the alternative of cointegration: $\lambda_1 \neq \lambda_2 \neq \lambda_3 \neq 0$ by computing F-statistics. One of the major advantages of the ARDL method is that the test can be used without considering whether the time series are either I(0) or I(1), therefore the ARDL bounds tests are not subject to the stationarity of the data. The calculated F-statistic will be compared with two different asymptotic critical values provided by Pesaran et al. (2001). The first set of critical values assumes that all variables are I(0) whereas the other set assumes that they are I(1). If the computed F-statistic is lower than the lower bound of the critical values, we cannot reject the null of no co-integration. Once the F-statistic is greater than the upper bound of the critical value, then we can reject the null hypothesis and conclude that cointegration equilibrium does exist between the series. However, if the F-statistic falls between the lower bound and upper bound of the critical values, the result is inconclusive.

Moving to the conditional volatility, (General) Autoregressive conditional heteroskedasticity [(G)ARCH] models are widely used to forecast market volatility. This is because of their ability to capture the time-varying conditional variances and show time series features such as volatility clustering. Multivariate GARCH models are found to have the forecasting ability to examine the dynamics of stock market volatility among different financial institutions. By specifying the conditional variance and covariance equations, MGARCH models have widely been used to examine how the correlation and covariance between different variables change over time. Multivariate volatility models such as BEKK (Baba, Engle, Kraft and Kroner), CCC (Constant Conditional Correlation) or DCC (Dynamic Conditional Correlation) specifications with dynamic covariances and conditional correlations are more relevant than univariate models. This is particularly the case when investigating volatility interdependence and transmission mechanisms among different financial time series (Arouri et al., 2011b).

A number of existing empirical studies confirm the superiority of these models (see Chang et al., 2011; Agnolucci, 2009; Hammoudeh et al., 2009; Hassan and Malik, 2007). However, existing studies examining volatility transmissions using MGARCH only focus on the bivariate relationship. Our work examines the trilateral dynamics of the mentioned markets. In terms of interpreting and capturing the spillovers between commodity and other markets, the GARCH model with BEKK specification has been successfully utilised (Salisu and Oloko, 2015; Jouini and Harrathi, 2014). Here we follow the trivariate BEKK-GARCH approach (Engle and Kroner, 1995) to investigate the return and volatility transmission in China. By adding VAR(1) term into BEKK-GARCH, we can specify our model under the conditional mean equation and conditional variance equation. The conditional mean model of VAR(1) can be outlined as:

$$R_t = \mu + GR_{t-1} + \varepsilon_t, \varepsilon_t | \Omega_{t-1} \sim N(0, H_t) \quad (8.4)$$

where R_t denotes a vector of stock market return, oil market return and commodity market return: $R_t = (R_{st,t}, R_{oil,t}, R_{cm,t})'$, G is a (3×3) matrix of VAR coefficients, ε_t represents a vector of Gaussian error: $\varepsilon_t = (\varepsilon_{st,t}, \varepsilon_{oil,t}, \varepsilon_{cm,t})'$ and μ is a vector of constants: $\mu = (\mu_{st}, \mu_{oil}, \mu_{cm})'$.

In terms of conditional variance, several different multivariate GARCH specifications have been developed in the literature. Bollerslev et al. (1988) introduced a general VECH GARCH where the conditional variance and covariance are a linear function of all lagged squared errors and conditional variance and covariance. However, this produces another econometric challenge because the number of parameters is very large. It is also hard to guarantee a positive conditional variance and covariance matrix H_t without restrictions on parameters. By reducing the number of parameters, Engle and Kroner (1995) proposed a BEKK-GARCH model which simplifies the estimation process so that VECH parameterisation problems can be overcome. This model uses the quadratic form to release the positive restriction on the conditional variance matrix and further simplifies the estimation process. The conditional variance equations are specified as follows:

$$H_t = C'C + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'H_{t-1}B \quad (8.5)$$

where

$$H_t = \begin{bmatrix} h_{11,t} & h_{12,t} & h_{13,t} \\ h_{21,t} & h_{22,t} & h_{23,t} \\ h_{31,t} & h_{32,t} & h_{33,t} \end{bmatrix}, C = \begin{bmatrix} c_{11} & & \\ c_{21} & c_{22} & \\ c_{31} & c_{32} & c_{33} \end{bmatrix},$$

$$A = \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix} \text{ and } B = \begin{bmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \\ b_{31} & b_{32} & b_{33} \end{bmatrix}$$

where C is a 3×3 lower triangular matrix with six parameters. A is a 3×3 matrix, indicating how conditional variances are correlated with past shocks. B is also a 3×3 matrix, showing the effects of past conditional variances on current conditional variances. The total number of estimated parameters for our trivariate variance equations is 24. Following Hassan and Malik (2007), the conditional variance for each market, ignoring the constant coefficients, can be expanded as below:

$$\begin{aligned} h_{11,t} = & a_{11}^2 \varepsilon_{st,t-1}^2 + 2a_{11}a_{12} \varepsilon_{st,t-1} \varepsilon_{oil,t-1} + 2a_{11}a_{31} \varepsilon_{st,t-1} \varepsilon_{cm,t-1} + a_{21}^2 \varepsilon_{oil,t-1}^2 \\ & + 2a_{21}a_{31} \varepsilon_{oil,t-1} \varepsilon_{cm,t-1} + a_{31}^2 \varepsilon_{cm,t-1}^2 + b_{11}^2 h_{11,t-1} + 2b_{11}b_{12} h_{12,t-1} \\ & + 2b_{11}b_{31} h_{13,t-1} + b_{21}^2 h_{22,t-1} + 2b_{21}b_{31} h_{23,t-1} \\ & + b_{31}^2 h_{33,t-1} \end{aligned} \quad (8.6)$$

$$\begin{aligned} h_{22,t} = & a_{12}^2 \varepsilon_{st,t-1}^2 + 2a_{12}a_{22} \varepsilon_{st,t-1} \varepsilon_{oil,t-1} + 2a_{12}a_{32} \varepsilon_{st,t-1} \varepsilon_{cm,t-1} + a_{22}^2 \varepsilon_{oil,t-1}^2 \\ & + 2a_{22}a_{32} \varepsilon_{oil,t-1} \varepsilon_{cm,t-1} + a_{32}^2 \varepsilon_{cm,t-1}^2 + b_{12}^2 h_{11,t-1} + 2b_{12}b_{22} h_{12,t-1} \\ & + 2b_{12}b_{32} h_{13,t-1} + b_{22}^2 h_{22,t-1} + 2b_{22}b_{32} h_{23,t-1} \\ & + b_{32}^2 h_{33,t-1} \end{aligned} \quad (8.7)$$

$$\begin{aligned} h_{33,t} = & a_{13}^2 \varepsilon_{st,t-1}^2 + 2a_{13}a_{23} \varepsilon_{st,t-1} \varepsilon_{oil,t-1} + 2a_{13}a_{33} \varepsilon_{st,t-1} \varepsilon_{cm,t-1} + a_{23}^2 \varepsilon_{oil,t-1}^2 \\ & + 2a_{23}a_{33} \varepsilon_{oil,t-1} \varepsilon_{cm,t-1} + a_{33}^2 \varepsilon_{cm,t-1}^2 + b_{13}^2 h_{11,t-1} + 2b_{13}b_{23} h_{12,t-1} \\ & + 2b_{13}b_{33} h_{13,t-1} + b_{23}^2 h_{22,t-1} + 2b_{23}b_{33} h_{23,t-1} \\ & + b_{33}^2 h_{33,t-1} \end{aligned} \quad (8.8)$$

The diagonal elements of matrices A(a_{11} , a_{22} and a_{33}) and B(b_{11} , b_{22} and b_{33}) capture the effect of previous shocks and historical volatility to the current conditional variance,

respectively. On the other hand, the off-diagonal elements of matrices A(e.g. a_{12} , a_{13} and a_{21}) and B(e.g. b_{12} , b_{13} and b_{21}) measure the volatility spillovers across the markets. During the process of estimation, the following logarithm likelihood function should be maximised with a normal distribution for the error terms:

$$L(\theta) = \sum_{t=1}^T L_t(\theta) \quad (8.9)$$

The log-likelihood function of the joint distribution is given as:

$$L_t(\theta) = -\ln(2\pi) - \frac{1}{2} \ln|H_t| - \frac{1}{2} \varepsilon_t' H_t^{-1} \varepsilon_t \quad (8.10)$$

where θ denotes the vector of parameters to be estimated and T is the number of observations. Since the above function is non-linear, we will employ BFGS (Broyden, Fletcher, Goldfarb, and Shanno) algorithms as the maximisation technique to obtain the initial condition and the final parameter estimates of the variance–covariance matrix.

