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Modelling cross-market linkages between global markets and China's A-, B- and H-shares

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The Use of Thesis statement is not included in this version of the thesis.

Abstract

One of the biggest challenges in quantifying joint risk and forming effective policies in financial management and investment strategies is to fully understand the characteristics of market associations in low and high volatility periods. Market interdependence, therefore, is a hot topic that has received interest from academics and industry experts, especially since the Asian Financial Crisis in 1997. China, being the world's second-largest economy, has been the centre of many studies investigating stock market dependencies. While China has three major share types, namely A-, B- and H-shares, with different market players, market characteristics and operating efficiency, the number of studies on each of these share types remains conservative in comparison to the vast literature on the financial modelling of market interdependencies. Given the need for a more comprehensive understanding of the influence between these share types and other global markets, especially during market turbulences, this thesis examines the cross-market linkages between A-, B- and H-shares in China and several major emerging and advanced markets from 2002 to 2017, which is divided into two non-crisis periods and two crisis periods.

This thesis assesses market integration among 17 markets, including asymmetries and leverage effect in the marginal distributions, volatility spillover and tail dependence. The thesis aims to: 1) investigate the univariate asymmetries and leverage effect in the distributional volatility of each time series and to detect volatility spillover between China and other studied markets; 2) assess the dynamic multivariate dependence between China and other studied markets; 3) evaluate the bivariate dependence structure for each of China's markets and other studied markets using seven different copula functions; and 4) study the multivariate joint tail dependence structure of all studied markets using vine copulas.

There are various findings from the thesis. Many advanced and emerging markets experienced leverage effect and asymmetries in volatility. China's markets were much more prone to local shocks than external shocks and in many cases, there is evidence that China's markets diverged from the global trends especially during the crisis periods. Besides, segmentation between China's markets and the United States is clearly evident. In addition, regional dependence is stronger than intra-regional dependence. The thesis also found the existence of contagion effect between each of China's markets and various markets in the sample in the Global Financial Crisis. Finally, heterogeneity was found for A-, B- and H-shares in various aspects, from distributional asymmetries to joint behaviour in both crisis and non-crisis periods.

A novel aspect of this thesis is that it closes the gap in the literature of market linkages for A-, B- and H-shares with other global markets by assessing volatility spillover, time-varying co-movement, and tail dependence among the studied markets. This thesis provides various implications in both theoretical and empirical contexts in many areas including measuring joint risk at the tails, constructing an optimal portfolio, hedging, and managing financial exposures and contagious volatility from other

markets. The thesis provides some recommendations and suggestions regarding the policies implemented in China.

Declaration

I certify that this thesis does not, to the best of my knowledge and belief:

i. incorporate without acknowledgement any material previously submitted for a degree or diploma in any institution of higher education

ii. contain any material previously published or written by another person except where due reference is made in the text of this thesis

iii. contain any defamatory material.

Signature: [redacted]

Date: 28/07/2020

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Publications and Conferences

The publications and conference papers are given below:

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Paper prepared for submission to a journal special issue on financial markets and corporate governance:

Do, A., Powell, R., Singh, A., & Yong, J. (2019). *Multivariate dependence behaviour between global markets and China's A, B and H-shares using R-vines and C-vines.*

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Abbreviation and definitions

AS: A-shares

BS: B-shares

HK: Hong Kong

HKSE: Hong Kong Stock Exchange

HS: H-shares

INDO: Indonesia or Indonesia's stock market

GER: Germany or Germany's stock market

MALAY: Malaysia or Malaysia's stock market

SHA: Shanghai A-shares

SHB: Shanghai B-shares

SHSE: Shanghai Stock Exchange

SING: Singapore or Singapore's stock market

SZA: Shenzhen A-shares

SZB: Shenzhen B-shares

SZSE: Shenzhen Stock Exchange

THAI: Thailand or Thailand's stock market

Chapter 1 Introduction and background

This chapter provides an introduction to the thesis in section 1.1, followed by the motivation in section 1.2 and economic background of the selected countries in section 1.3. Background on return dependence and volatility dependence is presented in section 1.4. Research questions and objectives are presented in section 1.5. The significance of this study and the structure of this thesis can be found in sections 1.6 and 1.7 respectively.

1.1. Introduction to the thesis

Since the Global Financial Crisis (GFC) which commenced in late 2007, despite the United States (US) economy subsequently showing some signs of recovery, concern over the global economy and stock markets has been stirred by various events, coupled with fear over the instability in China's economy. Compared to the period before the GFC, attention from investors, analysts and economists to the movement in China's stock market has been growing considerably. This peaked with China's stock market crash in August 2015. In late 2017, another fall in global markets occurred due to a massive sell-off in the bond market in China. These events raised a flag about the stability of global markets. A big question that interests many analysts and investors is how far the impact can spread if the markets in China experience substantial falls. In order to answer this question, a thorough understanding of the nature of cross-equity linkages between China and other global markets is required, which is a key aim of this study.

The literature relating to cross-equity relations can be divided into two main streams. The first approach focuses on the synchronisation at the first moment (price return), while the second approach pays more attention to the joint behaviour at the second moment (volatility of returns). Examining relationships at the first moment is one of the most fundamental approaches in conventional financial modelling, which can be undertaken by various financial models such as autoregressive models (AR), linear correlation coefficient, panel regression models and Granger causality. However, these methods have their limitations. For example, Granger causality can only provide qualitative analysis while the linear correlation coefficient can only describe a linear relationship and fails to recognise non-linear association (Wen & Liu, 2009). Return correlations that are used to measure cross-equity dependence have faced years of controversy for not accurately and comprehensively describing the joint dependence structure relating to volatility. Return correlation was characterised by dynamic behaviours that were regime dependent and increased during a crisis (Bekaert & Ang, 1999; Forbes & Rigobon, 2002). However, co-crash probability was found to be indifferent regardless of the degree of pre-GFC correlation between two markets, suggesting that the degree of return correlation has little to no role in explaining the joint distribution of volatility, especially during an economic downturn (Hu, 2006). Markets that had low return correlation before a crisis had a joint probability of recession that is as high as markets with high correlation. The study of Kenourgios, Samitas, and Paltalidis (2011) found supporting evidence that the return correlations of equity markets are asymmetric; that is, the probability of a co-crash in a highly volatile period was higher than the co-movement in market upswings. In addition, the volatility of correlation coefficients was higher during a crisis, suggesting correlations might not be a reliable indicator of extreme risk in the context of market interdependence (Chiang, Jeon, & Li, 2007). Thus, these findings indicate that inferences on the cross-market volatility based on the return correlation can be misleading. This highlights the importance of studying the behaviour of joint distribution of volatility among different markets directly.

For this reason, many studies have shifted their focus to market dependencies at the second moment, adopting methods that can capture the joint behaviour of volatility directly and in which a generalised autoregressive conditional heteroskedasticity (GARCH) model is one of the most well-known models (Chou, 1988; Hamilton & Susmel, 1994). Using a similar perspective, this study examines the dependence at the second moment between major share markets in Mainland China namely A-shares (AS), B-shares (BS) and H-shares (HS) and other global markets in the US, the United Kingdom (UK), Japan, Hong Kong (HK), Germany, Australia, New Zealand (NZ) and the Association of Southeast Asian Nations (ASEAN)-5 countries consisting of Malaysia, Thailand, Singapore, Indonesia and the Philippines from 2002 to 2017, adopting an exponential GARCH (EGARCH) model, time-varying dynamic conditional correlation (DCC)-GARCH model, bivariate copulas and multivariate vine copulas.

The rationale for selecting equity markets for this study is that they are known for being highly responsive to changes in the economy, thus being a leading indicator of economic predictions. Even though many factors drive stock prices, macro-economic fundamentals play a significant role, in that stock prices are expected to reflect the changes in economic activity causing stock market movements similar to the business cycle (Candelona & Metiua, 2011). It is also found that equity markets during crises exhibited a higher degree of correlation which potentially manifested implied risks built up from market interdependence, as was observed in the Asian Financial Crisis (AFC) 1997-1998 and the GFC. Since there is abundant literature in this field examining the AFC (Cheng & Glascock, 2005; Chiang & Chen, 2016; Darrat & Zhong, 2002; Ho & Zhang, 2011; Johnson & Soenen, 2002; Sun, 2014), this study focuses on the period after the AFC.

There are two main reasons for selecting these equity markets in the sample. First, these markets are either leading established markets in the region or emerging markets that possess strong growth potential. Second, the selected countries are major trading partners of China; hence they are ideal candidates for a study of cross-equity linkages. More details of their economic background can be found in section 1.3.

This thesis examines four major objectives of market interdependencies found in the literature between the selected countries by: 1) investigating the univariate asymmetries and leverage effect in the distributional volatility of each time series and detecting volatility spillover between China and other markets in the sample using a univariate GARCH and EGARCH model; 2) assessing the dynamic multivariate dependence between China and other markets in the sample using a multivariate time-varying DCC-EGARCH model; 3) evaluating the bivariate joint tail dependence between China and other markets using bivariate copula functions; and 4) studying the multivariate joint tail dependence structure of all markets in the sample using vine copulas. This thesis also discusses various important concepts and theories that were documented in several global financial markets during the GFC including volatility spillover, contagion effect and decoupling-recoupling hypothesis. These concepts are defined in sections 1.4.2 and 1.4.3. To establish whether they apply to the markets in the sample, this thesis examines each of these concepts and theories as outlined above using four different models on the same dataset in four sub-periods including non-crisis periods (pre-GFC period from 1 May 2002 to 26 February 2007); post-crisis period (from 7 June 2012 to 31 July 2017); crisis periods (GFC period from 27 February 2007 to 29 May 2009); and extended-crisis period (from 30 May 2009 to 6 June 2012). The complete description of the data of this thesis, the four sub-periods and the preliminary analysis are presented in Chapter 2. The objectives for each chapter are presented in section 1.5.

The modelling of the associations between these financial markets in the sample starts with simple GARCH models in Chapter 3 which account for major distributional properties of the studied financial markets. Chapter 3 examines the leverage effect and the asymmetry in volatility for each market using the EGARCH model, and the volatility spillover between two markets using the EGARCH model with an auxiliary term of a spillover effect. The thesis then assesses, in Chapter 4, the dynamics of multivariate dependence structure of the 17 studied markets using a time-varying DCC-EGARCH model. Chapter 5 quantifies the joint tail and general dependence structure of a pair of markets using seven bivariate copulas. Chapter 6 assesses the dependence structure of 17 markets under a multivariate context using vine copulas (R-vine and C-vine). Volatility spillover is mainly addressed in Chapter 3, while tail dependence, general return dependence, contagion effect and decoupling-recoupling hypothesis are discussed in Chapter 3 through to Chapter 6.

1.2. Motivation

It is well documented that a shock can be transmitted from one market to another, which is also called volatility transmission or 'spillover' (Kanas, 1998; Li & Giles, 2015). The consequences of this behaviour in equity markets can be severe, as proven through the AFC 1997-1998 and the GFC 2007-2008. The common theme among these catastrophic events is that the crises started locally, and then spread to other countries in an unruly manner. The AFC originated from the currency crisis in Thailand, and the GFC was caused by the sub-prime crisis in the US. This spread could have been the result of various factors, but most studies agree that globalisation plays a vital role in creating higher market interdependence through financial and economic integration. Li and Rose (2008) revealed that market integration at the local and regional levels was responsible for the extreme movement of stock market returns in Asia-Pacific Economic Cooperation (APEC) countries. Apart from that, deregulation could also be the reason. Li (2012) found that China's liberalised capital policies also had an impact on volatility spillover from China to other global stock markets, including the US, Korea and Japan. Another important phenomenon that was documented during the GFC is the recoupling and decoupling among emerging and advanced markets, with some mixed findings (Park, 2012; Wyrobek & Stańczyk, 2013) as mentioned in section 1.4.2. In addition, recoupling among markets was recorded during the GFC after decoupling occurred briefly at the beginning of the GFC which has raised doubts on the effectiveness of protection policies in many countries against the external crisis (Korinek, Roitman, & Végh, 2010). Since this is a popular topic in financial modelling and existing findings are subject to on-going debates, examining the dependence structure among these studied markets provides an opportunity for these concepts to be reviewed.

Existing literature concerning the relations between China's equity markets and other global markets is abundant, but the majority focus on the period around the AFC and GFC. Since the peak of the GFC in 2008, many catastrophic events have occurred, including the Eurozone crisis in late 2010 and the US downgrade crisis in 2011. In addition, the emergence of China's economy and other countries in the Asia-Pacific has shifted the world trading landscape. China's equity market has evolved from a small market to one of the largest global markets, with capitalisation reaching US$7.3 trillion in 2015. It is worth noting that the number of retail investors accounted for 90% of the market, which possibly explains why China's equities were impacted by herding, especially during an economic downturn (Lao & Singh, 2011; Teng & Liu, 2014). Since China became a new global trading hub and the second-largest economy in the world in 2013, its impact on other markets is more visibly significant, and therefore its role in the global market cannot be ignored. Furthermore, the joint distribution of market integration exhibits asymmetries, indicating that the spreading effect is larger during an economic downturn than upturn, and big shocks create more immense spillover effects than small ones (Fratzscher, 2002). The combination of these factors necessitates a more comprehensive understanding of the relationship between China and other major markets.

Apart from the need to re-examine the role of China in global markets regarding volatility spillover, another major motivation for this study in examining these markets is the increased economic integration between those countries (Fan, Lu, & Wang, 2009). All markets in the sample are major trading partners of China, in which some markets have close geographic proximity; for example, Australia, NZ and the ASEAN-5 countries (Indonesia, Malaysia, the Phillipines, Singapore and Thailand). Moreover, there are very few studies on dependence behaviour between the three types of Chinese equities (AS, BS, HS) and other global markets. Sun (2014) is one of the few studies on cross-equity relationships between the three different share types in China and other countries; however, it only focused on the co-integration during a short period after the GFC. Each share type provides a specific channel for a specific group of investors. Thus, they could be driven by a different set of factors and might not necessarily share the same cyclical pattern. Therefore, it is necessary to examine the dependence behaviour of each group separately. This thesis aims to provide a comprehensive view on the cross-market dependencies with China's major equity markets at the centre. The countries in the sample are selected for their economic significance in the region, as well as the strong established trading links and geographic proximity with China.

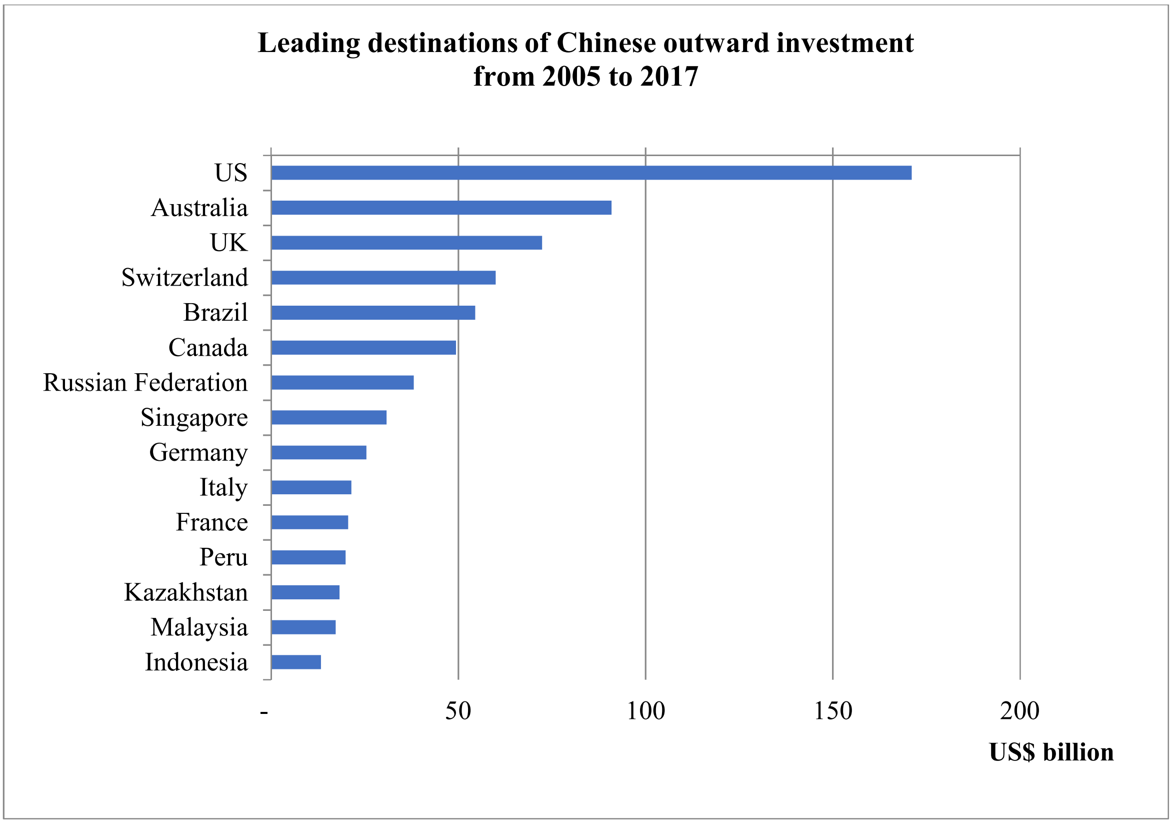
1.3. Economic background of the selected countries

1.3.1. China

China, as a new global trading hub, is a vibrant and promising economic area driven by its rapid economic and trading expansion in both volume and size. China's economy in 2005 grew from less than one-fourth to more than half the size of the US economy in 2015, averaging 10% growth per year. This impressive growth has been underpinned by accelerated trading volumes and foreign investment inflows to China, which was facilitated by the major economic reform in 1978 and the subsequent series of liberalised capitalisation policies during the 2000s. The reform covered a wide range of major areas including agriculture, state-owned enterprises, foreign trade and investments, market-determined pricing systems, non-state sectors, banking and financial sectors, economic and social infrastructure, and the social welfare system. It aimed to transform China from a centrally planned economy to a more market-oriented one. Following the reform, China imposed several capital liberalisation policies, with the Qualified Foreign Institutional Investor (QFII) policy in 2002 and the Qualified Domestic Institutional Investor (QDII) policy in 2006 being the major ones.