In this set-up, the conditional variance for the commodity market, for example, is not impacted only by its own past shocks and past conditional variance, but also by those of the stock and oil markets. This captures the direct shocks and volatility transmission between one market and another. Overall, our proposed model allows us to capture both return and volatility spillover effects between oil price, exchange rate and stock market returns and use the estimation results to compute the optimal weights for portfolio management and hedge ratios.

8.5 Major Findings and Analysis

8.5.1 The Results of Cointegration Tests

As noted in Table 8.1, we conclude that the prices for Chinese stock market, oil, gold, silver, copper, aluminium, and soy bean integrated of order 1 (I(1)). In contrast, the wheat prices are stationary, because ADF and PP statistics are significant for its level data, rejecting the null hypothesis of a unit root. As a result, we apply the bounds test for the group of stock market, oil prices and wheat prices. Table 8.3 reports results of both Johansen and Juselius and

bounds tests. The bounds tests suggest that the Chinese stock market, the global oil market and all the Chinese commodity markets are not cointegrated. The F-statistic for all cases is lower than the lower bound of the critical values. In other words, there is no common driving force for these three variables in the long run. Our findings here are in line with Sari et al. (2010) who find no evidence of long-term equilibriums for the oil prices, precious metal prices, and exchange rates. Results from the Johansen and Juselius cointegration tests also demonstrate no obvious long-run cointegration relationship among the stock market, crude oil prices and the major Chinese commodity markets. Further analysis shows that oil prices and soy bean futures tend to move together in the long-term. This supports what was documented by Nazlioglu and Soytas (2012), who argue that oil prices are important factors in determining the long-run behaviours of agricultural commodity markets.

8.5.2 VAR-BEKK-GARCH Results

Our estimation results of VAR(1)-BEKK-GARCH(1,1) are provided in Table 8.4 which consists of two sections. The first part presents the VAR results based on the estimation of conditional mean equations. Through these estimations, we aim to identify the return spillovers among these markets. The second part shows results from the conditional variance equations modelled by BEKK GARCH where we analyse volatility spillovers. Last but not least, the results and analysis of optimal portfolio weights and hedge ratios are provided.

8.5.2.1 Return Spillovers Results Based on VAR Estimations

In investigating return spillovers, we first examine the return behaviours for equity, oil and commodity markets based on our estimation from the conditional mean equations. We observe that the AR(1) parameter g_{22} for oil return is statistically significant for most groups at the 10% significance level. Therefore, oil return shows an autoregressive characteristic, suggesting that one-period lagged oil returns significantly influence the current values. Similarly, some of the Chinese commodity markets (gold, silver and copper) also have autoregressive features as g_{33} are statistically significant for their market returns. Thus current market returns for gold, silver and copper are significantly affected by their past values and

therefore show short-term predictability. However, we do not find strong evidence of serial correlation for the returns of Chinese stock market, aluminium, soy bean and wheat markets.

When we examine return spillover effects, lagged values of returns in oil market significantly affect the current returns of Chinese stock market as the coefficient g_{12} are statistically significant for all groups. It means that the Chinese stock market returns in the current time strongly depend on the past return in the oil market. This indicates there is a significant return spillover from the oil to the Chinese stock market. Looking at the sign of the coefficient, the positive sign indicates that the higher return in the oil market will possibly drive higher stock market return. This is not surprising since China is the world's largest net oil-importing country. In this regard, the oil market is expected to influence the Chinese stock market due to the strong dependence of its economy on oil imports. The oil market is often treated as the leading economic indicator. Thus rising oil prices due to oil demand increases reflect the expectation of future higher economic growth of the consuming country. This signals a higher stock market return.

Consistent with our finding, Park and Ratti (2008) report that oil price shocks have significant and robust impacts on real stock returns of the US and 13 European countries. Basher and Sadorsky (2006) also argue that oil price increases have positive impacts on excess stock returns in emerging markets. Yet, conversely, there is no evidence of return spillover from the Chinese stock market to the oil market, since the coefficient g_{21} is statistically insignificant for all groups. Thus the oil market tends to behave independently from the Chinese stock market. Our findings here are supported by Arouri et al. (2011b) who find strong market interdependence from lagged oil returns to stock market returns for most GCC countries, where the reverse does not hold. However, our results are contrary to Singhal and Ghosh (2016) who indicate insignificant spillovers from international crude oil returns on Indian stock market returns and Cong et al. (2008) who demonstrate that there is no significant impact from oil price shocks on the real stock returns of most Chinese stock market indices.

Looking at the return spillovers between Chinese stock and commodity markets, we find strong uni-directional return spillovers from the stock market to copper and aluminium markets respectively. The coefficient g_{31} is statistically significant at least at the 5% level for the groups of copper and aluminium. Looking at the coefficient signs, the impacts of the Chinese stock market on both copper and aluminium are negative. This indicates that a higher

stock return will lead to a fall in the copper and aluminium markets. However, we see no evidence of mean spillover effect from commodities to stock market. These results are similar to the findings reported by Nguyen et al. (2015) who highlight that the causality from equity returns to copper futures returns is significant whereas the causality from commodity futures to equity is less pronounced.

Similar results are observed when examining the interdependence between global oil market and Chinese commodity markets. Silver, copper and aluminium markets are found to be possibly influenced by oil return, given that the coefficient g_{32} is statistically significant at the 1% level. The positive sign of the coefficient indicates that a higher oil price will boost the markets of silver, copper and aluminium. The positive interdependence between oil and other commodities may be due to the influence of common macroeconomic drivers, for instance, interest rates, inflation rates and industrial production (Hammoudeh and Yuan, 2008). We do not find the return spillovers from the commodity markets to the oil market. Interestingly, both copper and aluminium are very sensitive to the shocks from both the Chinese stock market and global oil market. This suggests that these two commodity markets are vulnerable to the external effects or shocks. The lack of a relationship between gold and stock and gold and oil markets indicate that gold plays a safe-haven role as pointed out by Baur and McDermott (2010). For agricultural commodities, we cannot find significant evidence of spillover effects, implying weak integration among agricultural commodities, stock and oil market. Our findings here indicate potential diversification benefits between some commodities (gold, soy bean and wheat) and Chinese stock market and between those and oil markets.

8.5.2.2 Volatility Spillovers Based on BEKK GARCH

We next examine the volatility spillovers based on conditional variance equations. Ross (1989) emphasises that the market volatility is significantly influenced by the rate of information flow. Therefore, it is possible that linkages across financial markets not only exist in the returns but also in the market volatility. As noted in Table 8.4, the estimated coefficients for ARCH and GARCH models [A(1,1), A(2,2), A(3,3) and B(1,1), B(2,2), B(3,3)] in our conditional variance equations for all the groups are statistically significant at the 1% level. In this way, the Chinese stock market, Brent oil market and all the Chinese

commodity markets (gold, silver, copper, aluminium, soy bean and wheat) have strong ARCH and GARCH effects. Furthermore, the conditional variances of these financial markets are significantly influenced by their own lagged shocks and their own lagged conditional variance. Our findings are consistent with Beirne et al. (2013) who provide strong evidence of ARCH and GARCH effects in emerging markets and emphasise the appropriateness of the GARCH family models in these analyses. Moreover, the reported ARCH coefficients are relatively small in size compared with the GARCH coefficients. This suggests that the conditional volatility of corresponding markets does not change rapidly if there is a shock but rather fluctuate gradually over time. It also suggests that past value of their own volatility plays a more crucial role in forecasting their future volatility compared with their own shocks.

To analyse volatility transmissions, we first look at the nature of spillover mechanisms between the Chinese stocks and the international oil market. Based on the statistical significance of the off-diagonal coefficients in the matrix A and B of the BEKK model's variance equation (Eq(8.5)),²⁷ we can examine how shocks and volatility spillovers are transmitted. Our results show significant transmission of shock spillovers from the Chinese stock market to the oil price as the coefficients A(1,2) are significant at the 10% level for most groups except for copper. Thus past shocks in the Chinese stock market have significant effects on oil market's volatility over the sample period. Looking at the opposite effect, we see shock volatility spillover effect from the crude oil to the Chinese stock market is intermediate, as the coefficients A(2,1) are significant only for half of the groups. In terms of volatility spillovers, we find that the fluctuation in oil returns induces moderate volatility spillovers to China's stock market. However, the coefficient B(1,2) is only significant for the copper and soy bean groups. These results indicate that the volatility spillovers from the stock market to oil market are weak.

Our findings demonstrate a bi-directional shocks spillover between the Chinese stock market and oil market but a uni-directional volatility spillover from oil to stock market. These results remain qualitatively unchanged when we swap our methodology to bivariate models.²⁸ Our findings here are consistent with Jouini and Harrathi (2014) who show evidence of

²⁷ The off-diagonal elements of matrices A(ij) capture the shock spillover effects from market i to market j. Similarly, the volatility spillovers are measured by the off-diagonal elements of matrix B(ij).

²⁸ The full robust test results are available upon request. Here we only show the results for the coefficients of shock and volatility spillovers. A(1,2): -0.053 (0.030); A(2,1): 0.026 (0.047); B(1,2): -0.010 (0.110); B(2,1): 0.005 (0.058).

bilateral shock transmission between the oil and UAE/ Bahrain stock markets. It is also consistent with Arouri et al. (2011b) who find past oil shocks to have significant effects on stock market volatility for 13 GCC countries. Overall, our results suggest that the shocks from both Chinese stock market and oil price dramatically affect the other markets' volatility. However, only volatility from the oil market has an impact on China's stock market. These results support the view that the Chinese markets are integrating with the rest of the world following the gradual financial liberalisation reforms over the last few years. We believe this could also be explained by the fact that China is the top oil importer of oil. As financial liberalisation and the financialisation of commodity markets are enhanced, Chinese financial markets are becoming more responsive to fluctuations in global oil prices. Thus international oil market volatility is able to exert a strong negative impact (both in terms of shock and volatility) on the stock market in China.

We next analyse shock and volatility spillover between stock and commodity markets. As reported in Table 8.5, the off-diagonal elements of matrix A --- $A(1,3)$ are statistically significant at the 5% level for most commodity markets (e.g. gold, copper, soy bean and wheat). This evidence highlights significant shock spillovers from the stock market to commodity markets. The highest absolute value of coefficient $A(1,3)$ is given as 0.319 for wheat and is significant at the 1% level, implying the wheat market is the most sensitive market to the shocks from the Chinese stock market.

Regarding the off-diagonal elements of matrix B --- $B(1,3)$, we do observe volatility spillover effect from stock market to gold and copper as the corresponding coefficients are significant at the 1% level. In terms of the absolute value of the coefficient, it is relatively small compared with $A(1,3)$. This suggests that the volatility spillover effect from stock to commodity is marginal compared with shock spillovers. In the opposite direction, we find no evidence of both shock and volatility spillover effects from commodity to stock markets, as neither $A(3,1)$ nor $B(3,1)$ are statistically significant for all groups. It can be also seen that both gold and copper are influenced by past shocks and volatility from the stock market while soy bean and wheat are only influenced by previous shocks. However, we see no statistical evidence of shock and volatility spillovers from the Chinese stock market in the cases of silver and aluminium. In summary, our results indicate uni-directional shock (strong) and volatility (moderate) spillover effects from the stock market to the commodity markets in China.

Moving to the interdependence between the oil market and the Chinese commodity markets, there is strong evidence of shock spillovers from oil prices to gold, soy bean and wheat markets. Those respective $A(2,3)$ coefficients are statistically significant. For volatility spillovers, we can only find contagion from oil to soy bean market as the respective $B(2,3)$ coefficient is significant at the 5% level. In terms of the magnitude, the oil market has the largest impact on the wheat market with $A(2,3)$ valued at 0.173. Similarly, our results reveal no shock and volatility spillover effects from all the commodity markets to global oil market as $A(3,2)$ and $B(3,2)$ coefficients remain insignificant. In line with the findings of Ji and Fan (2012), we find crude oil market has significant volatility spillover effects on non-energy commodity markets, showing oil market's core global influences.

Overall, our evidence suggests that metal futures are more sensitive to the fluctuation in the local stock market while the agricultural commodities react more to the shocks in the oil market. Our empirical results are robust with regard to the lack of significant spillovers from commodity markets to either the stock market or oil market. However, the spillover levels of the stock and/or oil market to commodity markets depend on the individual commodity. It is interesting to see that volatility spillover effects are not homogenous across commodity markets. We believe the mixed results on volatility transmissions reflect the different level of financial integration in these commodity markets with the stock/oil market. This is also partly contributed by the nature of the commodity, size and liquidity of the markets, the degree of financial liberalisation and other deeper causes not limited to those financial factors.

Table 8. 4: VAR-BEKK-GARCH Results

	Gold		Silver		Copper		Aluminium		Soy Bean		Wheat	
	Mean Equation											
Dependent variable: R_{st}												
Constant	0.043	(0.183)	0.057*	(0.079)	0.053	(0.114)	0.055*	(0.086)	0.039	(0.245)	0.078**	(0.015)
$R_{st}(-1)$ ---g ₁₁	0.036	(0.254)	0.025	(0.403)	0.044	(0.167)	0.034	(0.287)	0.014	(0.654)	0.042	(0.166)
$R_{oil}(-1)$ ---g ₁₂	0.048***	(0.007)	0.040**	(0.030)	0.035*	(0.058)	0.049***	(0.009)	0.046***	(0.007)	0.058***	(0.001)
$R_{cm}(-1)$ ---g ₁₃	-0.023	(0.474)	0.004	(0.866)	0.027	(0.312)	-0.028	(0.373)	0.027	(0.292)	-0.011	(0.651)
Dependent variable: R_{oil}												
Constant	-0.041	(0.334)	-0.024	(0.565)	-0.083*	(0.069)	-0.043	(0.312)	-0.035	(0.425)	-0.060	(0.158)
$R_{st}(-1)$ ---g ₂₁	-0.023	(0.483)	-0.027	(0.407)	-0.025	(0.471)	-0.011	(0.736)	-0.018	(0.579)	-0.021	(0.515)
$R_{oil}(-1)$ ---g ₂₂	-0.057*	(0.059)	-0.054*	(0.074)	-0.044	(0.169)	-0.052*	(0.086)	-0.054*	(0.074)	-0.082**	(0.011)
$R_{cm}(-1)$ ---g ₂₃	-0.012	(0.781)	-0.008	(0.807)	-0.040	(0.394)	-0.074	(0.291)	0.010	(0.796)	0.049	(0.157)
Dependent variable: R_{cm}												
Constant	-0.018	(0.576)	-0.050	(0.224)	-0.013	(0.650)	-0.025	(0.133)	0.006	(0.857)	0.076*	(0.052)
$R_{st}(-1)$ ---g ₃₁	-0.026	(0.216)	0.006	(0.805)	-0.043**	(0.030)	-0.033***	(0.001)	0.003	(0.892)	0.030	(0.315)
$R_{oil}(-1)$ ---g ₃₂	0.017	(0.318)	0.084***	(0.000)	0.105***	(0.000)	0.043***	(0.000)	0.011	(0.518)	0.021	(0.320)
$R_{cm}(-1)$ ---g ₃₃	-0.113***	(0.000)	-0.106***	(0.004)	-0.066**	(0.050)	-0.007	(0.824)	-0.024	(0.559)	0.017	(0.710)

Table 8.4: VAR-BEKK-GARCH Results (Continued)