Strong links between China and the selected countries in this thesis have been established through trade and capital investments. According to the World Bank, China was the top exporter, with US$2.3 trillion in 2015 – above the US at US$1.8 trillion. It was also the world's second-largest consumer of imported goods and services (US$1.3 trillion) after the US (US$2.1 trillion) in 2015. China was among the top three trading partners of major markets such as the US, European Union (EU), Australia and Asia, from 2010 to 2015. Its role in the Australian economy could be even more critical compared to other countries, due to Australia's significant iron ore export exposures to China.

In addition, China and other major economies are financially associated through foreign direct investments (FDI). According to China's Ministry of Commerce (2019), Australia, Singapore, the UK, Malaysia and the US are among the top 10 leading destinations of China's outward investments in various sectors including energy, real estate and entertainment, with the investment size ranging from US$260 million to US$43 billion to June 2017. The US, Australia, the UK, Singapore, Germany, Malaysia and Indonesia are among the top destinations of Chinese investments from January 2005 to December 2017, as shown in **Figure 1-1**. Total inward FDI to China increased significantly by 10% per year on average from 2010 to 2015, up from US$114.5 trillion to US$135.6 trillion. It has remained in the world's top three FDI destinations since 2005, according to the data collected by the United Nations Conference on Trade and Development (2019).



Source: Ministry of Commerce (2019)

Figure 1-1. Leading destinations of Chinese outward investment from 2005 to 2017

China's stock markets

China's equities comprise three major stock exchanges: the Shanghai stock exchange (SHSE), Shenzhen stock exchange (SZSE) and Hong Kong stock exchange (HKSE). Shares traded on these markets are categorised into three major classes: AS, BS and HS, with the main differences being in the denominated currency, investors and the trading regulations.

AS, officially known as RMB Common Stocks, are denominated in China's currency; that is, Renminbi (RMB), and they are listed on the SHSE and SZSE. These securities are issued by Chinese companies registered in Mainland China and were initially traded by investors within the territory (excluding Taiwan, HK and Macau) until the introduction of the QFII in 2002. Shanghai AS are referred to as SHA, and Shanghai BS are abbreviated to SHB.

BS which are issued by local Chinese companies are accessible to foreign investors. BS have face value in RMB and are traded in US dollars on the SHSE, and in HK dollars on the SZSE. Only some local investors with current accounts in foreign currency can trade this type of stock. Shenzhen AS are referred to in this thesis as SZA and Shenzhen BS are referred to as SZB.

HS are issued by Mainland Chinese companies and traded on the HKSE. HS are listed according to the HKSE's listing and reporting regulations. They are denominated in HK dollars and available to both local and foreign investors.

China's liberalisation policies from 2002 to 2016

Since A-shares are considered as "policy" markets and the existing literature in section 3.7.3 shows mixed evidence of liberalisation effects on China's regional dependence, therefore it is important to know the major liberalised capital polices in China's stock markets. Since China's accession to the World Trade Organization (WTO) in 2011, several reforms in capital deregulation were implemented in China's equity market from 2002 to 2016 including the: 1) QFII program in 2002; 2) RMB exchange rate reform in 2005; 3) QDII program in 2006; 4) Renminbi Qualified Foreign Institutional Investors (RQFII) scheme in 2011; 5) Shanghai-Hong Kong (SH-HK) Stock Connect program in 2014; and 6) Shenzhen-Hong Kong (SZ-HK) Stock Connect program in 2016.

1. <u>The QFII program 2002</u>

Launched in 2002, the QFII scheme permitted inward capital from qualified foreign investors initially to China's AS, which then expanded to stock index futures and fixed income products in 2012. According to information published on the SHSE website, the investment quota was increased from US$4 billion in 2002 to US$10 billion in total, in 2005, and foreign ownership is up to 20% in AS and 80% in bonds in the latest revised regulation (Shanghai Stock Exchange, 2017). The RQFII scheme, which applies to HK funds and securities companies, was introduced in late 2011 to use offshore RMB raised in HK to invest in securities in Mainland China up to a certain quota. By 31 July 2017, 284 QFIIs had been granted, with a total investment value of US$93.3 billion (Shanghai Stock Exchange, 2017).

2. <u>The RMB exchange rate reform 2005</u>

In July 2005, China implemented the RMB exchange rate reform, introducing a 'reference basket' of currencies for determining the target value of the RMB. This reform allowed the variation of the RMB exchange rate up to 0.3% and later 0.5% daily against the basket. The reform was suspended during the GFC 2008 and resumed in June 2010, after the peak of the GFC. The spot exchange rate against the US dollar was allowed to move within 1% daily on April 2012 and further lifted to 2% and 3% in March 2014 and July 2015 respectively.

3. <u>The QDII program 2006</u>

The QDII scheme, initiated in 2006, allows approved domestic investors access to foreign capital markets up to a quota of US$5 billion per single investor, and further increased to US$90 billion in March 2015. Foreign capital markets were initially restricted to fixed income and money market products and subsequently expanded to equity markets and related products; however, investment is capped at 50% of the net value of the product.

4. The RQFII program 2011

In December 2011, the RQFII scheme was implemented as a continuation of the commitment from China to market openness. This program initially allowed qualified investors to fund their investments in Mainland China's equity markets with a permitted quota of RMB-denominated funds in HK, and later expanded to other approved countries. By 31 July 2017, 185 RQFIIs had been approved, with a total value of RMB¥548.2 billion (Shanghai Stock Exchange, 2017).

5. The SH-HK Stock Connect program 2014

In an attempt to increase the integration with the HK market and to reduce the gap in the trading premium between AS traded on the SHSE and its counterparts in HKSE, the SH-HK program was introduced in November 2014. This program allows accessibility for investors to both the HK and Shanghai markets in order to reduce the trading gap in the premium of AS and HS that were issued by the same company (counterparts). Contrary to the QFII and RQFII, there is no eligibility requirement for the participants of this scheme, and there is no lock-up period. The investment scope is limited to 568 SHA with RMB-denominated trading currency and a daily quota of RMB¥1.3 billion RMB. (HKEX, 2019)

6. The SZ-HK Stock Connect program 2016

Following the SH-HK Stock Connect program in 2014, the SZ-HK Stock Connect program was introduced in 2016 to allow investors to access both markets. Similar to the SH-HK Stock Connect program, the SZ-HK Stock Connect program is open to everyone with an investment scope of 880 SZA and a daily limit of RMB¥1.3 billion (HKEX, 2019).

1.3.2. ASEAN-5

The ASEAN was formed in 1967 and comprises 10 members (Cambodia, Laos, Malaysia, Singapore, Brunei, Myanmar, Indonesia, the Philippines, Thailand and Vietnam), in which the ASEAN-5, comprising Indonesia, Malaysia, the Philippines, Singapore and Thailand and, accounted for 88% of the aggregate Gross Domestic Product (GDP) of all members in 2015. Thus, the ASEAN-5 is included in this research not only because of its geographic proximity and financial bonds to China, but also because of a strong potential for growth in the region.

Even though the GDP growth rate of these countries from 2005 to 2015 experienced high ups and downs, bringing the average GDP growth to 10.31% per year on average from 2005 to 2015, they are alternate destinations for global investment during the deceleration of China's economy. FDI inflows to the ASEAN-5 are 1.5 times higher on average than to China in the last two decades. In total, the ASEAN-5 received almost US$361 billion in foreign investment, topping China's FDI receipts of US$250 billion in 2015.

Moreover, the ASEAN-5 countries with unequal economic growth and different development stages make up a diversified sample. **Table 1-1** shows that Singapore is the most developed country, with a GDP per capita of US$52,889 in 2015, followed by Malaysia and Thailand, which achieved US$9,768 and $5,815 respectively. These countries offer global-standard regulations and business governance, a highly skilled workforce and established infrastructure. Indonesia and the Philippines, on the other hand, benefit investors with attractive labour costs, with the GDP per capita being US$3,346 and US$2,904 respectively.

Table 1-1. Economic indicators of China and ASEAN-5 in 2015

Country	GDP (US$ billion)		GDP per capita (US$)	FDI net inflows (US$ million)
	2005	2015		
China	2,286	11,008	8,028	249,859
Singapore	127	292	52,889	65,263
Malaysia	143	296	9,768	10,963
Thailand	189	395	5,815	9,004
Indonesia	286	861	3,346	20,054
Philippines	103	292	2,904	5,835
ASEAN-5	849	2,438	N/A	360,977
World	47,392	74,152	10,093	2,135,702

Source: World Bank, Bloomberg

1.3.3. Other global markets

Table 1-2 illustrates that these countries combined were responsible for 40% of the world GDP in 2015, with an average GDP per capita ranging from US$32,477 (Japan) to US$56,116. The total capitalisation of these equity markets comprises to 72% of the total value for global equities in 2015. These mature markets have a long history of trading that offer a wide range of sophisticated products such as derivatives (futures, options, swaps), and permit high-risk trading activities such as short sales, which are usually restricted in immature markets. They are also major markets representing their local economic areas; for example, the US for the Americas, the UK and Germany for Europe, and Japan and Australia for the Asia-Pacific.

Table 1-2. Economic indicators for other global markets in the sample, in 2015

Country	GPD (US$ billion)		GDP per capita (US$)	FDI net inflows (US$ million)
	2005	2015		
United States	13,094	18,037	56,116	379,434

United Kingdom	2,508	2,858	43,876	50,439
Germany	2,861	3,363	41,313	46,227
Australia	693	1,339	56,311	38,639
Japan	4,572	4,123	32,477	-41,885
World	47,392	74,152	10,093	2,135,702

Source: World Bank, Bloomberg

1.4. Background on return dependence and volatility dependence

1.4.1. General review

A study on six Balkan states during the GFC revealed that export and import activities have a direct and positive impact on the absorption of the external crisis to the domicile state (Pula, 2014). In particular, export-oriented states suffered more severely from the crisis than the import-oriented states. Similarly, it was found that there was an upward trend in stock market synchronisation measured by return correlations between Asian countries and other global financial centres such as the US, Japan and HK, mainly caused by an increase in trading and capital flows (Johnson & Soenen, 2002; Rim & Setaputra, 2010). Thus, it was evident that economic and financial integration plays a major role in both market integration and risk transmission across countries. Therefore, top trading partners should be considered for studying cross-equity dependence.

The existing literature also suggests that a crisis was more likely to be transmitted to countries with weak banking systems and low liquidity (low capital reserves relative to short-term debt) during a market downturn, due to investors' fear over capital loss, which was induced by the devaluation of domicile currency from external accounts adjustments (Sachs, Tornell, & Velasco, 1996). This implied that crises from developed economies were more likely to be transmitted to emerging markets. If China encounters an economic downturn, the spreading effect can be global to both developed and developing markets. China's rapid expansion, in the context of its current banking system and political factors, raises concern among investors over its long-term financial stability. In addition to environmental and social issues, such as rising income inequality and poor environmental management due to extraordinary growth, a lack of strong internal control systems raises questions about China's ability to achieve a smooth transition from a growth phase to a mature phase with a more sustainable growth rate. Existing literature also finds that economic integration of Chinese markets was higher after the introduction of the liberal capitalisation policies (Tam, Li, Zhang, & Cao, 2010). This reinforced the need to study cross-market linkages between China and those countries in relation to volatility dependence, especially during periods of economic turbulence.

Sun (2014) is one of the few papers that studied cross-equity relationships between the three different share types in China and other countries. That study only focused on the cointegration in a short period after the GFC and did not account for stochastic dependence behaviours such as asymmetries in volatility, time-varying correlations or specific-regime volatility spillover which were found in empirical studies regarding cross-equities between Shanghai stock markets in Mainland China and other markets (Chiang & Chen, 2016; Fang, Liu, & Liu, 2015). Another related paper is the study of Cheng and Glascock (2005), which examined the equity associations between major markets (the US and Japan) and the Greater China Economic Areas (GCEA) including Mainland China, HK and Taiwan. Their study found that HK was the most influential market among the GCEA and that no cointegration, but rather a non-linear relationship existed between developed markets and the GCEA using autoregressive integrated moving average (ARIMA) and general GARCH models.

1.4.2. Return dependence

With regards to economic integration and globalisation, a tremendous amount of research has focused on market co-movement estimated by correlation among these countries. It was commonly found that economic integration had a positive impact on short-term and long-term cross-equity correlations between European countries (Dockery & Vergari, 2001; Fratzscher, 2002) and Asian markets; that is, Australia, NZ, HK, Malaysia and Japan (Chaudhry, Boldin, Affaneh, & Khan, 2012; Johnson & Soenen, 2002).

Contagion and recoupling of stock market behaviour are important concepts in financial modelling, which is supported by the findings in chapters 4, 5 and 6 of this thesis. Typically, an instantaneous and significant increase in the return correlation between markets (strictly speaking, creating a structural break in the return correlations) in a crisis is defined as contagion (Forbes & Rigobon, 2002).

In the literature related to cross-market linkages, recoupling referred to the event where there was an increased integration among stock markets which was usually recorded in a crisis such as the AFC or GFC. For this reason, recoupling can also be called contagion. Recoupling also referred to the event where cross-border market dependence appeared during a crisis period. This phenomenon has been documented in both the GFC and the Greek sovereign debt crisis (Wyrobek & Stańczyk, 2013; Yeyati & Williams, 2012). On the other hand, decoupling referred to the segmentation between, in many cases, emerging markets such as Brazil, Russia, India, China and South Africa (BRICS) and their lead markets such as the US during the GFC, which reflected a break in a previous integration (Dooley & Hutchison, 2009; Floros, Kizys, & Pierdzioch, 2013; Willett, Liang, & Zhang, 2011). Disintegration in stock behaviour in emerging markets from advanced markets could reflect the recoupling–decoupling in economic growth rates, which could be facilitated by market openness and economic development (Cutrini & Galeazzi, 2012).

It was also found that this phenomenon had a rapid swing back and forth over a short period, in which decoupling usually occurred at the start of the GFC and then quickly came back to recoupling for the rest of the crisis (Dooley & Hutchison, 2009). For this reason, it was concluded that the government policies that occurred before the GFC, such as a significant increase in reserve position or reduction of foreign debt at both national and company levels which aim to minimise the dependence of the emerging markets on advanced markets in a crisis, were inadequate (Park, 2012). Decoupling was documented shortly after the GFC, which could be explained by a shift in investors' preferences from advanced markets that were heavily impacted by the GFC to the emerging markets that were believed to be the world growth locomotive, due to their loss in confidence in those emerging markets. Hence, this phenomenon was viewed in the short to medium term. Therefore, by dividing the whole sample period into four sub-periods, this thesis was able to capture this important and interesting phenomenon in the stock behaviours of the markets in the sample. While this thesis does not focus extensively on the causal factors of recoupling-decoupling, the findings recorded and discussed this phenomenon in various advanced and emerging markets in the studied sample.

A study based on the Engle and Granger (1987) two-step approach examining stock markets during 2003 to 2007 suggested that HK, as part of China, had the most robust capacity to drive the whole region into a fully fledged and integrated commercial area (Tan, Cheah, Johnson, Sung, & Chuah, 2012). One of the reasons for this conclusion could be the brevity of market history that leads to survivorship bias, which in turn overlooks the long-term effects of market integration in the region (Goetzmann & Jorion, 1999). This is important, especially where cross-equity linkages are dynamic and time-varying. Masih and Masih (1997) employed Granger causality tests and found causal linkages between HK and established markets (the US, the UK, Japan and Germany) and newly industrialised markets (Singapore, Taiwan and South Korea) in both the short-run and long-run from 1982 to1994. On the other hand, a related study by Cheng and Glascock (2005) showed that there was a random walk between US, Japan and the GCEA consisting of Mainland China, HK and Taiwan using a GARCH model and ARIMA model from 1993 to 2004.

Dynamic behaviours of correlations in a crisis were well-documented in the empirical literature. Chiang et al. (2007) noted that correlations between Asian countries, including Malaysia, Thailand, Indonesia, the Philippines, Korea and HK, increased at the early stage of the AFC in 1997 and were then intensified due to herding behaviour in the later stage. Asymmetries in correlation distributions are another critical finding. Higher correlation and volatility are commonly associated with the market downturn. However, there was not enough evidence to conclude that financial crises are a significant factor that drive cross-equity correlation. As an example, correlations between the US and G-7 countries were higher if two markets were both in a downturn and lower in the other economic states including growth periods or out of phase, but the impact was not substantial (Erb, Harvey, & Viskanta, 1994). A related study by Ang and Chen (2002) included skewness as an endogenous variable of the US equity correlations at a domestic level. Similar to cross-equity research, asymmetries in correlation were found to be most significant in downside moves. However, in contrast to conventional wisdom, asymmetries in correlation at the domestic level were not found to be derived from skewness and co-skewness of return distributions.

Even though empirical literature studying cross-market dependence focusing on China and other global markets is abundant, conclusions about market segmentation between these countries are conflicting, and thus inferences are not comprehensive. Long-term co-movement was found between stock markets in China and other major economies, including the US, UK, HK and Japan from 1999 to 2008 (Fan et al., 2009). In contrast, Palamalai, Kalaivani, and Devakumar (2013) argued that the disparity between Japan, China and ASEAN-3 (Malaysia, Indonesia and Singapore) was significant during 2000 to 2013, employing variance decomposition analysis. Little evidence was found for market integration between China and the US during 1993 to 2004 based on an ARIMA model and a GARCH model (Cheng & Glascock, 2005). Similar results were found for the US, HK and China from 2001 to 2008 using three different GARCH models, namely BEKK (named after Baba, Engle, Kraft and Kroner, 1990), constant conditional correlation (CCC) and DCC (Mohammadi & Tan, 2015). Fan et al. (2009) adopted a Markov-switching framework and found evidence of long-term co-integration between China and the US, the UK, Japan and HK from 1992 to 2008, while the short-term causality was one way to China and varied with economic regimes. In another related study over a similar period, Moon and Yu (2010) used a GARCH-in-mean (GARCH-M) model and found a structural break in the mean of China's stock market return in December 2005 that Fan et al. did not consider in their study. They also found that the influence of China's stock market to the US's market was evident after 2005. The inconsistent findings of those studies can be due to different methodologies, the brevity of the data after the GFC, model specification or the structural break that one of the studies did not account for. Thus, this creates an opportunity to review the linkages between those countries using a more comprehensive approach and recent data. It is also of interest to ascertain which of these countries are the most and least sensitive to the external shocks from China's markets.

1.4.3. Volatility dependence

Empirical literature indicating return correlations and co-integration is perhaps too restrictive in explaining dynamic cross-equity linkages during economic turbulence. Apart from the contagion effect and the recoupling-decoupling hypothesis defined in section 1.4.2, another critical concept referring to the causal relationship of cross-market returns and mostly volatility is spillover. This thesis adopts the conventional definition of volatility spillover, which is the instantaneous transmission of shocks in one market to another market (Cheung & Ng, 1996; Karolyi, 1995; Liow, 2015). Volatility dependence or spillover across countries was found to be stronger during turbulent periods, whereas disparity in market performance – that is, decoupling – was found among ASEAN-5 countries before, during and well after the AFC (Rim & Setaputra, 2010). Except for Indonesia and the Philippines, ASEAN-5 markets were weakly integrated during and after the Asian crisis, even though there was evidence of unidirectional relationships between these countries before the crisis. Similarly, both return and volatility dependence between the US and BRIC countries (Brazil, Russia, India and China) were weakened after the GFC

(Xu & Hamori, 2012). Volatility spillover was also documented in many other papers (Białkowski & Serwa, 2005; Mishra, Swain, & Malhotra, 2007; Reboredo, Rivera-Castro, & Ugolini, 2016).

Financial time series such as stock returns commonly display excess kurtosis and skewness (Ang & Chen, 2002). Instead of using a Gaussian distribution, adoption of general error distribution (GED) or Student-t-distribution for the disturbances can address excess kurtosis in marginal distributions of volatility. Skewness, on the other hand, can only be captured by an appropriate model specification. Asymmetries in financial time series can stem from two sources: the skewness of the marginal distribution and the cross-sectional asymmetric response of volatility from a joint distribution (Longin & Solnik, 2001; Patton, 2004).

Skewness in marginal distributions can be addressed by the adoption of univariate asymmetric GARCH models such as EGARCH. He (2000) showed that EGARCH has a more vibrant autocorrelation structure than the standard GARCH one. Similarly, Hansen and Huang (2015) found that the EGARCH model with a realised measure of volatility with better goodness of fit test was superior to the symmetrical GARCH model when using the S&P 500 index.

Skewness in joint distributions, on the other hand, can be handled by multivariate/bivariate GARCH or copulas. Fortin and Kuzmics (2002) found that the return pairs on three European stock indices (Germany: DAX 30, UK: FTSE 100 and France: CAC 40) displayed asymmetric tail dependence. Consistent with this finding, Peng and Ng (2012) revealed that the upper time-varying tail dependence coefficient was higher for volatility index returns in the US and the UK from 2001 to 2009. Hu (2006) documented an asymmetric left tail dependence in volatility pairs on the US (S&P 500), HK (Hang Seng), Japan (Nikkei) and UK (FTSE) markets.

Asymmetries in different regimes were also evident in international equity markets. It was found that there were two distinct regimes in the dependence structure of the US and UK markets using Markov-copulas models including a bear regime (negative expected returns and high volatility) and normal regime (high and stable expected returns) (Okimoto, 2008). In addition, asymmetric lower tail dependence was detected in the bear regime. Edwards and Susmel (2001), who studied the dependence of volatility regimes in emerging Asian and Latin American stock markets, revealed that there was evidence of regime dependence behaviour across countries employing univariate three-states switching autoregressive conditional heteroskedasticity (SWARCH) models. Bivariate SWARCH models further detected the existence of strong volatility co-movements between those countries. In a similar study about stock return co-movement in different regimes, high correlation was associated with high volatility in a bear market; however, evidence was found of higher volatility induced by market downturn rather than higher correlation (Bekaert & Ang, 1999).

There are several factors and theories that can explain the cause of risk transmission and an increased probability of co-crashes during crises; for example, the positive association between domestic and international systematic risks (Bekaert, Ehrmann, Fratzscher, & Mehl, 2014).

Interestingly, economic and financial integration are also driving factors that impact the correlation but are not single elements for risk transmission. Increased trade associations can have a positive effect on market integration, but political issues, poor economic development, high unemployment rate, enormous government budget deficit and trade coordination policies can also be determinant factors (Rafi & Lewis, 2012). Notably, these internal exposures can escalate the vulnerability of a particular country to shocks from another country (Bekaert et al., 2014). Inequality in economic development and growth can also diminish integration among emerging markets (Chaudhry et al., 2012).

Baillie and Bollerslev (1992) showed that failure to model all the properties of normalised residuals distributions possibly generated spurious results. Harvey and Siddique (1999) highlighted that the existence of skewness in asset returns could impact the distributional properties of the conditional mean and variance, which in turn introduced bias to the assessment of volatility spillover across countries. Ané and Labidi (2006) showed that when the marginal distributions and dependence structure were appropriately specified, the spillover effect disappeared, indicating that without addressing the distribution properties adequately, the results can be spurious. Therefore, this thesis examines the data using four different methodologies, namely univariate GARCH and EGARCH models, the multivariate DCC-GARCH model, bivariate copulas and multivariate vine copulas that will account for skewness and leptokurtosis in marginal distributions, asymmetries in joint distributions and tail dependence. Since there is no single model that is perfect for all data, the adoption of various methods will provide the benefit of comparison, in order to determine the best-fit model and to avoid spurious results.

1.5. Research questions and objectives

This thesis examines cross-equity linkages particular to the joint behaviour of volatility dependence between three different share types in China, namely AS, BS and HS, and other global markets in the US, the UK, Germany, Australia, NZ, Japan and the ASEAN-5 during the period from 8 May 2002 to 31 July 2017.

The research objectives and research questions are developed in four chapters, as follows:

<u>Chapter 3 – Dependence analysis using univariate GARCH and EGARCH</u>

- The first research objective: to investigate the univariate asymmetries and leverage effect in the distributional volatility of each time series and to detect volatility spillover between China and other markets in the sample using a univariate GARCH and EGARCH model.
- Research questions:
  1. Is there evidence of leverage effect in the distributional volatility of each market in the sample?
  2. Is there evidence of volatility spillover between China and other markets in the sample?

<u>Chapter 4 – Dependence analysis using multivariate DCC-EGARCH</u>

- The second research objective: to assess the dynamic multivariate dependence between China and other markets in the sample using a multivariate DCC-EGARCH model.
- Research questions:
  1. Is volatility spillover under the multivariate context evident between China's markets and other studied markets, especially for the A-share market, since it is a 'closed' market?
  2. Is there evidence of time-varying correlation between China and other markets in the sample?
  3. Are the joint dependence structures in terms of return correlation and volatility spillover of AS, BS and HS homogenous or heterogeneous?
  4. Did China's equities experience market segmentation during the GFC and extended-crisis periods (decoupling effect), as found in existing literature, or contagion effect?

Chapter 5 – Dependence analysis using bivariate copulas

- The third research objective: to evaluate the bivariate dependence structure bewteen China and other studied markets using seven different copula functions.
- Research questions:
  1. What is the structure of the joint dependence between each of China's markets and other markets in the sample?
  2. Is there a change in the dependence structure of these markets in the crisis periods?
  3. Is there heterogeneity in the regional and global joint dependence structure among AS, BS and HS?

Chapter 6 – Dependence analysis using multivariate vine copulas

- The fourth research objective: to study the multivariate joint tail dependence structure of all markets in the sample using vine copulas.
- Research questions:
  1. What is the tail dependence structure in a multivariate context of the 17 markets in the sample, in crisis and non-crisis periods?
  2. What is the role of HS and HK markets in the regional and global dependence of Chinese AS and BS?
  3. Is there evidence of inter-regional dependence and intra-regional dependence for these studied markets?

The same data is used across the whole thesis and is tested using the four different methods to address each of the objectives; that is, univariate GARCH and EGARCH models are used in Chapter 3, the multivariate time-varying DCC-GARCH model is used in Chapter 4, bivariate copulas are used in

Chapter 5 and multivariate vine copulas are used in Chapter 6. The data and the results from preliminary testing are presented in Chapter 2. The hypotheses for each research question are given above and are also shown in each respective chapter.

1.6. Contribution

The contribution of this thesis to the existing literature of cross-equity volatility dependence regarding asymmetries, tail dependence and regime-dependence behaviour is from both theoretical and practical aspects such as portfolio selection, risk management, hedging and option valuation, as summarised in this section.

A significant contribution of this thesis is to provide a useful comparison of estimated covariance between two markets and the persistence of shock transmitted across markets by adopting different methodologies. Differences in the persistence of shocks transmitted across markets from using different methods were documented (Karolyi, 1995). Nevertheless, the results also supplement each other, as they document multiple aspects of volatility dependence that helps explain volatility asymmetry using univariate and multivariate models, regime-dependence behaviour and asymmetries in tail dependence at a cross-market level. This thesis argues that volatility dependence across markets, especially between AS, BS and HS and other markets in the sample, are subject to asymmetries, particularly in regards to leverage effect (volatility in one market is more prone to bad news than good news in another market). This behaviour is, however, not constant but varies in different economic states and regimes. The tail distributions of volatility dependence between these markets are also subject to asymmetry.

This study applies directly to global markets, which can provide important insights to not only domestic, but also to global investors. International diversification is a well-known application in portfolio construction. Theoretically, systematic risk reduction can be attained by holding assets in various countries that have low correlations of returns. Ammer and Mei (1996) researched 28 countries from five different groups including high-income countries, Western European countries, common market countries, developing countries and the US, and claimed that, in an ideal world, an optimal portfolio should include all countries' securities. However, the benefits from international diversification need to be considered, given the increased market interdependence due to globalisation and higher economic integration. Thus, this thesis has extensive coverage of interested audiences and provides benefits in both academic and practical settings.

The major contribution of each chapter as follows.

1.6.1. Chapter 3 – Dependence analysis using univariate GARCH and EGARCH

The contribution of this chapter is two-fold. First, it examines the asymmetry in distributional volatility of global stock markets over the past 15 years and extends the study of volatility spillover between major financial centres with three different Chinese equities, which has received minimal attention in empirical studies. The chapter covers a broader sample of countries than is usually studied in the literature, including global financial centres from different geographic locations. Hence, it reveals possible exposures of these markets to the volatility of each type of China's equities and vice versa over the last 15 years. Second, the study covers a long period before, during and after the GFC, which gives a good insight into changes of volatility and shock transmission behaviour over this period. This is extremely useful to policymakers and investors who are interested in China's stock markets and their impact on other global markets.

Studying asymmetric volatility dependence between equity markets is essential in pricing an option, specifically to multi-asset options which can benefit the process of hedging undesired risks in an international portfolio. For example, it was found that an asymmetric GARCH option pricing model that accounts for asymmetry in volatility innovations is superior to other symmetric GARCH models and ad hoc Black–Scholes models (Barone-adesi, Engle, & Mancini, 2008). Even though this finding is from the study of a single asset option, it set a strong foundation for further study of multi-asset options.

Findings on volatility dependence can also have important implications for financial market regulations. Understanding the dynamic behaviours of market volatility transmission can support regulators and policymakers in forming risk management frameworks and controlling systems to minimise the risk from economic integration (Plummer, 2009). For example, risk management policy should take into account: a) the fact that volatility of stock returns is asymmetric; and b) the level of exposure to external factors, to mitigate the risk of increased correlation during a market downturn.

In addition, this chapter surveys stylised facts in financial time series relating to asymmetries in volatility dependence between major markets in China and other countries. Accounting for asymmetries of volatility dependence boosts the precision of forecasts of variance correlations, hence improving the quality of portfolio choices based on this technique, compared to the symmetric GARCH model.

1.6.2. Chapter 4 – Dependence analysis using multivariate DCC-EGARCH

Chapter 3 discusses the importance of studying the three major share types in China separately and concurrently, due to the differences in market accessibility and operational features. This area, however, has received little attention from existing literature regarding modelling dependence in both univariate contexts, as discussed in Chapter 3, and multivariate contexts (Li & Giles, 2015; Moon & Yu, 2010). The closest article to this multivariate study is Allen, Amram, and McAleer (2013), which modelled the time-varying volatility spillover between Chinese stock markets and its major trading partners including Australia, HK, Taiwan, Singapore, Japan and the US. Chatper 4 extends the sample size of existing literature to 17 countries and the sample period to 2017, which includes the major market deregulation policies from 2011 to 2016 in China's equity markets, as mentioned in section 1.3.1. In addition, this chapter examines dynamic correlation of multivariate dependence structures, which have received limited attention in existing literature regarding three major share types in China in a multivariate context. The findings of this study distinguish the behaviour associated with volatility and return spillover of AS, BS and HS, so they help investors to form appropriate investment and hedging strategies for each of these share types.

Moreover, asset correlation is critical in asset pricing as well as in financial risk management such as hedging. If the correlation is time-varying (as examined in this study), hedging ratios should be continuously adjusted to reflect this change. It is also found that a model which accounts for time-varying properties in conditional correlations can generate lower optimal portfolio variance and higher portfolio returns than a model which uses constant correlation (Billio, Caporin, & Gobbo, 2006).

1.6.3. Chapter 5 – Dependence analysis using bivariate copulas

This chapter is significant for many reasons. Firstly, it examines tail dependence, which is fundamental to many important concepts in financial modelling associated with a crisis such as a contagion effect and recoupling hypothesis. The study of tail dependence among stock markets, therefore, provides crucial implications for estimating an optimal portfolio, hedging and options pricing. Moreover, evaluating tail dependence using a copula approach is a recently developed method in modelling joint dependence of stock returns, hence this chapter creates an empirical context for applying copula in evaluating the joint dependencies between global stock markets and major Chinese share types. Given the size of China's economy and the rapid expansion of China's stock markets, evaluating the global and regional dependence of the three major share types in China is of interest to global investors, fund managers and policymakers. This chapter expands limited literature on the joint dependence of China's AS, BS and HS with various advanced and emerging markets over the last 15 years. Finally, this chapter provides critical findings confirming the differences in the joint dependence structures and behaviours of these Chinese share types in both non-crisis (pre-GFC and post-crisis periods) and crisis periods (GFC and extended-crisis periods). Thus, investors and fund managers should take these differences into account when forming investment and hedging strategies for these stocks.

1.6.4. Chapter 6 – Dependence analysis using multivariate vine copulas

This chapter is significant for many reasons. It includes modelling of multivariate tail dependence. The modelling of co-dependencies of international financial returns around the tails is vital in evaluating portfolio risk because it is found that the probability of extreme events is higher for a joint distribution with significant tail dependence than a normal distribution (Chollete, Heinen, & Valdesogo, 2009; Longin & Solnik, 2001; Støve, Tjøstheim, & Hufthammer, 2014). Correct specification of the joint tail distribution structure is crucial in portfolio selection, investment hedging strategy, Sharpe ratio targeting, option pricing and credit risk analysis (Poon, Rockinger, & Tawn, 2004). Failing to account for tail dependence structure in a multivariate joint distribution leads to an underestimation of the risk of loss.

For this reason, R-vine and C-vine outperform alternative linear portfolio optimisation models in optimising an efficient portfolio (Bekiros, Hernandez, Hammoudeh, & Nguyen, 2015), and are useful for both passive and active portfolios (Brechmann & Czado, 2013). Hence, the findings of this study contribute to the limited literature of copula applications in separately modelling the co-dependencies of AS, BS and HS at the regional and global levels. This has important implications for a wide range of audiences including policymakers, international institutional and retail investors, fund managers and financial risk managers in various areas such as portfolio construction, estimating hedging ratios and evaluating tail risks.

1.7. Design of the thesis

The remainder of this thesis is structured as follows. Chapter 2 describes the data used across the whole thesis, provides descriptive statistics and undertakes preliminary tests for this dataset including normality, stationarity, heteroskedasticity and correlation. Chapter 3 deals with the first objective as mentioned in section 1.1 page 17, which is addressed by univariate GARCH and EGARCH models. The findings of asymmetries and leverage effect in the volatility of marginal distribution for each time series and volatility spillover between China and each of the studied countries in the sample are also discussed in this chapter. Chapter 4 presents the application of a multivariate time-varying DC-EGARCH model in addressing the second objective, and discusses the results of the dynamics of market dependencies. Chapter 5 is an application of bivariate copula, which aims to scrutinise general and tail dependence for each of China's markets and other markets in the sample. Chapter 6 further explores the joint tail dependence structure of 17 markets in the sample using multivariate copulas; that is, vine copulas. Chapter 7 summarises the main findings and conclusions from each of the three models. **Table 1-3** summarises the research question and methods that will apply to chapters 3 to 5. The overall structure of this thesis is presented in **Figure 1-2**.