	Gold		Silver		Copper		Aluminium		Soy Bean		Wheat	
	Conditional Variance Equations											
C(1,1)	0.053	(0.164)	-0.054	(0.143)	0.111	(0.000)	0.062	(0.026)	0.067	(0.005)	-0.027	(0.495)
C(2,1)	-0.033	(0.695)	-0.021	(0.808)	-0.122	(0.000)	-0.019	(0.778)	-0.013	(0.850)	-0.058	(0.758)
C(2,2)	0.104	(0.008)	0.104	(0.004)	0.012	(0.739)	0.111	(0.000)	-0.102	(0.017)	-0.109	(0.360)
C(3,1)	-0.037	(0.854)	-0.285	(0.580)	0.118	(0.060)	0.028	(0.395)	-0.271	(0.116)	-1.024	(0.021)
C(3,2)	0.049	(0.751)	0.088	(0.774)	0.298	(0.000)	0.019	(0.414)	-0.065	(0.800)	-0.223	(0.908)
C(3,3)	0.110	(0.154)	0.470	(0.100)	0.000	(1.000)	-0.037	(0.238)	0.457	(0.000)	0.000	(1.000)
A(1,1)	-0.231	(0.000)	-0.214	(0.000)	0.220	(0.000)	-0.222	(0.000)	-0.205	(0.000)	-0.214	(0.000)
A(1,2)	-0.042	(0.056)	-0.056	(0.013)	-0.003	(0.879)	-0.047	(0.054)	-0.053	(0.020)	-0.079	(0.005)
A(1,3)	-0.022	(0.023)	-0.006	(0.842)	-0.069	(0.000)	-0.010	(0.249)	-0.086	(0.000)	-0.319	(0.000)
A(2,1)	0.027	(0.026)	0.023	(0.035)	0.021	(0.106)	0.027	(0.017)	0.019	(0.129)	0.020	(0.134)
A(2,2)	-0.211	(0.000)	-0.204	(0.000)	-0.199	(0.000)	-0.194	(0.000)	-0.216	(0.000)	-0.191	(0.000)
A(2,3)	0.015	(0.084)	0.009	(0.739)	-0.005	(0.769)	-0.001	(0.934)	-0.041	(0.055)	0.173	(0.000)
A(3,1)	0.041	(0.113)	-0.020	(0.483)	-0.004	(0.833)	-0.007	(0.671)	-0.024	(0.289)	0.012	(0.506)
A(3,2)	0.026	(0.433)	0.040	(0.176)	0.016	(0.635)	-0.067	(0.183)	-0.004	(0.925)	-0.012	(0.654)
A(3,3)	0.059	(0.000)	-0.348	(0.000)	0.337	(0.000)	-0.242	(0.000)	0.370	(0.000)	-0.293	(0.000)
B(1,1)	0.973	(0.000)	0.978	(0.000)	0.973	(0.000)	0.975	(0.000)	0.978	(0.000)	0.974	(0.000)
B(1,2)	-0.007	(0.224)	-0.009	(0.122)	0.014	(0.005)	-0.008	(0.195)	-0.009	(0.093)	-0.009	(0.161)
B(1,3)	-0.007	(0.005)	0.009	(0.355)	0.021	(0.000)	-0.002	(0.354)	0.001	(0.867)	0.009	(0.856)
B(2,1)	0.005	(0.075)	0.003	(0.110)	0.004	(0.042)	0.004	(0.046)	0.004	(0.163)	0.004	(0.108)
B(2,2)	0.975	(0.000)	0.977	(0.000)	0.978	(0.000)	0.978	(0.000)	0.975	(0.000)	0.978	(0.000)
B(2,3)	0.001	(0.524)	0.002	(0.769)	0.004	(0.400)	-0.001	(0.555)	-0.015	(0.034)	0.006	(0.878)
B(3,1)	0.005	(0.616)	-0.015	(0.453)	-0.006	(0.553)	-0.002	(0.600)	0.008	(0.575)	0.046	(0.350)
B(3,2)	-0.007	(0.582)	0.002	(0.920)	0.000	(0.975)	-0.012	(0.337)	0.006	(0.854)	-0.104	(0.276)
B(3,3)	0.991	(0.000)	0.860	(0.000)	0.887	(0.000)	0.970	(0.000)	0.821	(0.000)	-0.377	(0.000)

Note: The figures in brackets are P-values which indicate the statistical significance of the coefficients.

8.5.2.3 Optimal Portfolio Designs and Hedging Ratios

Understanding volatility spillover effects are crucial for risk management and efficient portfolio diversification. Given the insignificant volatility spillover effects from commodity market to stock/oil market, potential opportunities for portfolio diversification are substantial by investing in both stock/oil and commodity markets. To mitigate risk exposures of volatile markets and wild price swings, portfolio managers need to quantify both optimal weights and hedging ratios to minimise the extra risks without decreasing the expected returns. Similarly, investors can also achieve greater diversification gains by investing in both stock and commodity or oil and commodity markets. To illustrate the implications of our empirical findings on optimal portfolio design and risk hedging, we consider a portfolio of stock and commodity (oil and commodity) in mitigating the risks exposure to both the Chinese stock and global oil markets. We apply the estimation results from our trivariate VAR-BEKK-GARCH model to compute the optimal portfolio weights as well as the optimal hedge ratios.

Based on the method developed by Kroner and Ng (1998), we calculate the optimal portfolio weights by constructing a risk minimised portfolio without reducing expected returns. The optimal portfolio weight of holdings of two assets (e.g. stock and commodity or oil and commodity) is given by:

$$W_{st-cm} = \frac{h_{33,t} - h_{13,t}}{h_{11,t} - 2h_{13,t} + h_{33,t}} \quad \text{or} \quad W_{cm-st} = \frac{h_{11,t} - h_{13,t}}{h_{11,t} - 2h_{13,t} + h_{33,t}} \quad (8.11)$$

$$W_{oil-cm} = \frac{h_{33,t} - h_{23,t}}{h_{22,t} - 2h_{23,t} + h_{33,t}} \quad \text{or} \quad W_{cm-oil} = \frac{h_{22,t} - h_{23,t}}{h_{22,t} - 2h_{23,t} + h_{33,t}} \quad (8.12)$$

where $W_{i-j} = \begin{cases} 0, & \text{if } W_{i-j} < 0 \\ W_{i-j}, & \text{if } 0 \leq W_{i-j} \leq 1 \\ 1, & \text{if } W_{i-j} > 1 \end{cases}$, represent the weight of asset i in a one-dollar

portfolio of asset i and asset j at time t, particularly W_{st-cm} refer to the weight of stock market in a one-dollar portfolio of stock and commodity while the optimal weight of commodity in the considered portfolio is W_{cm-st} and W_{oil-cm} is the optimal weight of oil in the considered portfolio of oil and commodity whereas W_{cm-oil} represents the optimal weight of commodity in the same portfolio.²⁹

²⁹ $W_{oil-cm} + W_{cm-oil} = 1$ and $W_{st-cm} + W_{cm-st} = 1$

We also compute the optimal hedge ratio for their portfolio according to Kroner and Sultan (1993). The risk of this portfolio is minimal if a long position of one dollar in the stock/oil market can be hedged by a short position of β_t dollar in the Chinese commodity market. Hedge ratio is computed using the formula:

$$\beta_{cm-st} = \frac{h_{13,t}}{h_{33,t}} \quad (8.13)$$

$$\beta_{cm-oil} = \frac{h_{23,t}}{h_{33,t}} \quad (8.14)$$

The average values of optimal portfolio weights and hedging ratios for the 6 commodities are detailed in Table 8.6.

Firstly, we look at the optimal portfolio weights of the commodity market in a portfolio constituting the Chinese stock and commodity holdings. Based on our results, most commodity weights are more than 50% except silver³⁰, varying from 50.52% in wheat being the lowest to the highest of 75.66% for aluminium. This means that 50.52% (75.66%) of the portfolio's value should be invested in the wheat (aluminium) futures market and the remaining 49.48% (24.34%) should be held in the Chinese stock market. The results indicate the allocation of commodity in a one-dollar portfolio consisting of both stock and commodity is more than half for most cases, implying that investor should hold more commodities than stock in order to reduce the portfolio's risk without decreasing its expected return. In terms of the optimal portfolio weights of the commodity for a portfolio constituting of the oil and commodity holdings, similar results are observed with a maximum of 85.61% for aluminium and minimum of 58.18% for silver. The results can be interpreted as that the allocation of the commodity in a one-dollar portfolio is 85.61 cents and 58.18 cents for aluminium and silver respectively. These outcomes indicate that investors need to invest more in the commodity market than oil market in terms of capital allocation, simply because investors can reduce their investment portfolios' risks. The findings may serve as an incentive to increase the investment in commodity markets. These findings are in line with the view that investors in

³⁰ The weight for silver is 46.48% which is only slightly below 50%.

stock or oil markets are able to gain diversification benefits. They are also consistent with Öztekin and Öcal (2017) who provide empirical evidence that commodity markets deliver better portfolio diversification opportunities. Investors are able to hedge financial risk when they invest in both commodity and stock markets.