Table 1-3. Summary table of research questions and methodology

	Research question	**Hypothesis**	**Method**
Chapter 3	Q1: Is there evidence of leverage effect in the volatility of each market in the sample?	**H_0**: There is no evidence of leverage effect in the marginal distribution of volatility of each market. **H_a**: There is evidence of leverage effect in the marginal distribution of volatility of each market.	EGARCH
	Q2: Is there evidence of volatility spillover between China and other markets in the sample?	**H_0**: There is no evidence of volatility spillover. **H_a**: There is evidence of volatility spillover.	EGARCH with an added auxiliary term of volatility spillover
Chapter 4	Q1: Is volatility spillover under the multivariate context evident between China's markets and other studied markets, especially for the A-share market since it is a 'closed' market?	**H_0**: There is no evidence of multivariate volatility spillover between China's markets and other markets in the sample. **H_1**: There is evidence of multivariate volatility spillover between China's markets and other markets in the sample.	DCC-EGARCH
	Q2: Is there evidence of time-varying correlation between China and other markets in the sample?	**H_0**: There is no evidence of time-varying correlation between China's markets and other markets in the sample. **H_1**: There is evidence of time-varying correlation between China's markets and other markets in the sample.	DCC-EGARCH
	Q3: Are the joint dependence structures in terms of return correlation and volatility spillover of AS, BS and HS homogenous or heterogeneous? Q4: Did China's equities experience market segmentation during the GFC and extended-crisis periods (decoupling effect), as found in existing literature, or contagion effect?	Research questions 3 and 4 are for comparison purposes. Therefore, there is no hypothesis for these questions. Instead, they will be addressed in the discussion of the empirical analysis.	DCC-EGARCH
Chapter 5	If there is evidence of dependence: Q1: What is the structure of the joint dependence between each of China's markets and other markets in the sample? Q2: Is there a change in the dependence structure of these markets in the crisis periods?	**H_0**: There is no evidence of dependence between each of China's markets and the other markets in the sample. **H_1**: There is evidence of dependence between each of China's markets and the other markets in the sample.	Bivariate copulas

	Q3: Is there heterogeneity in the regional and global joint dependence structure among AS, BS and HS?		
Chapter 6	Q1: What is the tail dependence structure in a multivariate context of the 17 markets in the sample in crisis and non-crisis periods? Q2: What are the roles of HS and HK markets in the regional and global dependence of Chinese AS and BS? Q3: Is there evidence of inter-regional dependence and intra-regional dependence for these studied markets?	There is no hypothesis for this chapter. The research questions are addressed in the findings of the multivariate vine-copula functions. The unconditional tree, estimated Kendall's tau parameters and the specification and copula matrices will show the dependence structure, dependence type, and whether or not if there is an inter- or intra-regional dependence.	Multivariate vine copulas

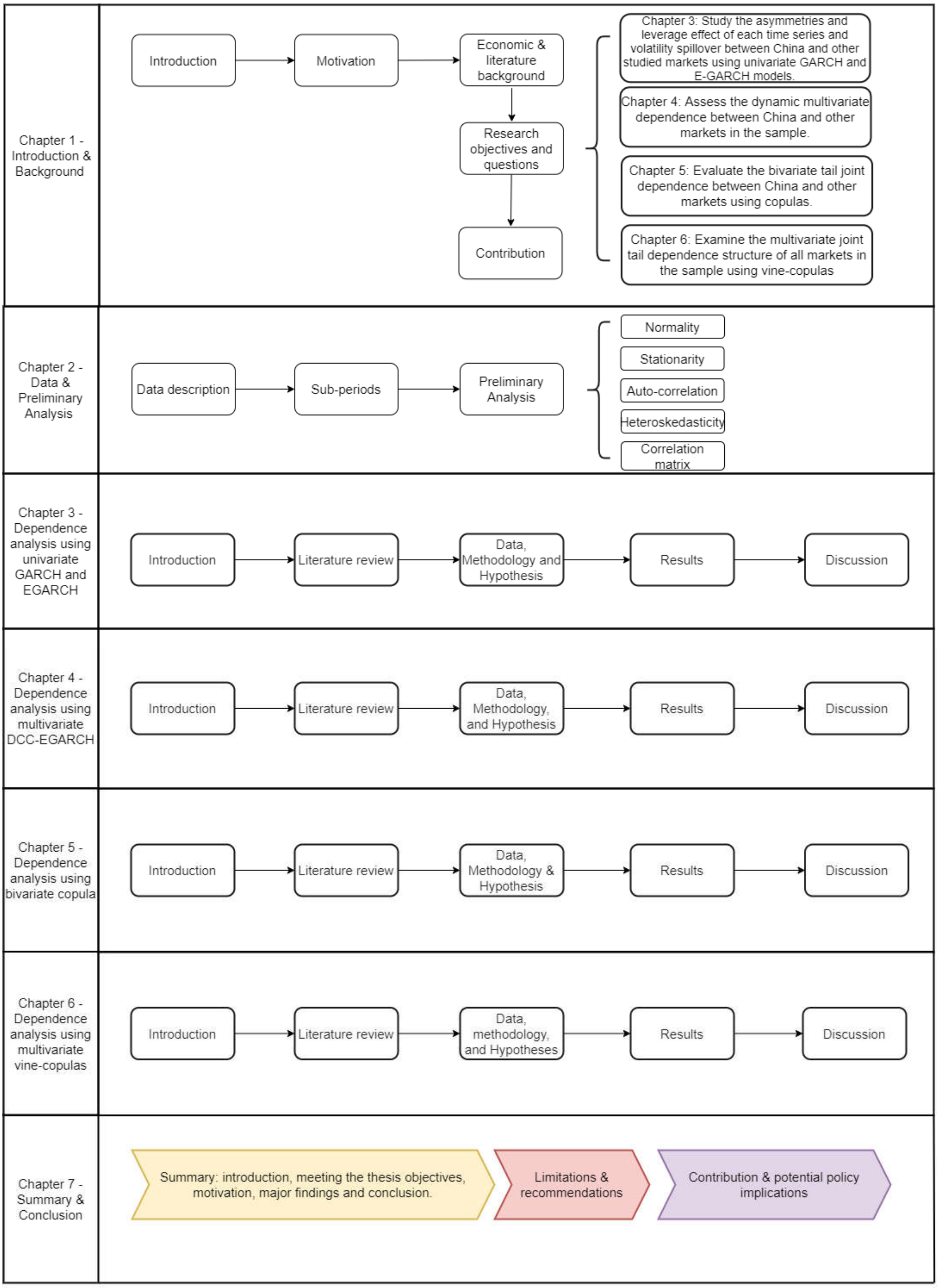


Figure 1-2. The main structure of the thesis

Chapter 2 Data and preliminary analysis

This chapter describes the data used for this thesis and the preliminary testing and analysis including descriptive statistics, normality, stationarity, autocorrelation, heteroskedasticity and correlation. The preliminary analysis highlights the need to examine the studied data using a model that can account for the stylised facts observed in the data, including heteroskedasticity and autocorrelation, confirming the appropriateness of GARCH models that can meet those requirements. Section 2.1 describes the data used for this thesis. Section 2.2 presents the sub-periods. Section 2.3 discusses the preliminary analysis.

2.1. Data description

The data comprises daily equity index prices in US dollars for the last 15 years from 1 May 2002 to 31 July 2017, which are obtained from Bloomberg. **Figure 2-1** presents information including the number of constituents, a brief description, stock exchange, commencement date and market capitalisation for each stock index in the sample. The selected indices in this sample include global indices that are commonly used in empirical studies to represent the economies of their countries. This thesis studies 17 equity indices as shown in **Figure 2-1**. Six out of these 17 equity indices are among the world top 10 countries that have the highest equity market capitalisation, according to Bloomberg, namely the US, China, Japan, HK, UK and Germany. The aggregate value of all 17 equities in this thesis is approximately US$64.8 trillion in 2016, according to data published by the World Bank. These studied markets account for 60% of the world market capitalisation.

Since the data from this thesis involves different stock markets that are traded at different hours around the globe, there could be two issues that arise from this non-synchronous trading time zone. The first one is the non-synchronous return observations, due to different opening and closing hours. However, the impact is significant on minutes data or close-to-opening price changes rather than on daily data (King & Wadhwani, 1990). Furthermore, different time zones also do not have any critical impact on the correlation between the two markets (Jaffe & Westerfield, 1985). However, its implication should be incorporated into the discussion when interpreting the results of daily data (Eun & Shim, 1989). Taking the US and Germany's markets as an example, since the German market opens before the US market in any given calendar day, the German market is closed before the US market opens. If the US market influences the German market, the transmission will be significant at a one-day lag. On the other hand, the US market will respond to the German market on the same day if the impact from the German market is significant.

The second issue from different trading times could be bias in the estimation of covariances, betas and cross-autocorrelations coefficients, or so called non-synchronous trading effect II, which could be the result of non-trading days (Campbell, Lo, & MacKinlay, 1997; Eun & Shim, 1989). Several approaches have been applied in the existing literature to deal with this problem including, firstly, using lower frequency data such as weekly or monthly (Liow & Ye, 2017; Masih & Masih, 2001); secondly, decomposing the daily close-to-close returns into close-to-open and open-to-close components (Hamao, Masulis, & Ng, 1990); thirdly, rolling average returns (Forbes & Rigobon, 2002); and fourthly, simulating the data (Barucci & Reno, 2002). The first approach of using lower frequency data reduces the sample size that can reduce the efficiency of multivariate modelling, particular to time-varying parameters (Martens & Poon, 2001). It was also found that using weekly returns does not address the problem of non-synchronous trading, but created a significant loss in information (Schotman & Zalewska, 2006). Also, lower frequency data can impact the estimated coefficients and might not be able to detect contemporaneous relations in daily returns. This is important to this study, as spillover usually occurs simultaneously and thus its existence cannot be found in weekly or monthly data. The second approach of using opening and closing prices can face the issue of changes in opening hours of many emerging markets, especially during the early stages where some markets only opened for a few hours a day (Schotman & Zalewska, 2006). Thus, overlapping trading hours is not common between emerging markets and developed markets in these periods. New information reflected in the closing prices in the developed markets cannot be reflected in the closing prices of those emerging markets in the same calendar day. In addition, this method adds another layer of complexity onto the model specification to address the disaggregation between differences in the distributions of open-to-close and close-to-open returns. The third approach of using rolling average returns is an easy and commonly used approach; however, it creates a bias in the size and significance of the estimated parameters. Applying this approach for the dataset of this thesis created distorted results with very small p-values for all parameters. The fourth approach is to adjust the closing prices of an index which incorporates simulated non-trading data; however, this approach introduces manipulation in the data and does not guarantee a correct calculation (Barucci & Reno, 2002). There is no clear distinction between spillover and contemporaneous correlation using this approach (Martens & Poon, 2001).

Another simple, yet effective approach, called the ‘common trading window’, is to remove the non-trading dates, which is very popular in the existing literature (Chang, Nieh, & Wei, 2006; Chowdhury, 1994; Li & Majerowska, 2008; Olbrys, 2013). This approach is suitable for a large sample size, as the number of omitted dates will not have a significant impact on the results. It does not require using a lower frequency data and allows the daily frequency to be retained, as required by the thesis objectives. This approach does not have any manual manipulation of the data and hence prevents the results from distortions due to model complexity. Therefore, a similar approach is taken by removing the data in non-trading dates and keeping the data in common trading dates across all markets in the sample. The resultant data sample, which ranges from 8 May 2002 to 31 July 2017, includes 2,732 observations. There were 768 observations omitted using this method. Since the sample size is large, the elimination of non-trading data is not expected to have any effect on the empirical findings (Mbululu & Chipeta, 2012). It clears out the distortions in the results that were observed in the old data set, where the p-values of the GARCH model for many pairs are abnormally small. The Akaike information criterion (AIC) for the new dataset is lower, confirming a higher accuracy of the coefficients.

No.	Index	No. of constituents	Description	Stock exchange / country	Commenced year	Market cap (US$ billion)
1	S&P/ASX 200 (AXJO)	200	Consists of 200 largest stocks by market capitalisation	Australia Stock Exchange/Australia	2000	1,174
2	Deutsche Boerse AG Stock Index (GDAXI)	30	Consists of selected blue-chip stocks	Frankfurt Stock Exchange / Germany	1987	1,154
3	Hang Seng China Enterprise Index (HSCE)	40	Consists of 40 H-shares listed on the Hong Kong Stock Exchange	Hong Kong Stock Exchange / Hong Kong-China	2000	548
4	Hong Kong Hang Sang Index (HSI)	51	Consists of a selection of companies that are divided into four sub-indices: commerce and industry, finance, utilities and properties	Hong Kong Stock Exchange / Hong Kong-China	1964	1,795
5	Jakarta Stock Exchange Composite Index (JKSE)	564	Consists of all stocks listed in the Jakarta Stock Exchange	Indonesia Stock Exchange / Indonesia	1982	425
6	Nikkei 225 Index (N225)	225	Consists of 225 top-rated companies in the First Section of the Tokyo Stock Exchange	Tokyo Stock Exchange / Japan	1949	2,911
7	FTSE Bursa Malaysia KLC Index (FBMKLCI)	30	Consists of full market capitalisation largest stocks	Bursa Malaysia's Main Board / Malaysia	2009	222
8	S&P/NZX 50 Gross Index (NZSE50F)	50	Consists of the top 50 companies by market capitalisation	NZ Stock Exchange	NA	210
9	Philippines Stock Exchange Index (PSE)	30	Consists of 30 companies that are representative of the Industrial, Properties, Services, Holding Firms, Financial and Mining & Oil Sectors	Philippines Stock Exchange / NZ	1990	165
10	Shanghai A-shares Index (SHASHR)	1360	Consists of all A-shares that are restricted to local investors and	Shanghai Stock Exchange / China	1990	4,080

			qualified institutional foreign investors			
11	Shanghai B-shares Index (SHBSHR)	51	Consists of all B-shares that are available for investment by foreign investors	Shanghai Stock Exchange / China	2001	15
12	Straits Times Index (STI)	30	Consists of the largest and most liquid stocks listed on the Singapore Stock Exchange	Singapore Stock Exchange / Singapore	1905	319
13	Shenzhen A-shares Index (SZASHR)	2053	Consists of all A-shares that are restricted to local investors and qualified institutional foreign investors	Shenzhen Stock Exchange / China	1991	3,200
14	Shenzhen B-shares Index (SZBSHR)	48	Consists of all B-shares that are available for investment by foreign investors	Shenzhen Stock Exchange / China	2001	12
15	Stock Exchange of Thailand (SET)	577	Consists of all stocks listed on the Bangkok Stock Exchange	Bangkok Stock Exchange / Thailand	1975	420
16	FTSE 100 Index (UKX)	100	Consists of 100 most highly capitalised stocks	London Stock Exchange / United Kingdom	1983	2,379
17	S&P 500 Index (SPX)	500	Consists of 500 largest stocks by market capitalisation representing all major industries	New York Stock Exchange / United States	1941	20,026

Source: Bloomberg

Note: Market capitalisation of these indices is at 31 December 2016. These indices are considered as either benchmark indices, or representative of the equity market for each country, which are commonly used by both industry experts and academics in related literature.

Figure 2-1. Market index description and market capitalisation as of December 31, 2016.

These indices in the sample are classified into developed and emerging markets, according to the classification of MSCI Investable Market Indices, as shown in **Table 2-1**. There are some significant differences between a developed market and an emerging market, including market accessibility to foreign investors, investment facilities and a degree of consistency, transparency, operational efficiency and regulatory environment. In general, an advanced market is most accessible to foreign investors, with a fully developed investment landscape; for example, derivatives, short selling, stock lending, a high degree of consistency, a high level of transparency and operational efficiency, and a robust regulatory environment. Emerging markets, on the other hand, are less accessible relative to developed markets and are more restricted to trading. Therefore, this type of classification provides more useful insights by comparing the linkages between China and the country in each group. The lack of derivatives such as futures and options in an emerging market may also hamper the efficiency of that market. There is no significant evidence that derivatives will have a direct and positive impact on market efficiency (Kapusuzoglu & Tasdemir, 2010). However, derivatives can provide reliable signals about stock prices and volatility, which adds value to a pricing mechanism in terms of increased market liquidity and information flow (Maheshwari, 2012).