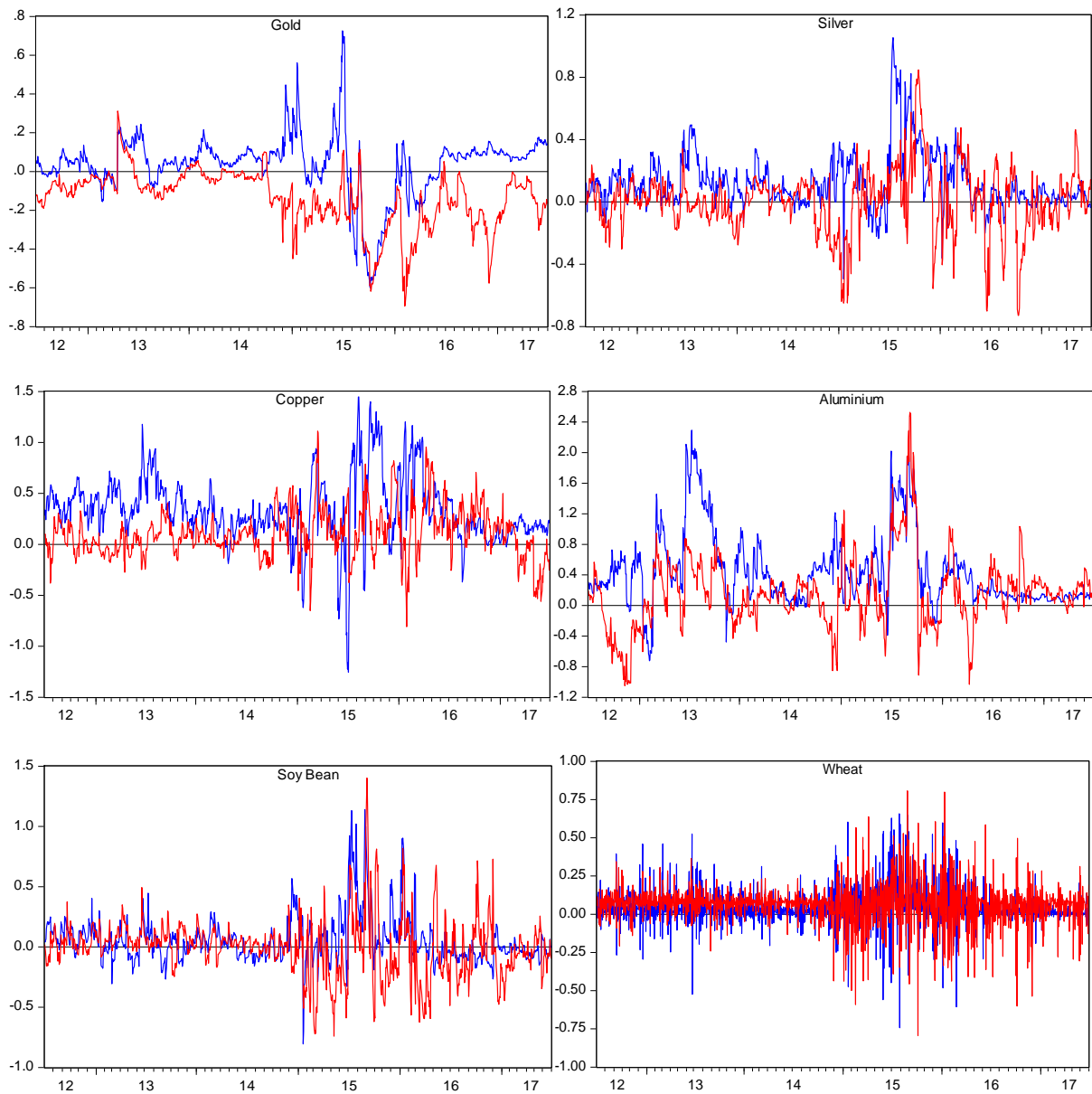
Moving on to the average hedge ratios calculated using equations (8.13) and (8.14), the ratios differ greatly across commodities. We observe positive values of the average hedge ratios for all pairs of commodity-stock. The ratio varies from the minimum of 0.445 for aluminium-stock to the maximum of 0.033 for gold-stock. We can see that the ratios are kept at low levels generally, suggesting excellent effectiveness in hedging the risk in the Chinese stock market. Taking aluminium for example, a highest average hedge ratio is observed for an aluminium-stock portfolio which means this is the most expensive hedge. The ratio (0.445) indicates that hedging a one-dollar long position (buy) in the Chinese stock market requires a short position (sell) of 0.445 cents in the aluminium futures market. In terms of the average hedge ratios for commodity-oil, we observe negative values for gold and soy bean.

This interesting finding shows that the short position should be changed to the long position since the oil market returns are negatively correlated with the returns of gold or soy bean, on average, during the sample period. For the remaining commodities, the hedging ratios are positive, implying that oil price risk exposure can be hedged by shorting in the commodity markets. Regarding the absolute value, it ranges from the lowest of 0.0050 for silver to the highest of 0.1567 for aluminium. The ratios' small size implies that the market movements of the non-energy commodities are not highly correlated with crude oil prices, indicating an effective hedge. For example, for one dollar that is the long position in the oil market, investors should short or sell 10.62 and 15.67 cents in the copper and aluminium futures markets respectively.

Overall, our empirical results indicate that inclusion of commodity in a well-diversified portfolio of stock or oil can reduce risk without sacrificing the return. Additionally, the Chinese commodity markets can help investors to hedge their risk exposure from both the local stock market and global oil market. As a result, these findings are important for investors to improve the risk-adjusted performance by establishing more diversified portfolios and executing the hedge strategy more effectively.

Figure 8.2 illustrates the evolution of the time-varying hedge ratios for both commodity-stock and commodity-oil pairs over the sample period. The graphs indicate considerable variability across the sample period, implying that investors need to adjust their hedging strategies frequently when market conditions change. More importantly, the patterns for hedge ratios differ across commodities studied here, implying that those commodities have different functions in hedge strategy due to their unique characteristics.

Figure 8. 2: The Time-varying Hedge Ratios



Note: The blue line and red line refer β_{cm-st} and β_{cm-oil} respectively.

Table 8. 5: Optimal portfolio weights and hedging ratios

	W_{cm-st}	W_{cm-oil}	W_{st-cm}	W_{oil-cm}	β_{cm-st}	β_{cm-oil}
Gold	0.5838	0.6853	0.4162	0.3147	0.0329	-0.1380
Silver	0.4648	0.5818	0.5352	0.4182	0.1282	0.0050
Copper	0.6577	0.7339	0.3423	0.2661	0.3395	0.1062
Aluminium	0.7566	0.8561	0.2434	0.1439	0.4446	0.1567
Soy Bean	0.5557	0.6560	0.4443	0.3440	0.0546	-0.0080
Wheat	0.5052	0.6236	0.4948	0.3764	0.0482	0.0623

Note: Optimal portfolio weights--- W_{cm-st} and W_{cm-oil} are the weights of the commodity in one-dollar portfolio which consists of commodity and stock/oil. Therefore, the corresponding weights for stock market (oil market) are $W_{st-cm}=1-W_{cm-st}$ ($W_{oil-cm}=1-W_{oil-st}$). The table only reports the average values of optimal portfolio weights and hedging ratios across the sample period.

8.6 Conclusion

The aim of this research is to examine the dynamic relationship between the Chinese stock market, international oil price and commodity markets. We employ dynamic frameworks to investigate the degree of interdependence between three different financial markets. Firstly, we undertake the bounds and Johansen and Juselius tests to examine cointegration relationships among our key market variables. We then apply the well-known VAR-BEKK-GARCH framework to capture both mean and volatility spillover effects. The estimated results indicate significant uni-directional return and volatility interaction from the Chinese stock market and global oil markets to our key selected commodities. Particularly, we find the return spillover effect goes from the international oil market to the Chinese stock market, emphasising the strong dependence of the Chinese stock market on energy prices in this case. However, the oil market tends to behave independently from the Chinese stock market since there are no return spillovers from the stock to oil market.

In terms of the spillover effect in the returns between the stock and commodity markets in China, we can see significant contagion from the Chinese stock market to copper and aluminium futures. Similar results are observed for the interdependence between global oil market and Chinese commodity markets. To a large extent, silver, copper and aluminium markets are found to be influenced by oil returns. In terms of forecasting, we see that a higher oil price is more likely to boost the prices of silver, copper and aluminium futures. However, we find no evidence of the return spillover effects from commodity markets to both the Chinese stock market and the oil market. This may imply weak information efficiency for the Chinese commodity futures. Interestingly, we see no return spillovers between gold and stock and gold and oil market, suggesting the safe-haven role of the gold. The insignificant

spillover effects between the returns of the agricultural commodities and stock/oil markets suggest that they are weakly integrated.

From the volatility behaviours, we report a significant ARCH and GARCH effects in all the markets. Our results demonstrate that both shocks and volatility in the oil market are able to be transmitted to the Chinese stock market while only shocks in the Chinese stock market can spillover to the oil market. The findings highlight that the Chinese stock market is now more integrated with the international global markets, although still less efficient in terms of information transmission. We see strong uni-directional shock spillover effects from the stock market to most commodity markets (e.g. gold, copper, soy bean and wheat) and volatility spillover effect from the stock market to a few commodities like gold and copper. Interestingly, we note that metal futures are more sensitive to the fluctuation in the local stock market whereas the agricultural commodities react more to the shocks in the oil market. Not surprisingly, the heterogeneous volatility spillover effects across commodity markets reflect the different levels of integration between these commodities and stock or oil markets. However, there is no evidence of spillover effects from all the commodity markets to either stock market or oil market.

Given the high level of uncertainties and volatile nature of financial markets in today's world, it is necessary to adopt effective risk management and hedging strategies. Our results for optimal portfolio weights and hedging ratios suggest that by adding the Chinese commodity futures into a well-diversified portfolio of stock or oil, the investment risk can be minimised without sacrificing portfolio performance. From the optimal portfolio weights, we observe the optimal portfolio weights of both a portfolio constituting of the Chinese stock and commodity, and a portfolio holding of commodity and oil products are more than half, except for silver. It therefore provides better hedging opportunities for investors to hold more commodities to reduce their portfolio's risk. We can see that the hedge ratios are generally low, suggesting excellent hedging effectiveness of the Chinese commodity markets. The time-varying hedge ratios imply that investors need to adjust their hedging strategies frequently. Overall our results provide an incentive to raise the investment in the Chinese commodity markets which are important to achieve a portfolio's diversification benefit and improve risk-adjusted performance.

In terms of policy implications, our findings provide valuable insights to investors, policy-makers and portfolio managers. We observe that the interactions are uni-directional

from both the Chinese stock market and the international oil market to other markets. It is evident that these two markets provide important signals that may drive a change in investors' sentiments and approach. The Chinese commodity markets' weak market integration indicates their usefulness in portfolio management and providing hedging opportunities. However, since some commodities are significantly influenced by the local stock market and global oil market, and therefore it shows that the commodity markets are very vulnerable to the shocks outside. Given the increased level of integration, regulators should carefully monitor systemic financial risks and carefully act when they observe extreme market movements. Policy-makers are advised to enhance financial liberalisation reforms on commodity markets in order to enhance information transmission.

With gradual financial openness policy pursued in recent years and as a major oil consumer and importer of oil, China is now more likely to be affected by extreme fluctuations. Such market swings may also have stronger spillover and contagion effects on the local stock market. Investors and policy-makers therefore cannot ignore the impacts emanating from the oil market and they should be prudent and focus more on the fluctuations from the oil market which has strong predictive power. According to our optimal portfolio weights, investors and portfolio managers are suggested to allocate some investment into the Chinese commodity markets. Regulators therefore need to gradually liberalise the Chinese financial markets so that international investors are able to have more opportunity to trade in the Chinese domestic financial markets. However, market speculation can be very damaging to the stability of local financial markets, economies and society. For this reason, they should be expressly prohibited by setting up some restrictions.

Chapter 9: Conclusion and Some Policy Implications

9.1 Introduction

Studying financial integration and spillover effects has significant implications for both practitioners and regulators. This chapter summarises the outcomes and key findings of our study. It also provides some important policy implications, while highlighting potential areas of future research. The key objective of our research is to analyse market co-movements and volatility spillover effects between the Chinese stock market and other financial markets. While an attempt is made to examine information transmission channels, we also investigate the extent of its economic influence and impacts of China's economic development. Several dynamic econometric models, such as VAR and GARCH family models, are utilised to test for return and volatility spillovers amongst the Chinese stock markets (including Hong Kong stock market) and financial linkages between main financial derivative markets (stock index futures market and commodity markets). We further use a sample of selected the Asia-Pacific stock markets to re-examine China regional financial influence. In addition, this research empirically examines the impact of the recently pursued financial liberalisation reforms and the contagious effect of the 2015-16 Chinese stock market crash on dynamic linkages between China's stock market and relevant markets. It should be noted that Shanghai-Hong Kong Stock Connect and QFII have been the major outcomes of the latest opening up of the country's financial system.

Over the past four decades, the Chinese government has gone to great lengths to open up the country's economy, particularly its financial markets. Although investors actively look for diversification opportunities, the increased globalisation and financial integration have resulted in reduced diversification benefits. As a major example of financial liberalisation, China introduced the QFII program in 2002 just after its accession to the WTO, removing barriers to capital participation and further opening its securities markets. The implication of the QFII initiative not only provides foreign institutional investors opportunities to participate in trading on China's capital market and share the fruits of China's big economic growth, but also fosters the progressive market interaction between the Chinese and international markets. Since the QFII program allows qualified foreign institutions direct access to the capital market in China with a hugely expanded investment quota, it makes a significant contribution

to the increased supply of long-term stable capital inflow into the local stock market, making the Chinese stock market more transparent and efficient.

In addition, the Shanghai-Hong Kong Stock Connect which was launched in November 2014 has accelerated the pace of Chinese financial liberalisation progress. Both Chinese domestic and Hong Kong investors are able to trade eligible stocks listed on the other exchange through their local brokers, enabling global investors to invest in eligible A shares listed on Shanghai through this new investment channel. Therefore, the Stock Connect represents a further opening of the Chinese stock markets. Due to huge capital inflow through Shanghai-Hong Kong Stock Connect initiative, China's stock market started to surge dramatically and had been more than doubled within 7 months after the Stock Connect program started. However, this super bull market which was not solidly supported by the strong economic growth had a very short life and the stock market bubble suddenly collapsed after June 2016. The major slowdown in the Chinese economy possibly resulted in the bursting of the Chinese stock market bubble and could have serious repercussions for the global economy. The devaluation of the RMB has also facilitated the stock market crash with strong contagion effects on global markets, signalling further recession in the Chinese economy. The slowdown of the Chinese economy is likely to have significant impacts on both local and global oil and commodity markets due to its massive demand and consumption of oil and commodities. This is because a fall in demand could possibly reduce revenues for oil and commodity producers during times of recession.

Based on recent financial developments, the liberalisation process and “new normal” of China's economic growth, it is timely to assess market co-movement and volatility spillovers centred in the country. This study empirically analyses several relationships: (a) the impact of Shanghai-Hong Kong Stock Connect and spillover effect between the Shanghai and Hong Kong stock markets; (b) the financial integration between China and the Asia-Pacific region and the influence of China's stock market crash during 2015-2016; (c) dynamic nexus between stock and its index futures market in China and the effect of QFII; and (d) the impacts of equity and energy markets on market movement and volatility of China's commodity futures market. The next section summarises the key findings of the above empirical studies.