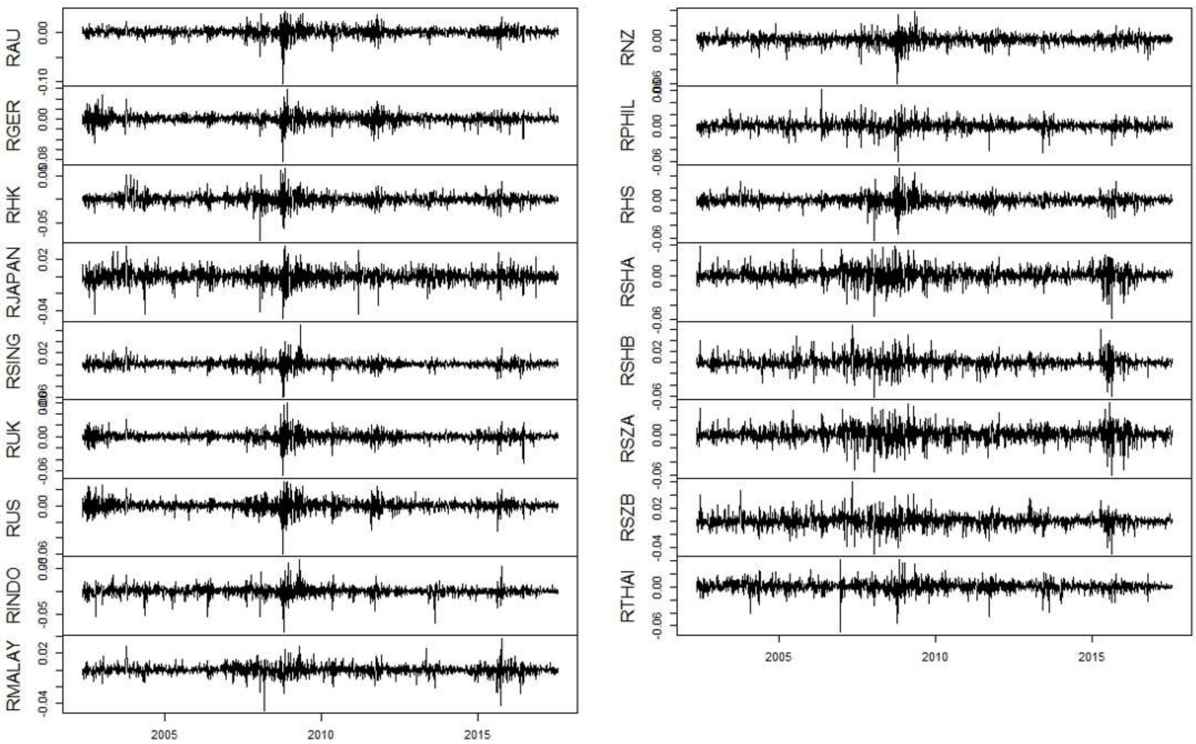
Continuously compounded returns (denoted as R_t) are calculated as the difference in natural logarithms of the closing index value (denoted by P_t) for two consecutive days; that is, $R_t = \ln(P_t) - \ln(P_{t-1})$.

Figure 2-2 presents charts of the daily returns of each market over the whole sample period. RHK is the return of the HangSeng China Enterprises (HSCE) Index (HK market) and RHS is the return of HS. Other of China's share markets that are included in the sample are RSHA (return of SHA), RSHB (return of SHB), RSZA (return of SZA) and RSZB (return of SZB). The returns of most markets are moving around zero. China's AS and BS have more extensive variation than HS and other markets in the sample. The reasons could be because those markets are emerging markets, in which stocks are less liquid compared to other global markets in the sample. Despite the reforms in capital liberation policy, AS and BS as shown in the next sections had weak regional integration, and instead expressed a high level of market synchronisation among each other. These reasons may explain the lower degree of liquidity and market efficiency of these markets, which explains a higher variation in stock returns. Most countries had downside spikes around the GFC 2007-08. Other than that, each stock market was also impacted by its local events; for example, Brexit occurred in May 2016, which impacted the UK and Germany. The Fukushima in March 2011, which was a 'panic reaction' in Japan to the weak economic data released by China in May 2013, and the increased uncertainty in the world markets that exploded with the fall of the US retail sector in both volumes and value in October 2014 are some events that created long downward spikes in the Nikkei 225 index from 2002 to 2017.

Table 2-1. MSCI market index classification

Country	Region	Classification
China	Asia	Emerging
Indonesia	Asia	Emerging
Malaysia	Asia	Emerging
Philippines	Asia	Emerging
Thailand	Asia	Emerging
Australia	Pacific	Developed
Hong Kong	Pacific	Developed
Japan	Pacific	Developed
NZ	Pacific	Developed
Singapore	Pacific	Developed
United States	Americas	Developed
Germany	Europe	Developed
United Kingdom	Europe	Developed

Source: MSCI



Source: Bloomberg

Figure 2-2. Daily returns of each market – full sample

2.2. Sub-periods

This thesis studies the cross-equity relationships before, during and after the GFC. The period under review is divided into four sub-periods, including the pre-GFC, GFC, extended-crisis period and post-GFC. The pre-GFC and post-GFC are referred to as the non-crisis periods, while the GFC and extended-crisis periods are referred to as the crisis periods. Given the extensive work undertaken in the literature on defining the crisis periods and in undertaking structural break tests, the periods used in this thesis will be determined through an extensive review of the existing literature rather than re-undertaking structural break tests. There are differences in the literature regarding the dates of these periods, in particular the end date of the crisis period. This section examines these differences in selecting the dates for these periods to be used in this thesis.

There is no universal date or method for determining the crisis period in the existing literature. A common approach is to measure 'extreme' returns (Mierau & Mink, 2013; Xu & Hamori, 2012). A disadvantage of this approach is determining the percentile for the crisis quantile when there is no universal benchmark for defining extreme values. Another common approach is based on the critical event date, and if possible, cross-checking using structural break tests (Forbes & Rigobon, 2002). Liow and Ye (2017) argued that the GFC started around July-August 2008 because there is a structural break at that time, while Chang, Chou, and Fung (2012) looked to regulatory and policy actions such as European Central Bank interventions on 9 August 2007 for the start date. Other studies used 15 September 2008, marked by the collapse of Lehman Brothers, as the starting date of the GFC (Bekaert et al., 2014; Mierau & Mink, 2013). Dungey, Milunovich, Thorp, and Yang (2015) contended that changes in regulations only followed the market by reacting to an occurred crisis. Therefore, they should not be used to determine the actual commencement date of the crisis. Dungey et al. (2015) proposed a different approach to identify the crisis and non-crisis periods using smooth transition functions through a multivariate structural GARCH model and found that the GFC period should be from 3 July 2007 to 15 May 2009. Some studies used 13 March 2007 – the date where the New Century Financial Corporation was terminated from the New York Stock Exchange (Gorton, 2009; Nieh, Yang, & Kao, 2012). The Federal Reserve Bank of St Louis (2018) used an even more conservative approach by proposing that the commencement date of the GFC was 27 February 2007 because this is one day before the Freddie Mac's official announcement of cutting off the riskiest sub-prime mortgage and mortgage-backed securities from their portfolios. This thesis follows the Federal Reserve Bank of St Louis approach because it is by far the most conservative and is well accepted among academics (Devos, Ong, Spieler, & Tsang, 2012; Teng & Liu, 2014). Therefore, the GFC period in this thesis commenced on 27 February 2007 and the period before this date is the pre-GFC period. As such, there are 870 observations for the pre-GFC period.

There is also no consensus in the existing literature for the GFC end-date. Some studies used around March 2009, which was marked by the relaunch of the Term Asset-Backed Securities Loan

Facility in the US financial markets (Aloui, Aïssa, & Nguyen, 2011); others used mid-2009, pointing out an increase in GDP and based on positive results from the stress tests and capital raising for the US, and on the LIBOR rate (Dungey & Gajurel, 2014; Dungey et al., 2015). October 2009 was also on the list, based on the first-time increase in the Dow Jones Industrial Average (DJIA) index closing prices after a long fall over in the prior months, since October 2008 (Teng & Liu, 2014). Some studies extended the date to March 2010 after an increase in credit rates and minimum bid rate for primary credit loans, given the continued improvement in the financial markets that was announced by the Federal Reserve Board (Nieh et al., 2012; Xu & Hamori, 2012). Of these approaches, this thesis selects 29 May 2009 as the end-date for several reasons. Firstly, in May 2009, the US economy was shrinking at a slower pace than expected, and there was a resumption of the mortgage-backed securities in the US financial markets (Federal Reserve Bank of St Louis, 2018). Secondly, there were positive signs indicating a recovery in the world economy after an extended economic downturn since mid-2007: for example, in the second quarter of 2009, growth was reported for Germany, Japan, the Philippines and Malaysia, whereas the UK, NZ, Thailand and Singapore were shrinking at a much slower pace (Ministry of Finance of Malaysia, 2010; OECD, 2018); the world's GDP in 2010 increased by 4% after a negative growth of 2.4% in 2009; borrowing costs started to rise in both developed countries such as the US, Germany and China; current account balances rose in China, Japan and Germany (United Nations, 2012); the employment rate rose in some developing countries (US, Germany, Japan) (OECD, 2018); and the unemployment rate fell in many countries (Australia, Singapore, Indonesia, Malaysia, Thailand, the Philippines and China), according to the World Bank. In addition, the date matched the structural break that was found by Dungey and Gajurel (2014) in the volatility of the US equity market and financial sector returns which were 29 May 2009 and 1 June 2009 respectively. Therefore, the GFC period in this thesis is from 27 February 2007 to 29 May 2009, with 410 observations.

In the post-GFC period, further research shows that various economic indicators imply an extended-crisis period that is worth considering. According to data from the U.S. Bureau Labor of Statistics (2018), the unemployment rate in the US in October 2009 remained at double pre-GFC figures until June 2012. Similarly, the confidence indicator for the US remained very low until June 2012 (OECD, 2015), and the Dow S&P / Case-Shiller US National Home Price Index, a leading measure of US residential real estate price, showed that the US market was on a continuing downward trend from pre-GFC levels until February 2012 (United Nations, 2015). After a slowing down when the crisis hit in 2008, China quickly went back to a growing trend and broke through the crisis period with an average growth of 9.6% for 2008-2011. However, after 2011, China's economic growth showed a weaker momentum and fell to 7.7% in 2012. In the first half of 2012, deceleration was reported in many leading economies at an uneven pace, due to the slowdown in China's economy, reduction in domestic consumption (Japan), declining global commodity prices and the contagious effect from the European debt crisis through trade at different degrees. Countries like Australia, NZ and Indonesia had smaller changes in growth rate compared to other countries in the sample including Japan, HK, Malaysia, the Philippines, Singapore and Thailand (International Monetary Fund, 2015).

Moreover, examining the relative performance of gold-versus-stock prices gives further insights into economic performance, particularly regarding some 'extreme' movements. The reliability of gold as an indicator of market swings, especially in the long run, is well documented in the existing literature. Gold is a highly liquid asset that maintains its value with time. Therefore, it is widely used by central banks and investors around the world as a hedging asset, and a cushion or insurance against market crises (Cai, Cheung, & Wong, 2001; Pullen, Benson, & Faff, 2014; Shen, Chen, & Chen, 2007; Sherman, 1982). The movement in the gold price is also related to the volatility of the world's economy; for example, all major recessions in world history as well as low volatility periods are well captured in the gold price (Baur & Lucey, 2010; Hillier, Draper, & Faff, 2006). From the onset of the GFC, the gold price increased sharply until it turned around on 6 June 2012 and maintained a downward trend, apart from a short resistance in late 2012 – which could be an indicator that market confidence was restored, as shown in **Figure 2-3**. Thus, a combination of some key economic indicators for the US and other major economies (GDP growth, unemployment, house prices and business confidence), the European debt crisis and the gold price indicate that there may be some justification in extending the crisis period to mid-2012. Moreover, Asia's growth picked up in the second half of 2012 (International Monetary Fund, 2015).

Therefore, this thesis chooses 6 June 2012 as the end time of the extended-crisis period. As such, it provides 539 observations, leaving the post-crisis period ranging from 7 June 2012 to 31 July 2017, with 912 observations.

In summary, this thesis studies four sub-periods as follows:

1. Pre-GFC period: from 1 May 2002 to 26 February 2007 (871 observations).
2. GFC period: from 27 February 2007 to 29 May 2009 (410 observations).
3. Extended-crisis period: from 30 May 2009 to 6 June 2012 (539 observations).
4. Post-crisis period: from 7 June 2012 to 31 July 2017 (912 observations).

Source: Bloomberg

Figure 2-3. Daily price of gold from 2002 to 2016

2.3. Preliminary analysis

In many empirical studies – such as Bekaert et al. (2014), Campbell and Hamao (1992) and Forbes and Rigobon (2002) – the daily prices of all markets were downloaded in US dollars to ensure comparability among different markets. Each time series was tested for normality, unit root, autocorrelation and heteroskedasticity.

2.3.1. Descriptive statistics

Table 2-2 presents a summary of return and risk characteristics for each series for the whole period and during the four sub-periods. The mean and standard deviation are provided as annualised values.

Over the whole period under review, the majority of the top performing markets with the highest annual return mean are emerging markets, and in the following order: Indonesia (12.35%), SZB (11.41%), the Philippines (10.84%), Thailand (10.15%) and HK (10.11%). In the pre-GFC period from 2002 to 2007, HK (32.34%), Indonesia (24.25%), Australia (19.27%), the Philippines (18.50%) and NZ (17.59%) are the top performers in the list. Australia's economy was boosted significantly from the mining industry, in which a majority of the demand was from China. Other top stock markets like HK – an international financial hub, Indonesia and the Philippines were fuelled by substantial economic expansion and investment inflows, with rising household wealth during this period.

The five markets which experienced the biggest loss during the GFC period consisted of NZ (-21.07%), the UK (-18.70%), US (-16.11%), Australia (-15.37%) and Japan (-14.44%). Apart from the UK, US and Japan, which were heavily impacted by the GFC, Australia and NZ were also on the list. HK was one of the few markets that made it above zero during this financial outburst. It is worth noting that SZA was the top performer and was China's only market in this period that earned a significantly high return of 12.92%. This showed that SZA performed much better than SHA. The reason could be because the majority of SZA constitute private companies, with many operating in growing industries in China such as the internet, technology, exports, automation, manufacturing and health care, whereas SHA comprise more state-owned companies. Those private companies attracted growing interest from local investors due to enormous growth potential. Therefore, SZA performed better and was less impacted during the GFC than SHA. For this reason, Shenzen AS and BS are among a few markets on the list that broke through the GFC with a high performance.

In the extended-crisis period, many markets performed better, with emerging markets comprising the top five including the Philippines (27.79%), Indonesia (26.86%), Thailand (26.17%), Malaysia (15.93%) and SZB (14.50%). This is not surprising, as European countries such as Germany and the UK were impacted by the European debt crisis. Other countries such as HK, Japan and Singapore were also impacted by the crisis during this period, with a slow recovery from the GFC. Since the GFC, global growth transition has shifted, with emerging markets being the leading source of growth, as mentioned above. In the post-crisis period, the top performers were the US (28.72%), Germany (11.49%), SZA (11.82%), SZB (10.76%) and NZ (10.44%). This period was marked by the quick recovery in the German economy after the European debt crisis and the sharp recovery from the US economy from a prolonged recession due to the sub-prime crisis. Shenzhen markets which are either AS and BS are also among the top performers during this period, despite the instability in China's long-term growth. As mentioned above, Shenzhen markets have attracted an excessive amount of attention from global investors, as Shenzhen was an emerging market, with promising growth in Mainland China.

In terms of risk, SHA (13.55%), Indonesia (13.43%), SZB (13.31%), HK (12.94%) and Germany (12.94%) are the riskiest markets, with the highest annualised standard deviation in the pre-GFC period.

During the GFC, HK (25.71%), SHA (23.44%), Indonesia (22.50%), SZA (22.20%) and Australia (21.12%) were the riskiest. Standard deviation increased significantly during the GFC, which is not surprising. In the extended-crisis period, as expected, Germany was the riskiest market (15.08%), followed by SZA (13.91%), Australia (13.56%), HK (13.46%) and SHA (12.73%). The reason could be because, during this period, the Australian economy was heavily impacted by the fall in mining activities due to the big slump in China's demand for iron ore and other resources. This impact was significant because mining is a major source of growth for the Australian economy. Germany, on the other hand, was impacted by the European debt crisis in 2010-2011. Similarly, the contagion effect of this crisis in other markets outside of Europe, such as Asian markets, is less direct compared to Germany. During the post-crisis period, SZA (14.90%), SHA (13.84%), Singapore (12.24%), HK (11.20%) and SZB (10.66%) have the top five largest standard deviations. Over the whole period, apart from Indonesia (14.16%) and HK (15.17), SHA (15.38%), SZA (15.15%) and SZB (13.39%) have the highest standard deviations, suggesting that China's markets were riskier than other markets in the sample. In addition, emerging markets in the sample also generally had a higher standard deviation than the advanced markets. This is consistent with the common knowledge that emerging markets are generally riskier than advanced markets, for reasons already discussed in section 2.1 such as accessibility, consistency, transparency, operational efficiency and regulatory environment. Given its recent history, China's stock market is less mature and sophisticated than other markets in the sample; for example, the US, UK, Japan, HK, Australia and Germany, hence it is less efficient than the US market. Moreover, irrational investment decisions such as herding behaviour is evident in China's equities, which is another example of market inefficiency (Lao & Singh, 2011; Teng & Liu, 2014). This phenomenon relates to the tendency of investors to base their decisions on the market consensus and deliberately ignore their own information and analysis because of cognitive biases; for example, to feel more confident (Christie & Huang, 1995) or based on the presumption that other people possess more reliable information or analytical skills (Devenow & Welch, 1996).

2.3.2. Normality

Table 2-2 presents the results of skewness, kurtosis and the Jacque-Berra (JB) test – a commonly used test of normality for financial time series (Engle & Sheppard, 2001; Peng & Ng, 2012), for the entire study period and each sub-period. The results show that the distributions of all series displayed excess kurtosis (kurtosis > 3) and negative skewness over the entire period studied, except for Singapore. The hypothesis of normality is overwhelmingly rejected for all markets as shown by the *p*-values of the JB tests having a lower than 1% significance level. This means the returns are not normally distributed, which is consistent with the existing literature on stock markets (Fang et al., 2015; Mohammadi & Tan, 2015; Wang, Miao, & Li, 2013).

The kurtosis of all markets was larger than three in each sub-period, which indicates that the distribution of each series consistently exhibited fat tails. Changes in the degree and sign of skewness were evident from one period to another. The daily returns distributions of Australia, Indonesia, Japan, NZ and Thailand were characterised by negative skewness, while other markets were skewed to the right. During the GFC period, apart from BS, all remaining markets in the studied sample were characterised by negative skewness, even though the degree of skewness varied by country. During the extended-crisis period, the return distribution of every series was skewed to the left. The distribution of these markets remained negatively skewed in the post-crisis period, and many were at a higher degree compared to the crisis period; for example, Germany, HS, Indonesia, the Philippines, Singapore, AS, BS, Thailand, the UK and the US. A shift from positive skewness to negative skewness indicates a riskier exposure. This finding also explains why negative skewness was found in each series over the whole period, because the negative skewness was overwhelming in three out of the four periods. One of the possible reasons explaining the negative skewness in these stock returns, especially during the crisis periods, is the higher uncertainty in these markets that increases the risk of market downturns.

Table 2-2. Descriptive statistics of the daily returns for each market

	AU	GER	HK	HS	INDO	JAPAN	MALAY	NZ	PHIL	SING	SHA	SHB	SZA	SZB	THAI	UK	US
Panel A: Full sample from May 8, 2002 to July 31, 2017 (2733 observations)																	
Daily mean return	0.015%	0.018%	0.026%	0.013%	0.032%	0.011%	0.011%	0.018%	0.028%	0.014%	0.013%	0.015%	0.025%	0.030%	0.027%	0.004%	0.013%
Annualised mean return	5.550%	6.868%	10.114%	5.012%	12.346%	4.134%	3.983%	6.907%	10.840%	5.319%	5.012%	5.589%	9.473%	11.407%	10.154%	1.456%	4.859%
Median	0.035%	0.043%	0.028%	0.027%	0.050%	0.020%	0.014%	0.043%	0.036%	0.019%	0.026%	0.024%	0.060%	0.047%	0.049%	0.022%	0.031%
Maximum	4.216%	5.847%	6.777%	5.236%	6.827%	3.599%	3.810%	3.948%	6.146%	3.902%	6.802%	7.017%	4.624%	6.127%	4.142%	5.917%	3.048%
Minimum	-10.282%	-8.461%	-8.718%	-6.378%	-8.828%	-4.997%	-4.828%	-5.962%	-6.021%	-5.857%	-6.194%	-5.867%	-5.995%	-4.997%	-6.988%	-6.832%	-5.984%
Daily std. dev.	0.784%	0.835%	0.960%	0.714%	0.896%	0.732%	0.507%	0.585%	0.732%	0.836%	0.973%	0.652%	0.958%	0.847%	0.708%	0.705%	0.595%
Annualised std. dev.	12.402%	13.207%	15.174%	11.294%	14.164%	11.576%	8.010%	9.256%	11.576%	13.220%	15.383%	10.304%	15.152%	13.392%	11.198%	11.145%	9.406%
Skewness	-1.239	-0.551	-0.088	-0.252	-0.713	-0.563	-0.447	-0.816	-0.259	-0.314	-0.103	0.021	-0.466	-0.027	-0.860	-0.346	-0.583
Kurtosis	19.298	11.243	11.071	11.571	15.841	8.065	12.531	11.724	10.409	7.566	9.279	15.849	6.951	7.948	12.766	13.228	11.409
Jarque-Bera	30935***	7873***	7418***	8392***	19001***	3065***	10431***	8967***	6279***	18794***	2418***	4493***	1876***	2787***	11194***	11964***	8203***
Panel B: Pre-GFC period from May 8, 2002 to February 27, 2007 (871 observations)																	
Daily mean return	0.048%	0.034%	0.077%	0.027%	0.060%	0.027%	0.026%	0.044%	0.047%	0.029%	0.009%	0.038%	0.022%	0.042%	0.039%	0.024%	0.013%
Annualised mean return	19.274%	13.293%	32.341%	10.235%	24.248%	10.235%	10.074%	17.589%	18.493%	11.326%	3.404%	15.043%	8.360%	16.564%	15.085%	9.313%	4.668%
Median	0.065%	0.056%	0.076%	0.037%	0.085%	0.029%	0.018%	0.055%	0.021%	0.005%	-0.051%	0.042%	0.008%	0.009%	0.045%	0.022%	0.030%
Maximum	2.070%	4.828%	5.340%	3.100%	3.520%	3.599%	2.851%	2.261%	6.146%	3.840%	4.719%	3.065%	3.757%	4.664%	4.088%	3.007%	2.581%
Minimum	-2.536%	-4.657%	-2.836%	-2.475%	-5.560%	-4.452%	-1.529%	-2.755%	-2.810%	-3.955%	-3.754%	-1.930%	-3.809%	-3.863%	-6.988%	-2.311%	-1.870%
Daily std. dev.	0.518%	0.800%	0.818%	0.512%	0.849%	0.717%	0.371%	0.476%	0.673%	0.710%	0.857%	0.531%	0.739%	0.842%	0.716%	0.551%	0.510%
Annualised std. dev.	8.184%	12.646%	12.940%	8.088%	13.429%	11.329%	5.861%	7.523%	10.635%	11.226%	13.546%	8.394%	11.680%	13.312%	11.313%	8.704%	8.057%
Skewness	-0.381	0.046	0.728	0.259	-1.022	-0.386	0.486	-0.486	0.826	0.649	0.637	0.363	0.412	0.481	-1.092	0.097	0.279
Kurtosis	5.295	8.306	8.906	6.105	10.223	7.637	8.904	6.272	12.538	7.459	7.959	5.879	6.629	6.423	16.122	6.648	6.668
Jarque-Bera	212***	1021***	1341***	359***	2042***	801***	1298***	422***	3397***	782***	951***	320***	502***	458***	6415***	484***	499***
Panel C: GFC period from February 27, 2007 to May 29, 2009 (588 observations)																	
Daily mean return	-0.046%	-0.026%	0.011%	-0.009%	-0.005%	-0.043%	-0.014%	-0.065%	-0.025%	0.004%	-0.002%	-0.024%	0.033%	-0.004%	-0.018%	-0.057%	-0.048%
Annualised mean return	-15.367%	-8.988%	4.021%	-3.292%	-1.694%	-14.435%	-5.051%	-21.069%	-8.689%	1.352%	-0.753%	-8.254%	12.922%	-1.313%	-6.223%	-18.669%	-16.105%
Median	0.059%	0.038%	0.077%	0.016%	0.059%	-0.017%	0.006%	-0.006%	-0.029%	0.096%	0.049%	0.019%	0.114%	0.060%	-0.006%	-0.011%	0.018%
Maximum	4.216%	5.847%	6.777%	5.236%	6.827%	3.594%	2.795%	3.948%	3.642%	3.902%	6.802%	7.017%	4.508%	6.127%	4.142%	5.917%	3.048%
Minimum	-10.282%	-8.461%	-8.718%	-6.378%	-8.828%	-4.997%	-4.828%	-5.962%	-6.021%	-5.525%	-6.194%	-5.867%	-5.508%	-4.997%	-5.640%	-6.832%	-5.984%
Daily std. dev.	1.336%	1.125%	1.626%	1.264%	1.423%	1.033%	0.755%	0.932%	1.079%	1.253%	1.482%	1.138%	1.404%	1.223%	0.959%	1.136%	0.980%
Annualised std. dev.	21.119%	17.781%	25.711%	19.990%	22.500%	16.328%	11.931%	14.735%	17.053%	19.810%	23.437%	17.997%	22.198%	19.331%	15.155%	17.966%	15.490%
Skewness	-1.419	-0.857	-0.275	-0.212	-0.330	-0.624	-0.461	-0.898	-0.430	-0.109	-0.042	0.177	-0.308	0.041	-0.559	-0.040	-0.628

Kurtosis	13.077	13.150	6.805	6.574	10.567	6.405	7.846	9.083	6.794	4.078	5.133	9.807	4.174	5.807	9.680	9.574	7.449
Jarque-Bera	1872***	1810***	252***	221***	986***	225***	416***	687***	259***	21***	78***	794***	30***	135***	784***	738***	365***
Panel D: Extended-crisis period from May 30, 2009 to June 6, 2012 (788 observations)																	
Daily mean return	0.024%	0.008%	-0.006%	0.003%	0.065%	0.007%	0.041%	0.026%	0.067%	-0.005%	0.022%	0.025%	0.010%	0.037%	0.064%	0.013%	0.031%
Annualised mean return	9.114%	2.824%	-2.284%	1.009%	26.859%	2.438%	15.928%	9.793%	27.787%	-1.830%	8.281%	9.513%	3.717%	14.498%	26.166%	4.859%	12.060%
Median	0.025%	0.010%	0.000%	0.014%	0.106%	0.015%	0.051%	0.071%	0.069%	0.026%	0.092%	0.056%	0.111%	0.067%	0.099%	0.025%	0.049%
Maximum	3.671%	3.390%	3.020%	2.616%	3.477%	3.097%	1.977%	3.101%	3.105%	2.392%	3.909%	1.887%	3.246%	3.288%	2.426%	2.370%	2.443%
Minimum	-3.744%	-4.268%	-2.896%	-2.392%	-4.173%	-4.443%	-1.988%	-2.045%	-4.166%	-3.047%	-3.578%	-2.898%	-3.496%	-3.068%	-4.516%	-3.308%	-2.995%
Daily std. dev.	0.858%	0.954%	0.851%	0.667%	0.788%	0.674%	0.487%	0.588%	0.705%	0.722%	0.805%	0.614%	0.880%	0.768%	0.718%	0.734%	0.614%
Annualised std. dev.	13.563%	15.084%	13.459%	10.545%	12.453%	10.660%	7.692%	9.302%	11.139%	11.408%	12.725%	9.710%	13.909%	12.145%	11.346%	11.598%	9.703%
Skewness	-0.044	-0.373	-0.005	-0.069	-0.520	-0.613	-0.174	-0.022	-0.230	-0.420	-0.668	-0.487	-0.478	-0.376	-0.543	-0.251	-0.258
Kurtosis	5.405	5.051	4.108	4.020	7.453	7.906	5.685	5.097	6.576	4.904	6.892	4.675	4.881	4.936	6.399	4.264	5.580
Jarque-Bera	130***	107***	28***	24***	470***	574***	165***	99***	292***	97***	380***	84***	100***	97***	286***	42***	155***
Panel E: Post-crisis period from June 7, 2012 to July 31, 2017 (912 observations)																	
Daily mean return	0.006%	0.030%	0.006%	0.018%	0.003%	0.025%	-0.009%	0.027%	0.015%	0.014%	0.018%	0.006%	0.031%	0.028%	0.014%	0.007%	0.069%
Annualised mean return	2.229%	11.489%	2.296%	6.868%	1.190%	9.353%	-3.133%	10.436%	5.782%	5.242%	6.868%	2.207%	11.815%	10.759%	5.089%	2.719%	28.723%
Median	-0.004%	0.046%	-0.010%	0.026%	0.017%	0.029%	-0.004%	0.032%	0.043%	0.015%	0.042%	0.008%	0.080%	0.059%	0.038%	0.024%	0.028%
Maximum	2.914%	2.624%	3.894%	3.036%	5.420%	2.764%	3.810%	1.878%	2.387%	2.741%	5.928%	2.812%	4.624%	3.584%	2.159%	2.738%	2.063%
Minimum	-3.625%	-3.791%	-3.601%	-2.981%	-6.901%	-2.774%	-4.200%	-2.760%	-4.566%	-5.857%	-5.946%	-2.695%	-5.995%	-4.982%	-3.942%	-4.588%	-3.152%
Daily std. dev.	0.591%	0.612%	0.708%	0.546%	0.662%	0.606%	0.489%	0.461%	0.585%	0.774%	0.876%	0.442%	0.942%	0.674%	0.544%	0.548%	0.397%
Annualised std. dev.	9.337%	9.670%	11.198%	8.630%	10.470%	9.574%	7.729%	7.286%	9.256%	12.238%	13.844%	6.990%	14.896%	10.660%	8.606%	8.665%	6.280%
Skewness	-0.437	-0.857	-0.132	-0.371	-1.097	-0.283	-0.674	-0.423	-0.818	-1.226	-0.545	-0.374	-0.997	-0.718	-1.116	-1.320	-0.698
Kurtosis	6.453	8.365	6.468	6.950	22.755	5.453	16.886	6.029	9.980	11.033	13.689	9.417	8.537	11.384	10.435	14.594	9.867
Jarque-Bera	482***	1205***	460***	641***	15013***	241***	7396***	376***	1953***	2681***	4387***	1583***	1316***	2749***	2290***	5373***	1866***

Note: *** indicates significance at 1% level. Descriptive statistics for the return time series of each market are presented for the full sample period (panel A), pre-GFC period (panel B), GFC period (panel C), extended-crisis period (panel D) and post-crisis period (panel E). Daily mean return (DMR) is calculated as the first difference of natural logarithm of pries of two consecutive trading days in the sample using this formula: $DMR = \log P_t - logP_{t-k}$. Annualised mean return (AMR) is annualised from the DMR using this formula $AMR = (1 + DMR)^{365} - 1$. Over the whole period, all markets exhibit a small degree of negative skewness, except for Singapore, and are characterised by excess kurtosis and fat tails. All markets have positive but close to zero mean and median. All the time series are also not normally distributed, given significant Jarque-Bera t-statistics for each sub-period under review. Negative skewness is seen in many markets, especially during the GFC period and after the crisis period. Kurtosis is significantly higher than 3 is seen for all markets during each study period, indicating a fat tail distribution. Furthermore, China's markets, particularly AS and BS, show the highest standard deviation among all the markets, suggesting these markets are riskier than other markets in the sample. This is consistent with a common belief that emerging markets are riskier than advanced markets.

2.3.3. Stationarity

A time series is stationary when the mean and variance are constant over the whole period under analysis (Jondeau & Rockinger, 2006). This statistical property is commonly seen in financial time series because a permanent effect can be caused by a change in macro-economic fundamentals such as economic phase, regulations or technology. Economic conditions are reflected in the stock prices that cause various structural changes. This explains why financial time series like stock returns over a long horizon are usually found with variant statistical properties. The GFC, European debt crisis, Brexit and the stock crashes caused by the increased uncertainty in China's market are some examples that occurred in the study period that might cause structural changes in the stock series in the sample.

In addition, modelling non-stationary time series which are characterised by a unit root is challenging. Therefore, non-stationary time series are usually transformed to stationary before conducting an analysis. Transforming the series to stationary makes the interpretation of estimated statistics meaningful. This is especially important in assessing correlations with other variables because, if the mean and variances of a time series is not well-defined, the relationship between the time series with another variable cannot be defined correctly.

Augmented Dickey-Fuller (ADF), Philips-Perron (PP) and Kwiatkowski-Philips-Schmidt-Shin (KPSS) tests were performed in order to ensure the results were not biased due to the restriction in each model's specification. Over/under-rejection of the null hypothesis of non-stationary is commonly seen in ADF testing when using too few or too many lags. On the other hand, the PP test relaxes the assumption of no serial correlation and heteroskedasticity in the error term, hence it is an effective method to detect a unit root in financial time series. KPSS is used extensively in empirical studies, especially macro-economics and financial modelling (Caner & Kilian, 2001; Kuo & Mikkola, 1999) to complement a standard unit root test (that is, ADF and PP).

Table 2-3 presents the t-statistics of unit root tests including ADF, PP and KPSS for each time series over the four sub-periods. The results show that a first-difference time series does not contain a unit root, which indicates a presence of stationarity, consistent with the existing literature (Boubaker & Sghaier, 2013; Fan et al., 2009; Li, 2007). Individual unit root tests for each sub-period also yield similar findings that all stock returns in the sample at fist-difference are stationary. Consistent findings are seen throughout the entire period under review.