9.2 Main findings

Having examined the dynamic linkages between China's stock markets and its growing financial influence (both domestic and international), our main emphasis here has been the effect of Shanghai-Hong Kong Stock Connect, the influence exerted by QFII, and the impact of China's stock market crash in 2015-2016. Given remarkable market-oriented changes over the years, we also look at the interactions between stock/oil and commodity markets in China. It is widely accepted that the financial market has become more volatile because of globalisation and financial liberalisation. The information transmission mechanisms across different financial markets, through both returns and volatility, have both theoretical and practical significance for investors, policy-makers and portfolio managers. Volatility spillover effects occur when volatility in one market triggers volatility in another market and could become harmful to local economic performances and financial market stability, especially during the turmoil periods. Therefore, modelling and forecasting correlations and volatility interdependencies could lead to a better understanding of the origins and drivers of volatility across markets, which is important for asset pricing, risk management, portfolio optimisation and hedging strategies. In addition, the increased accessibility of foreign information could also speed up information transmission which can be incorporated into stock prices as foreign investors are likely to have an advantage in processing global information. As a result, the investigation of key financial liberalisation reforms and return and volatility spillovers between the stock market in China and other financial markets in various geographical regions has become an important topic.

Shanghai-Hong Kong Stock Connect, a pilot launched on 17 November 2014, has lifted restrictions on both domestic and international investors and established a feasible, controllable and expandable mutual access between Mainland China and Hong Kong stock markets. Since it provides the first opportunity for individual investors in Hong Kong and overseas to participate in trading of the Chinese A-share market, therefore significant increases in the capitals flow between Shanghai and Hong Kong stock exchanges in both directions are expected after the introduction of Shanghai-Hong Kong Stock Connect. The first empirical research utilises high-frequency data (1 minute) and different econometric models to comprehensively analyse dynamic market co-movement and volatility spillover effects between the Shanghai and Hong Kong stock markets. Also investigated is the impact of Shanghai-Hong Kong Stock Connect. This study breaks the sample into two sub-periods: Pre- and Post- Stock Connect periods and observes significant differences regarding

cointegration relationship and spillover effects. The results show the presence of a significant long-term cointegration relationship between the two stock markets in the Post-Connect period while there is no cointegration relationship between these two markets before this program, implying strengthened market integration after Shanghai-Hong Kong Stock Connect. In addition, the return spillover effect from Shanghai to Hong Kong is found to be faster and stronger compared with that from opposite direction in the Post-Connect period.

A similar conclusion can also be obtained based on the impulse response analysis which shows that Hong Kong tends to be more responsive to the shocks in Shanghai, but the Shanghai stock market reacts less significantly to the shocks in Hong Kong after the program. In terms of conditional volatility, our results indicate the increased conditional volatility of both stock markets since the implementation of Shanghai-Hong Kong Stock Connect. This is probably because this financial liberalisation reform shifted the investment restrictions and thus attracted huge capital flow and market participation for both stock markets, making the market more volatile. In accordance with the empirical results from the VAR BEKK model, both mean and volatility spillover effects from Shanghai to Hong Kong are found to be enhanced after Shanghai-Hong Kong Stock Connect whereas the contagion effects from Hong Kong to Shanghai have become weaker. The empirical evidence supports the contention that the Chinese mainland stock market starts to play a leading role in information transmission and is able to influence Hong Kong stock market through channels of return and volatility. It is concluded that Shanghai-Hong Kong Stock Connect could enhance the dominant position and improve the predictive power of the Chinese stock market (Shanghai).

From the end of 2014 until mid-2015, the Chinese stock market climbed to fresh heights since the GFC. The bull market was only a reflection of China's future growth potential with grand development strategies and reforms but without solid support of the actual country's fundamentals. Therefore, China's stock market bubble burst on 12 June 2015, and slumped again on 24 August 2015 with additional sinks on 4-7 January 2016. The second empirical study examines daily price and volatility transmissions across Asia-Pacific stock markets during the Chinese financial market crisis in 2015-2016, showing that China has become a major source of financial contagion which could be transmitted widely throughout the Asia-Pacific region during its recent stock market turbulence. No evidence can be found for the long-term cointegration relationship between China's and Asia-Pacific stock markets, implying potential diversification benefits over the long run for international investors. The

past value of market indices is observed to influence their current value, confirming the strong autoregressive characteristic for all stock markets. The study indicates the differences for both price and volatility spillovers between China and other markets during the crash and non-crash periods.

During the bullish period, price spillovers transmitted from China to other regional markets are found to be more significant since seven Asia-Pacific stock markets are deeply influenced by China's domestic prices. These Asia-Pacific financial markets are strongly affected by 'good news' emanating from China when its stock market increases. However, when the Chinese stock market crashed, its neighbours are found to make contributions to China's crash since significant evidence of price transmissions from these markets to China are detected, showing that China adjusts to the information flow from Asia-Pacific markets during the crash period. In terms of the transmission of shocks and volatility, notable shock and volatility spillover effects between China and Asia-Pacific stock markets are observed in both stable and turbulent periods because the majority of A(1,2) and B(1,2) are statistically significant, indicating the volatility in Asia-Pacific markets is deeply influenced by the market fluctuations in China. Moreover, the research finds enhanced volatility transmission from China to ten Asia-Pacific markets in the bearish period which means that Asia-Pacific stock markets are responsive to the market volatility from China during the crisis, confirming the important dominant position of China as a strategic financial centre in this region. The non-existence of price and shock spillovers between China and New Zealand during the bearish period demonstrates potential benefits of portfolio diversification opportunities to international investors.

This empirical study also provides a detailed analysis on how QFII influence the price discovery role of the Chinese stock index futures market and volatility behaviours between spot and future based on VECM and GARCH family models' estimations. The analysis results indicate a bi-directional asymmetric lead-lag relationship between the Chinese stock index futures and spot markets, implying a strong lead from the futures market to the spot market but a weak lead from the spot to futures market. Particularly, the price discovery role of the futures market can last longer with greater magnitude compared with that of the spot market and therefore the Chinese stock index futures market is more efficient due to its important price discovery role. Since the underlying spot market responds more to the price changes in its futures market following the QFII reform, it is concluded that QFII have

enhanced the price discovery role with the increased predictive power of the futures market. The findings indicate that foreign institutional investors' participation in the Chinese stock index futures market could improve its price discovery function with better information gathering and sharing.

For the impact of QFII on volatility, the reduced conditional and unconditional volatilities of the futures market and their persistence can be discovered after implementation of QFII, revealing the index futures market is less volatile (or risky) and perhaps more efficient after the QFII reform. In addition, the volatility asymmetric effect and spillover effect have substantially changed due to the influence of foreign capital inflows. Since uni-directional spillover effect from spot to futures market changes to bi-directional spillover effect between them in the Post-QFII period, the spillover effect from the futures market to the spot market has been strengthened. It suggests an improvement in information transmission running from the futures to spot markets in terms of volatility spillovers. Finally, the dynamic conditional correlations between the futures and spot market have been observed to decrease and become more volatile after the introduction of QFII.

Regarding the dynamic relationship between the Chinese stock market, international oil price and commodity markets in China, no cointegration relationship can be found among these three markets based on several mainstream cointegration tests, implying potential diversification opportunities. In terms of spillover effects, this study finds evidence of significant uni-directional return and volatility interaction from the Chinese stock market and global oil markets to some key commodities in China. In addition, the causal relationships on returns are only found: from oil market to China's stock market; from the Chinese stock market to copper and aluminium commodity markets; and from oil market to silver, copper and aluminium markets in China. However, this study cannot find evidence of the return spillover effects from the commodity market in China to both the Chinese stock market and the oil market. Moreover, no return spillovers between gold and stock (oil) markets can be found, suggesting the safe-haven role of the gold. With insignificant spillover effects between the agricultural commodities and stock/oil market, China's agricultural commodities are not well integrated with either the equity or energy market. Concerning volatility behaviours, the conditional variances are directly affected by their past shocks and volatility, confirming significant ARCH and GARCH effects for all markets. The empirical results demonstrate that both shocks and volatility in the oil market are able to be transmitted to the Chinese stock

market, while only shocks in the Chinese stock market can influence the oil market. This implies poorer efficiency of the stock market in China despite the good integration between stock and oil markets.

The study also finds notable uni-directional shock spillovers from the stock market to most commodity markets (e.g. gold, copper, soy bean and wheat) and volatility spillover effect from the stock market to a few commodities like gold and copper. Additionally, strong evidence of shock spillovers from oil prices to gold, soy bean and wheat markets together with volatility contagions from oil to soy bean market can also be observed. It looks as if the metal futures are more reactive to the fluctuation in the local stock market while the agricultural commodities respond more to shocks in the oil market. However, no volatility spillover effects from all the commodity markets to either stock market or oil market can be found. One notable feature of this study is that the time-varying optimal portfolio weights and hedging ratios are computed based on the estimation of conditional variance and covariance. The results provide an incentive to add the Chinese commodity markets to reduce or hedge against the risks of a well-diversified portfolio of stock or oil in order to achieve a portfolio's diversification benefit.

9.3 Policy Implications

As China continues to integrate with the wider world, both investors and policy-makers are facing an increasingly complicated situation in which both domestic and overseas shocks can affect the local stock markets, perhaps leading to some diversification benefits being sacrificed. A number of important policy implications can be drawn from the empirical analysis. Shanghai-Hong Kong Stock Connect has established mutual stock access between Shanghai (a Mainland China financial centre) and Hong Kong (an international financial centre). Both foreign and local investors can now benefit from information sharing and risk management strategies, thus noise can be reduced and efficiency can be improved in both stock markets. Since the Shanghai stock market is found to be more influential and plays a more important role in information transmissions, it is suggested that policy-makers should carefully monitor the stock market movement in Mainland China to avoid any substantial shocks which may harm local economic performance and the investment environment.

The increased predictive power of Shanghai can attract investors to reasonably forecast the movement and volatility of Hong Kong stock market. The success of Shanghai-Hong Kong Stock Connect as a part of the national opening strategy provides valuable operational experience for further financial liberalisation reforms. Its implementation has provided basic groundwork for its twin brother Shenzhen Hong Kong Stock Connect. It is expected that the linkages among the Hong Kong, Shanghai and Shenzhen stock markets will be further intensified and they will become more integrated with large improvements in their market efficiency. Solid operational record of Shanghai-Hong Kong Stock Connect could foreseeably cause it to become a model not only for other cross-border trading channels into Mainland China but also for other developing markets with significant regulatory barriers on foreign investment.

Nowadays, the Chinese stock market is becoming more integrated with the Asia-Pacific financial markets because of its geographical position, strong economic linkage and greater trade and financial relations in the Asia-Pacific region. The results of this research show that both Chinese and Asia-Pacific markets can be used as important market trading signals to predict each other at different stages. Given the observed enhanced volatility transmission from China together with the increased interdependencies among Asia-Pacific economies during China's crash, the risk exposure and vulnerabilities of a financial system in the region have increased. As a result, a sudden acceleration of systemic risk through deteriorations in both the capital flow and foreign market activities could probably happen in these regional economies in Asia-Pacific, especially during episodes of financial stress. Thus the financial stabilisation mechanisms against harmful international contagion are necessary to protect local markets. Given the increasing importance of China, policy-makers are advised to carefully monitor Chinese financial and economic conditions and establish warning systems to forecast potential financial crises. Since financial integration is able to promote regional success and connectivity, so it is necessary to encourage solid and friendly relationships in the Asia-Pacific region in order to foster the economic and financial cooperation. Also more economic and trading agreements between China and Asia-Pacific region are encouraged.

Moving to the Chinese stock index futures market, as the index futures market has a dominant position in the bilateral relationships between spot and futures in terms of both price discovery and volatility spillovers, it is suggested to more attention should be paid to

the Chinese stock index futures market in order to benefit from its predictive power. The Chinese regulators need to monitor the market movement of stock index futures and introduce innovative regulations that prohibit noising behaviours which disturb the market order. In addition, its openness to foreign institutional investors is found to reduce the risk level, enhance the rate of information flow, improve the quality of information and increase market efficiency, making a significant contribution to the development of the financial system in China. However, QFII reform only enables foreign institutional investors to participate in the stock index futures market trading whereas international individual investors are still prohibited from trading stock index futures contracts in China. Therefore it is necessary for China to continue further liberalising its financial markets. For example, China could propose several unconventional policies allowing qualified individual investors to trade in index futures contracts.

In terms of the impacts of stock and oil markets on commodities, uni-directional interactions (of return and volatility) from both the Chinese stock market and the international oil market are observed, hence equity and oil markets are able to behave as trading signals for the commodity markets in China. Also, the findings indicate that the commodity markets are very vulnerable to outside shocks, highlighting the influential power of the local equity and international oil markets. As a result, it is recommended that policy-makers carefully monitor the risks outside the commodity markets and issue warnings to investors when observing signs of a financial crisis. China's commodity markets are found to be less efficient because of its position as the net receiver under information transmissions, therefore regulators should promote some financial liberalisation reforms for the commodity markets in order to improve their market efficiency and integration. However, the weak market integration of the Chinese commodity markets indicates their efficiency in portfolio management and hedging strategy. Meanwhile, the influence from the oil market on China's stock market cannot be ignored. China, as one of the world's most important oil consumers and importers, should be prudent and keep an eye on the international oil market's behaviour to avoid any harmful and powerful contagions to its local equity market and economic performance.

Given the recent growth in financial globalisation, it is critical that China continues to develop and reform its financial markets so that the risk associated with large crises can be better managed. Policy-makers need to gradually liberalise local financial markets so that

international investors have more opportunity to participate in the growth of China's financial markets. It is believed that the country's key liberalisation reforms could consolidate its regional powerful position and help the development of its domestic economic and financial system. Enhanced financial openness and more independent market-based monetary policies should be promoted in China to improve the investment environment because both foreign and local investors can benefit from information sharing and risk management strategies.

The progressive transition towards a market-based financial system should also be supported by changes in legal and institutional frameworks. However, financial liberalisation should also follow a proper sequential process to avoid greater risk exposure and crisis. Market speculation is harmful to the stability of the local financial markets, economies and society and hence it should be prohibited by setting up relevant regulations to guarantee a safe, reliable, efficient financial system. The Chinese securities regulatory authority should welcome policies that will improve market transparency, promote harmonisation of financial rules, strengthen regulations and supervision and enhance better corporate governance. Also, it is recommended to reduce regulatory complexity and improve its financial institution's standards to align with international expectation.

9.4 Limitations and Some Suggestions for Future Research

Like other research work, certain limitations need to be mentioned in this thesis. The main limitation is that this study only examines market linkages from the Chinese perspective but not from the perspective of its trading partners. This is mainly because I have considered China to be the focus of the case study. Although China is the largest emerging country but still the world's second largest economy, this study concentrates on the impact of China on its neighbours in the Asia-Pacific, ignoring the influence of the US. Moreover, this study looks at relations between China's stock market and Hong Kong stock market, the 11 largest equity markets in the Asia-Pacific, CSI 300 index futures market and several key commodity markets. Although they are the most important markets which have the strongest relationship with China, other important financial markets are ignored. Further, this study has not incorporated macroeconomic and microeconomic factors, since the main purpose is not to focus on the factors which drive market interdependence. This study involves only a few important financial liberalisation reforms (Shanghai-Hong Kong Stock Connect and QFII)

and China's stock crash in 2015-2016, but ignores the impacts of fiscal and monetary policies. While the econometric models employed in this study are advanced, the analysis only implemented a quantitative research method based on mathematical models but not qualitative perspectives. Future research should consider interviews or surveys involving central government officials and chairpersons in charge of stock exchanges.

In future, a comparison between influence from Shanghai-Hong Kong Stock Connect and that from Shenzhen Hong Kong Stock Connect could be considered. In such a way, the relevance and level of influence of the two stock connect programs in market information transmission can be assessed, using a more recent sample period. Comparison between the impact of the US and China on the market interdependence in the Asia-Pacific could also be undertaken in order to better understand the nature and driver of regional volatility spillovers. Furthermore, future work might re-examine the similar issues addressed in this thesis using a relatively longer sample period to capture the effects of the Asian Financial Crisis, the Global Financial Crisis, the European Debt Crisis periods and China's Stock Crash. Future analysis can also involve other key trading partners of China, such as the European, African and Latin American countries. Finally, the influence from several key macroeconomic variables on stock market linkages could also be investigated in the future.

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