Table 2-3. Summary of t-statistics for Augmented Dicker-Fuller (ADF), Phillips-Perron (PP) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) unit root test for single series – full sample

	Pre-GFC period			GFC period			Extended-crisis period			Post-crisis period		
	ADF	PP	KPSS t-statistics	ADF	PP	KPSS t-statistics	ADF	PP	KPSS t-statistics	ADF	PP	KPSS t-statistics
HS	-28.409***	-28.394***	0.095***	-20.921***	-20.985***	0.199***	-22.827***	-22.847***	0.200***	-28.607***	-28.646***	0.118***
SHA	-30.532***	-30.627***	0.319***	-21.265***	-21.265***	0.412***	-22.722***	-22.719***	0.111***	-30.110***	-30.648***	0.245***
SHB	-26.403***	-26.403***	0.072***	-18.040***	-18.148***	0.296***	-21.761***	-21.759***	0.315***	-28.680***	-28.680***	0.061***
SZA	-28.577***	-28.568***	0.300***	-19.735***	-19.735***	0.356***	-21.808***	-21.772***	0.215***	-29.774***	-29.772***	0.091***
SZB	-27.083***	-27.086***	0.144***	-18.820***	-18.820***	0.329***	-21.733***	-21.740***	0.370***	-28.214***	-28.164***	0.084***
Indonesia	-30.631***	-30.681***	0.133***	-18.298***	-18.259***	0.237***	-21.726***	-21.793***	0.455***	-36.239***	-37.207***	0.086***
Malaysia	-25.652***	-26.061***	0.489***	-19.457***	-19.460***	0.267***	-21.387***	-21.356***	0.288***	-22.695***	-27.504***	0.145***
Philippines	-28.710***	-28.703***	0.167***	-19.211***	-19.196***	0.210***	-22.471***	-22.500***	0.102***	-29.408***	-29.408***	0.147***
Thailand	-27.867***	-27.881***	0.529***	-16.963***	-16.911***	0.307***	-21.832***	-21.812***	0.260***	-28.944***	-28.942***	0.131***
Australia	-28.770***	-28.798***	0.899***	-19.476***	-19.480***	0.208***	-22.167***	-22.160***	0.248***	-27.911***	-27.914***	0.095***
HK	-25.990***	-26.294***	0.630***	-16.254***	-20.171***	0.200***	-23.302***	-23.305***	0.195***	-23.143***	-26.367***	0.052***
Japan	-28.123***	-28.113***	0.414***	-23.389***	-23.574***	0.086***	-27.324***	-27.616***	0.151***	-28.459***	-28.498***	0.152***
NZ	-28.047***	-28.146***	0.983***	-17.991***	-17.896***	0.204***	-21.861***	-21.900***	0.135***	-28.715***	-28.842***	0.095***
Singapore	-27.900***	-28.059***	0.349***	-19.607***	-19.597***	0.222***	-22.032***	-22.042***	0.272***	-27.613***	-27.713***	0.147***
US	-27.863***	-27.893***	0.135***	-22.493***	-22.651***	0.169***	-24.660***	-24.907***	0.132***	-28.541***	-28.547***	0.143***
Germany	-31.471***	-31.632***	0.263***	-15.772***	-19.172***	0.220***	-23.706***	-23.790***	0.156***	-20.616***	-30.869***	0.253***
UK	-29.544***	-29.735***	0.176***	-19.329***	-19.381***	0.184***	-23.407***	-23.516***	0.145***	-20.144***	-29.391***	0.144***

Note: *** indicates significance at 1% level. The null hypothesis of the ADF and PP tests for each time series is that the time series has a unit root, whereas the null hypothesis of the KPSS test is stationary. All series in the sample pass the ADF and PP tests at 1%, which indicates a strong rejection of the null hypothesis, implying that there is no evidence of a unit root found for each time series. This suggests that each time series is stationary. The null hypothesis for KPSS tests is that the series is stationary. Critical values for KPSS tests are 0.739 at 1% level, 0.463 at 5% level and 0.347 at 10% level. None of the series in the sample has t-statistics higher than the KPSS critical values, which fails to reject the null hypothesis supporting the stationarity evidence in each time series, consistent with the results of the ADF and PP tests.

2.3.4. Autocorrelation

Autocorrelation is defined as the correlation between the residual factor and its lags, while serial correlation relates to cross-market correlation of the residuals (Fama, 1965). This is commonly observed in high-frequency data, where large (small) daily price changes tend to be followed by large (small) daily changes. Feedback trading refers to observations that investors make decisions based on previous stock prices or movements. In particular, buying winners and selling losers is referred to positive feedback trading. This is one of the theories explaining the cause of autocorrelation. Feedback trading is documented in many stock markets such as the US (De Long, Shleifer, Summers, & Waldmann, 1990), Germany (Pierdzioch, 2004) and China (Zhang & Wang, 2012). Autocorrelation can also be explained by non-synchronous trading, as discussed in section 2.3.4.

Based on the results from the correlogram specification for 36 lags, each time series shows that the autocorrelation dies out within the first five lags. This is supported by the findings based on the AIC. Testing the first 10 lags for each sub-period using an AR model, the most common model that has the lowest AIC for all series is within the first five lags with some exceptions, as shown in **Table 2-4**. Through further analysis of those exceptions that have more than five lags, it was found that those results are biased due to over-specification. For those cases, a declining pattern is recorded for the AIC in the first five days, which then increases when more variables are added to the model, indicating over-specification. These results are reported in **Table 2-5**. For example, during the extended-crisis period, the AIC for the HS model keeps increasing in the first seven lags and drops to the lowest level when the tenth lag is added to the model. The AIC of 10 lags is, however, very close to the AIC of one lag. This pattern is a clear indication of over-specification. A similar pattern and results are found for other markets in this group. For this reason, and for the purpose of consistency, five lags are determined as reasonable to test for autocorrelation. Therefore, this thesis tests for the existence of autocorrelation at five lags for each time series using Lagrange multiplier (LM) tests.

Table 2-4. Best lag length and AIC for each time series of the four sub-periods

	Pre-GFC		GFC		Extended-crisis		Post-crisis	
	Lag length	AIC	Lag length	AIC	Lag length	AIC	Lag length	AIC
HS	1	-6.042	2	-5.901	10 (1)	-7.194	5	-5.916
SHA	1	-5.385	1	-5.917	1	-7.026	1	-5.218
SHB	1	-5.022	3	-5.593	1	-6.806	6 (2)	-5.020
SZA	1	-5.307	1	-5.686	1	-6.628	6 (1)	-4.828
SZB	1	-5.047	1	-5.966	2	-6.917	5	-5.504
Indonesia	1	-5.034	1	-5.667	4	-6.878	4	-5.532
Malaysia	2	-6.703	1	-6.928	2	-7.827	2	-6.149
Philippines	1	-5.496	6 (1)	-6.229	1	-7.088	7 (2)	-5.801
Thailand	1	-5.372	1	-6.477	4	-7.047	2	-5.924
Australia	1	-6.018	1	-5.785	1	-6.710	5	-5.766
HK	2	-5.114	2	-5.402	10 (1)	-6.703	5	-5.395
Japan	1	-5.368	2	-6.325	1	-7.184	1	-5.738
NZ	1	-6.187	2	-6.518	2	-7.497	4	-6.251
Singapore	1	-5.968	1	-6.105	1	-7.358	8 (2)	-6.342
US	3	-6.060	1	-6.416	1	-7.374	4	-6.568
Germany	1	-5.150	2	-6.141	2	-6.474	10 (1)	-5.690
UK	1	-5.899	2	-6.117	2	-7.008	10 (3)	-5.931

Note: An AR(1,1) model is run for each time series from 1 to 20 lags. The model that has the lowest AIC is the model that has the best lag length. The table only reported the best lag length for each time series and its corresponding AIC. The AIC of other sub-models is not reported in this table. The best lag length after adjustment for over-specification is reported in the brackets.

Table 2-5. AIC for the AR model from 1 to 10 lags for time series that reported the best lag length greater than 5

Lag	1	2	3	4	5	6	7	8	9	10
Panel A: GFC period										
Philippines	-6.220	-6.214	-6.227	-6.229	-6.222	-6.230	-6.223	-6.217	-6.221	-6.215
Panel B: Extended-crisis period										
HS	-7.182	-7.181	-7.175	-7.171	-7.176	-7.184	-7.179	-7.177	-7.186	-7.194
UK	-6.696	-6.693	-6.689	-6.685	-6.688	-6.695	-6.690	-6.687	-6.698	-6.703
Panel C: Post-crisis period										
SHB	-4.981	-5.004	-5.001	-5.005	-5.016	-5.020	-5.016	-5.014	-5.014	-5.014
SZA	-4.821	-4.820	-4.819	-4.819	-4.825	-4.828	-4.828	-4.828	-4.828	-4.826
PHIL	-5.773	-5.779	-5.778	-5.783	-5.787	-5.785	-5.801	-5.799	-5.799	-5.796
SING	-6.337	-6.339	-6.337	-6.339	-6.341	-6.340	-6.336	-6.342	-6.339	-6.338
GER	-5.683	-5.681	-5.684	-5.684	-5.683	-5.686	-5.683	-5.681	-5.688	-5.690
UK	-5.906	-5.911	-5.925	-5.925	-5.922	-5.930	-5.928	-5.926	-5.925	-5.931

Note: AIC is reported for AR with a max length of 10 for the Philippines during the GFC and SHB in the post-crisis period because those markets reported the best lag length at 6. Therefore, it is not necessary to run until 15 lags for these markets. For other markets, AR is run for 15 lags because the best lag length reported ranges from 8 to 10 days.

Table 2-6 displays the results of t-statistics for each pair of countries for the full sample. Most countries exhibit strong evidence of serial correlation with other countries (except for China's AS), which can be classified into three groups. The first group was found to have strong evidence of serial correlation with all countries in the sample, and this group comprised Australia, Germany, HK, HS, Japan, the Philippines, Singapore, the UK and US. The second group comprised Indonesia, Malaysia, NZ, SZB and Thailand, which had evidence of serial correlation when pairing with some countries but not all. Since these markets are global and leading financial centres, they have attracted a tremendous amount of investment from foreign investors, which supports equity integration. China's AS, including both Shanghai and Shenzhen markets, fell into the last group for non-evident serial correlation with any of these countries in the sample. AS are exclusive to domestic investors and some eligible foreign investors up to a specific limit. This could explain why there is a lack of correlation between AS and other markets in the sample. Since BS are accessible by foreign investors, there was strong evidence of return movements between BS and some markets in the sample.

Before the GFC, no evidence of autocorrelation for any market was found. Since the GFC, autocorrelation was evident in many emerging and advanced markets in the sample; for example, HS, HK, Japan, Germany and the UK during the GFC, and Indonesia, Malaysia, Thailand, NZ and the UK in the extended-crisis period. Autocorrelation for some of China's markets (HS, BS, SZA), Indonesia, Malaysia, the Philippines, Australia, the US and UK was strongly evident after the crisis period. HK, Singapore and Germany were also found with autocorrelation at the 10% significance level during this period.

Feedback trading, as mentioned above, could be one of the reasons for autocorrelation. Feedback trading is documented for China's markets (HK, SHA, SZA, SZB, and HS) in the study of Sutthisit, Wu, and Yu (2012). Their study also found that autocorrelation in China's markets was asymmetrical, in which the market tends to have positive autocorrelation at low volatility and negative autocorrelation at high volatility. This is consistent with this result for the pre-GFC and post-crisis period. However, autocorrelation was not detected during the GFC and extended-crisis period. The difference could be attributed to the difference in models used and specification. The model for this thesis does not allow for asymmetries in autocorrelation, but only serves the purpose of testing for the presence of autocorrelation.

Among all of China's share markets in the sample, before the GFC, SHB and SZB showed a strong correlation with markets other than AS. As discussed above, a possible explanation is that BS are accessible to foreigners, whereas AS are accessible only to local investors. During the GFC, only HS had a strong correlation with other markets. The reason is that HS are listed on the HKSE. HK was heavily impacted by the US sub-prime crisis through contagious financial relations, as it is a well-established world financial market (Kong, Morales, & Coughlan, 2015).

On the other hand, AS and BS are listed in Mainland China. The degree of regional integration of these markets is noticeably lesser than the HK market. Interestingly, while the regional correlation was not evident during the study period, evidence of integration is documented among Mainland China's stock markets; that is, AS and BS. In the extended-crisis period, there was no evidence of serial correlation between China's share market with other markets in the sample, except for HS, for the same reason. During the post-crisis period, there was a shift in regional integration. Notably, there is strong evidence of serial correlation between China's markets (especially AS and BS) and other markets in the sample. The results for each sub-period are reported in **Appendix A**.

Table 2-6. Summary of the Breusch-Godfrey LM test statistics and p-values for the autocorrelation and serial correlation Lagrange multiplier test for each pair – full sample

	AU	GER	HK	HS	INDO	JP	MALAY	NZ	PHIL	SHA	SHB	SING	SZA	SZB	THAI	UK	US
AU	12.74**	10.82*	24.25***	39.86***	8.10	134.72***	1.32	5.21	16.43***	3.39	42.81***	10.23*	6.13	6.27	4.44	30.73***	24.15***
GER	44.17***	12.30**	31.91***	69.74***	8.08	195.61***	0.48	4.39	14.62**	2.75	44.55***	18.25***	5.70	7.65	6.77	35.38***	25.00***
HK	17.70***	11.78**	23.00***	14.41**	18.75***	85.01***	9.68*	10.93*	13.70**	5.12	38.62***	20.07***	5.08	4.25	14.06**	30.02***	20.34***
HS	16.10***	12.00**	34.73***	13.86**	19.95***	102.41***	6.94	9.98*	14.79**	3.39	44.00***	22.35***	6.12	6.23	12.52**	30.76***	22.93***
INDO	16.04***	11.30**	24.14***	17.893***	6.13	83.28***	1.38	12.60**	16.65***	2.42	44.58***	12.00**	6.11	6.79	5.73	29.60***	22.93***
JP	39.08***	10.47*	37.13***	15.19***	35.30***	5.47	22.46***	20.56***	18.77***	2.46	54.44***	27.28***	8.17	15.93***	21.66***	28.82***	25.97***
MALAY	17.45***	10.71*	24.45***	15.82***	18.41***	71.31***	0.32	12.81**	15.96***	2.36	46.01***	13.20**	6.78	8.26	12.23**	28.84***	19.79***
NZ	14.56**	10.34*	26.77***	33.29***	9.84*	96.30***	2.67	5.24	14.11**	2.66	43.43***	12.31**	5.76	6.88	4.83	29.90***	21.49***
PHIL	22.94***	10.46*	27.56***	14.69**	21.71***	54.47***	12.77**	18.27***	13.76**	2.23	47.04***	14.42**	6.84	9.45*	14.59**	28.62***	23.78***
SHA	21.74***	11.33**	29.95***	14.32**	25.56***	44.85***	18.23***	20.39***	18.05***	2.62	75.52***	17.54***	5.84	35.36***	27.31***	30.50***	21.39***
SHB	21.39***	11.07**	27.40***	14.12**	25.40***	45.14***	16.99***	21.06***	19.16***	5.01	21.74***	16.53***	5.22	6.67	26.80***	30.29***	21.16***
SING	15.51***	13.51**	22.85***	45.61***	6.67	143.22***	0.63	7.65	21.09***	3.28	42.50***	9.35***	5.81	5.21	7.12	33.87***	22.19***
SZA	21.51***	11.29**	30.66***	14.50**	26.10***	43.91***	18.12***	20.95***	19.11***	4.48	76.69***	17.91***	4.28	37.25***	28.46***	30.48***	21.31***
SZB	21.38***	11.73**	26.88***	13.70**	23.52***	45.25***	13.80**	20.41***	18.49***	4.38	25.80***	15.75***	4.13	3.38	23.54***	29.98***	22.70***
THAI	16.60***	10.31*	24.41***	16.26***	13.90**	77.19***	7.90	14.24**	16.67***	2.44	45.27***	14.04**	6.56	8.35	4.97	29.30***	19.77***
UK	63.18***	11.48**	33.89***	94.23***	4.71	178.88***	1.36	6.98	14.68**	3.03	43.23***	20.73***	5.62	6.73	5.22	30.65***	26.13***
AU	62.69***	63.97***	27.28***	72.24***	7.25	164.44***	1.26	8.45	12.13**	2.86	43.73***	25.11***	5.70	7.65	6.45	111.44***	15.95***

Note: The residual factors of the univariate and bivariate Autoregressive (AR) (1,1) models of each time series are tested with correlation at five lags using Lagrange multiplier (LM) tests. The null hypothesis is that there is no serial correlation at five lags. *, **, *** indicate significance at 10%, 5% and 1% levels. This table reports the estimated Breusch-Godfrey LM test statistics. Significant coefficients can reject the null hypothesis of no correlation at the significant level at 10%, which indicate an existence of serial correlation. Strong evidence of serial correlation is evident in all China's shares markets except for AS.

2.3.5. Heteroskedasticity

The term ‘heteroskedasticity’ refers to the relationship between the residual factors and the explanatory variables included in the model (White, 1980). Since the distribution of the standard deviation is not constant and changes with the explanatory variable, this character poses a difficulty in forecasting the level of volatility at any given point in time. Heteroskedasticity is critical in determining the efficient and unbiased estimators of the coefficients, which can have a significant impact on test validity. Failure to account for heteroskedasticity, despite its presence, leads to seriously misleading inferences; for example, the conditional distribution that accounts for heteroskedasticity is much more fat-tailed than a normal distribution (Gujarati & Porter, 2009; Schwert & Seguin, 1990). Heteroskedasticity also impacts the degree of autocorrelation in stock returns (Poterba & Summers, 1987). Forbes and Rigobon (2002) demonstrate that there is no contagion, but only interdependencies for some selected countries when accounting for heteroskedasticity, contrary to all prior studies that failed to take into account this issue. In this context, autoregressive conditional heteroskedasticity (ARCH) occurs when the conditional variance of the error term depends on past values of the error terms (Engle, 1982). **Table 2-7** and **Table 2-8** present the results for heteroskedasticity tests including the ARCH and White tests at five lags for each pair of countries in the sample because five lags are the best lag length, as mentioned in section 2.3.4. These tests show strong evidence of heteroskedasticity, in which most pairs are significant at a 1% and 5% level. A possible reason for this issue is the model misspecification, such as omitted variables. It indicates there are unobserved factors that are not included in the model but that are related to the observed factors – explanatory variables. The ARCH effect (an autoregressive structure on conditional variance), in particular, is found to be strongly evident at the 1% significance level for all pairs of countries. A tempting explanation for the presence of ARCH in financial time series is the assumption that the daily returns are generated by a combination of different distributions of information on arrival to market for individual stocks (Lamoureux & Lastrapes, 1990).

Table 2-7. Summary of t-statistics for the White test for each pair – full sample

	AU	GER	HK	HS	INDO	JP	MALAY	NZ	PHIL	SHA	SHB	SING	SZA	SZB	THAI	UK	US
AU	51.56***	42.19***	103.00***	105.20***	232.03***	177.28***	5.62**	41.90***	103.76***	4.62**	9.64***	69.32***	7.85***	15.86***	78.86***	33.88***	180.86***
GER	30.58***	36.01***	33.40***	40.07***	82.92***	117.28***	3.85**	33.85***	21.67***	0.61	2.04	30.84***	0.48	3.96**	50.35***	65.98***	134.80***
HK	60.52***	33.58***	106.00***	132.14***	209.08***	89.06***	14.31***	47.41***	121.20***	17.80***	24.33***	89.54***	18.36***	36.05***	48.48***	22.80***	112.23***
HS	62.04***	39.94***	95.27***	140.92***	276.93***	107.98***	16.96***	56.85***	153.41***	19.26***	30.09***	109.90***	22.15***	42.86***	55.59***	25.14***	142.94***
INDO	54.33***	10.18***	54.88***	70.72***	136.41***	125.51***	9.61***	138.70***	115.28***	2.32	6.76**	63.99***	4.89**	14.03***	45.38***	122.95***	45.10***
JP	23.32**	27.22***	93.37***	115.85***	112.14***	123.47***	14.81***	26.03***	43.74***	2.96*	6.62***	52.34***	8.67***	14.95***	19.99***	22.85***	50.20***
MALAY	10.91**	5.34**	12.13***	19.42***	73.00***	21.21***	36.62***	18.58***	55.65***	7.63***	8.54***	26.32***	7.82***	10.20***	16.74***	6.01**	21.17***
NZ	44.66**	43.21***	134.09***	124.54***	222.40***	176.05***	7.91***	70.40***	145.60***	5.56**	11.85***	74.26***	7.47***	16.37***	73.67***	43.71***	137.72***
PHIL	24.02***	4.50**	27.09***	26.20***	49.66***	38.87***	5.63**	50.91***	70.42***	4.66**	6.34**	13.10***	4.31**	3.69*	16.94***	83.97***	15.74***
SHA	10.30***	1.27	12.25***	20.11***	9.68***	8.86***	4.29**	2.92*	16.90***	68.59***	72.14***	12.90***	90.38***	36.80***	1.98	4.46**	12.30***
SHB	8.39***	1.94	17.12***	22.31***	4.38**	9.35***	0.83	3.67*	7.19***	53.21***	183.72***	7.93***	73.77***	48.43***	0.47	13.65***	13.14***
SING	37.46***	39.79***	58.39***	80.32***	225.54	87.97***	7.05***	49.93***	115.89***	5.29**	11.35***	107.80***	6.83***	15.63***	68.07***	23.55***	97.23***
SZA	6.23**	0.60	8.79***	16.18***	2.16	4.06**	1.99	1.08	4.63**	49.80***	70.67***	6.92***	73.39***	25.82***	0.08	5.28**	10.83***
SZB	9.96***	3.92**	14.21***	14.37***	9.25***	11.68***	2.90*	9.50	20.06***	36.72***	90.12***	8.63***	42.89***	40.07***	4.32**	21.19***	11.99***
THAI	23.76***	9.07***	65.84***	51.70***	90.83***	93.15***	9.40***	38.44	43.23***	1.75	4.35**	23.13***	3.25**	10.90***	223.41***	26.31***	33.03***
UK	34.30***	29.08***	88.16***	99.47***	72.73***	130.83***	10.86***	41.29	33.39***	3.98**	4.68**	80.53***	2.21	3.81*	54.43***	46.49***	132.66***
AU	36.47***	32.39***	60.51***	67.93***	43.95***	116.26***	13.09***	33.67	9.78***	7.68***	6.88***	42.16***	4.59**	3.85**	43.11***	79.04***	189.06***

Note: *, ** and *** indicate significance at 10%, 5% and 1% levels. Null hypothesis: no heteroskedasticity, which assumes the errors are homoskedastic and independent of the regressors, and that the linear specification of the model is correct. Failure of any of these conditions leads to significant test statistics. Non-significant t-statistics implies that none of the three conditions is violated.

Table 2-8. Summary of t-statistics of ARCH at five lag test for each pair of countries – full sample

	AU	GER	HK	HS	INDO	JP	MALAY	NZ	PHIL	SHA	SHB	SING	SZA	SZB	THAI	UK	US
AU	215.32	149.22	289.52	348.85	172.74	279.20	148.49	149.15	99.47	175.81	331.21	197.29	180.43	87.07	160.74	356.14	476.51
GER	166.52	149.80	263.82	327.16	154.28	257.83	143.26	113.75	80.60	170.77	325.09	182.73	179.46	80.48	165.76	355.96	477.26
HK	220.05	149.83	292.84	344.37	176.44	287.16	146.22	162.55	100.20	175.13	329.71	196.15	180.62	90.80	192.36	351.27	471.74
HS	218.75	149.79	290.06	342.68	175.90	285.51	145.68	159.13	98.64	174.00	330.87	196.21	180.53	88.70	189.81	354.47	474.19
INDO	217.98	149.45	290.60	349.61	190.05	289.64	146.62	167.73	114.83	174.14	333.85	201.89	182.65	86.45	193.59	356.59	476.64
JP	209.96	146.80	287.69	339.95	177.39	269.85	147.04	174.39	100.85	174.89	330.75	193.87	182.57	86.58	194.59	343.69	476.26
MALAY	221.33	149.60	290.94	347.95	179.60	290.10	144.37	169.19	106.78	172.21	328.61	201.57	180.68	85.60	208.75	354.73	475.67
NZ	216.26	149.25	287.59	345.99	168.56	277.34	148.81	157.93	97.30	171.85	330.43	197.81	177.52	83.66	158.89	357.17	476.39
PHIL	221.69	148.87	289.22	344.55	179.29	285.57	146.95	173.24	109.46	173.34	333.16	197.27	181.09	86.38	198.89	357.01	476.51
SHA	220.71	149.82	288.43	338.16	177.95	285.22	147.83	173.39	104.56	174.16	329.32	193.20	179.26	86.55	198.71	357.59	476.83
SHB	220.44	150.02	289.27	341.42	178.08	283.09	148.55	173.40	103.36	171.89	310.14	194.99	172.92	84.89	198.71	357.69	476.63
SING	211.86	150.55	285.56	352.17	166.78	272.84	151.10	147.11	93.53	172.84	333.37	205.63	180.95	88.09	182.47	363.34	474.71
SZA	220.77	149.77	289.14	339.89	177.89	283.81	148.04	173.38	103.31	174.40	327.92	193.36	178.41	86.75	199.72	358.44	476.38
SZB	221.09	149.81	289.38	342.42	178.87	283.25	148.42	173.42	104.11	173.87	318.95	195.95	178.23	85.76	197.74	356.90	476.36
THAI	216.73	149.76	288.50	343.96	183.57	286.45	149.95	161.29	110.67	173.00	328.35	197.23	181.28	83.58	232.29	359.78	476.85
UK	170.36	149.40	239.63	304.03	142.63	222.28	137.49	119.64	85.86	164.61	314.80	179.10	175.97	73.95	157.04	356.54	476.78
US	72.39	123.71	234.25	296.97	124.28	189.33	132.94	53.99	52.27	163.55	329.15	165.77	176.44	76.67	158.83	302.05	483.38

Note: Null hypothesis: there is no ARCH at five lags in the residuals. All t-statistics in this table are very large and higher than the critical values at the 1% level, hence all pairs reject the null hypothesis of no ARCH at the 1% significance level, suggesting ARCH is strongly evident at five lags for all pairs. Since all pairs are significant at the 1% level, we do not have the asterisk next to the t-statistics as presented in other tables to save space.

2.3.6. Correlation matrix

Table 2-9 summarises countries classified by the degree of correlation with each of China's markets. There are four groups: strong (correlation > 0.7), moderate (0.5 < Correlation ≤ 0.7), mild (0.2 < Correlation ≤ 0.5) and weak (Correlation ≤ 0.2). The correlation matrix between each series in the sample over the four sub-periods is given in **Table 2-10**. A positive number indicates a positive co-movement of the two return series. This is a simple method that is extensively used in financial investment areas to indicate the synchronisation at the returns level of two securities. The results show that the correlation of each pair is positive in any given period, indicating a positive association among these countries in the sample; however, at various degrees. For example, the correlation between AS and BS ranging from 0.734 to 0.820 is higher than with other markets in the sample. Herding behaviour that is documented in China's markets is a possible explanation for this correlation between AS and BS. In contrast, HS are more related to other countries than with other of China's share markets; for example, HS are strongly correlated with HK (0.703 in the pre-GFC period), whereas a moderate correlation is documented between AS and HK (0.226 on average). This is because HS are accessible to foreigners and listed on the HK market. Finally, the correlation among countries is generally higher during the GFC and the extended-crisis period compared to the prior and subsequent periods. For example, the correlations between SHA and Thailand increases from 0.086 in the pre-GFC period to 0.269 during the GFC period, then slightly increases to 0.281, then reduces to 0.163 in the post-crisis period. It is noted that the correlation is also higher in the post-crisis period relative to the pre-GFC period, suggesting a stronger cross-country integration for China's equities. Some pairs are observed to have a significantly high correlation, which is very close to one indicating a solid relationship; for example, SZA-SHA and HS-HK. The result is self-explanatory, since those pairs are listed in the same exchange.

Table 2-9. Summary of countries by the degree of correlation with each of China's share markets

	A-shares	B-shares	H-shares
Panel A: Pre-GFC period			
Correlation > 0.7	BS	AS	HK, UK
0.5 < Correlation ≤ 0.7			Australia, Japan, Singapore
0.2 < Correlation ≤ 0.5	HK	HK	Indonesia, Malaysia, NZ, Philippines, BS, Thailand, UK, US
Correlation ≤ 0.2	Australia, Germany, HS, Indonesia, Japan, Malaysia, NZ, Philippines, UK, US	Australia, Germany, HS, Indonesia, Japan, Malaysia, NZ, Philippines, UK, US	Germany, AS
Panel B: GFC period			
Correlation > 0.7	BS	AS	Australia, HK, Singapore
0.5 < Correlation ≤ 0.7			Indonesia, Japan, Malaysia, NZ, Philippines, Germany, Thailand, UK
0.2 < Correlation ≤ 0.5	Australia, HK, HS, Indonesia, Japan, Malaysia, NZ, Philippines, Singapore, Thailand	Australia, HK, HS, Indonesia, Japan, Malaysia, NZ, Philippines, Singapore, Thailand	AS, BS, US
Correlation ≤ 0.2	Germany, UK, US	Germany, UK, US	
Panel C: Extended-crisis period			
Correlation > 0.7	BS	AS	HK, Singapore
0.5 < Correlation ≤ 0.7			Australia, Germany, Indonesia, Japan, Malaysia, NZ, Philippines, Thailand
0.2 < Correlation ≤ 0.5	Australia, HK, HS, Indonesia, Japan, Malaysia, NZ, Philippines, Singapore, Thailand	Australia, HK, HS, Indonesia, Japan, Malaysia, NZ, Philippines, Singapore, Thailand,	AS, BS, UK, US
Correlation ≤ 0.2	Germany, UK, US	Germany, UK, US	
Panel D: Post-crisis period			
Correlation > 0.7	BS	AS	HK
0.5 < Correlation ≤ 0.7			Australia, Singapore
0.2 < Correlation ≤ 0.5	Australia, Japan, HK, HS, Singapore	Australia	Germany, Indonesia, Japan, Malaysia, NZ, Philippines, AS, BS, Thailand, UK, US
Correlation ≤ 0.2	Germany, Indonesia, Malaysia, NZ, Philippines, UK, US		

Table 2-10. Correlation matrix between each series – full sample

Panel A: Pre-GFC period from May 8, 2002 to February 27, 2007

	AU	GER	HK	HS	INDO	JP	MALAY	NZ	PHIL	SHA	SHB	SING	SZA	SZB	THAI	UK
GER	0.398															
HK	0.380	0.243														
HS	0.522	0.358	0.703													
INDO	0.401	0.221	0.408	0.441												
JP	0.570	0.328	0.406	0.549	0.424											
MALAY	0.305	0.136	0.386	0.403	0.414	0.375										
NZ	0.653	0.240	0.173	0.250	0.253	0.333	0.161									
PHIL	0.340	0.132	0.268	0.317	0.393	0.362	0.320	0.152								
SHA	0.092	0.066	0.244	0.140	0.095	0.115	0.138	0.084	0.041							
SHB	0.114	0.053	0.244	0.168	0.109	0.102	0.164	0.082	0.030	0.734						
SING	0.527	0.345	0.523	0.664	0.487	0.565	0.465	0.280	0.342	0.135	0.126					
SZA	0.098	0.052	0.208	0.125	0.080	0.111	0.128	0.082	0.016	0.936	0.770	0.113				
SZB	0.162	0.112	0.306	0.238	0.160	0.181	0.215	0.115	0.074	0.756	0.813	0.184	0.784			
THAI	0.387	0.221	0.341	0.392	0.442	0.374	0.328	0.260	0.273	0.086	0.102	0.429	0.083	0.131		
UK	0.453	0.745	0.267	0.395	0.227	0.304	0.168	0.269	0.170	0.048	0.059	0.365	0.040	0.100	0.225	
US	0.194	0.680	0.186	0.278	0.096	0.185	0.057	0.047	0.064	0.036	0.027	0.224	0.021	0.092	0.098	0.509

Panel B: GFC period from February 28, 2007 to May 29, 2010

	AU	GER	HK	HS	INDO	JP	MALAY	NZ	PHIL	SHA	SHB	SING	SZA	SZB	THAI	UK
GER	0.710															
HK	0.745	0.550														
HS	0.764	0.563	0.960													
INDO	0.690	0.484	0.674	0.709												
JP	0.723	0.418	0.640	0.663	0.533											
MALAY	0.688	0.509	0.655	0.672	0.654	0.524										

NZ	0.824	0.649	0.577	0.599	0.598	0.576	0.596									
PHIL	0.653	0.426	0.589	0.584	0.650	0.505	0.640	0.651								
SHA	0.325	0.165	0.527	0.477	0.291	0.309	0.364	0.258	0.319							
SHB	0.296	0.156	0.461	0.413	0.300	0.270	0.361	0.240	0.336	0.820						
SING	0.783	0.638	0.809	0.866	0.720	0.630	0.707	0.664	0.563	0.338	0.302					
SZA	0.236	0.102	0.408	0.374	0.248	0.239	0.311	0.182	0.242	0.922	0.835	0.268				
SZB	0.384	0.195	0.546	0.504	0.394	0.358	0.449	0.319	0.424	0.811	0.889	0.397	0.812			
THAI	0.650	0.493	0.636	0.658	0.691	0.488	0.596	0.581	0.556	0.269	0.245	0.679	0.171	0.333		
UK	0.738	0.868	0.561	0.585	0.543	0.449	0.504	0.709	0.501	0.167	0.155	0.643	0.110	0.218	0.511	
US	0.397	0.649	0.307	0.327	0.310	0.110	0.258	0.356	0.199	0.004	0.028	0.442	-0.017	0.048	0.375	0.603

Panel C: Extended-crisis period from May 30, 2010 to June 6, 2012

	AU	GER	HK	HS	INDO	JP	MALAY	NZ	PHIL	SHA	SHB	SING	SZA	SZB	THAI	UK
GER	0.664															
HK	0.680	0.408														
HS	0.692	0.404	0.959													
INDO	0.600	0.372	0.641	0.651												
JP	0.568	0.262	0.477	0.519	0.410											
MALAY	0.697	0.449	0.698	0.695	0.698	0.453										
NZ	0.784	0.681	0.515	0.540	0.457	0.441	0.558									
PHIL	0.563	0.323	0.551	0.547	0.587	0.402	0.643	0.501								
SHA	0.360	0.231	0.558	0.517	0.345	0.235	0.324	0.300	0.280							
SHB	0.286	0.147	0.439	0.413	0.317	0.214	0.269	0.254	0.260	0.820						
SING	0.785	0.583	0.765	0.789	0.712	0.521	0.744	0.665	0.560	0.388	0.317					
SZA	0.279	0.166	0.442	0.402	0.263	0.174	0.236	0.227	0.232	0.917	0.833	0.274				
SZB	0.403	0.230	0.579	0.542	0.420	0.290	0.413	0.333	0.373	0.834	0.846	0.433	0.816			
THAI	0.521	0.364	0.574	0.573	0.510	0.345	0.591	0.444	0.489	0.281	0.243	0.601	0.263	0.343		
UK	0.727	0.898	0.478	0.485	0.456	0.256	0.536	0.702	0.345	0.268	0.178	0.646	0.183	0.271	0.401	
US	0.557	0.772	0.289	0.296	0.283	0.141	0.357	0.583	0.240	0.167	0.102	0.475	0.117	0.160	0.273	0.765

Panel D: Post-crisis period from June 7, 2012 to July 31, 2017

	AU	GER	HK	HS	INDO	JP	MALAY	NZ	PHIL	SHA	SHB	SING	SZA	SZB	THAI	UK
GER	0.469															
HK	0.557	0.370														
HS	0.596	0.411	0.932													
INDO	0.445	0.342	0.430	0.467												
JP	0.476	0.241	0.436	0.468	0.299											
MALAY	0.575	0.462	0.485	0.524	0.596	0.347										
NZ	0.621	0.378	0.306	0.337	0.310	0.333	0.412									
PHIL	0.438	0.279	0.420	0.476	0.581	0.369	0.495	0.328								
SHA	0.268	0.109	0.637	0.537	0.175	0.235	0.185	0.159	0.191							
SHB	0.195	0.095	0.516	0.458	0.126	0.172	0.130	0.117	0.174	0.774						
SING	0.658	0.486	0.618	0.664	0.580	0.437	0.656	0.496	0.500	0.319	0.226					
SZA	0.229	0.139	0.496	0.438	0.130	0.201	0.153	0.145	0.178	0.868	0.787	0.260				
SZB	0.280	0.150	0.585	0.536	0.228	0.229	0.231	0.185	0.262	0.756	0.849	0.316	0.762			
THAI	0.433	0.374	0.438	0.453	0.590	0.299	0.505	0.304	0.512	0.221	0.163	0.529	0.174	0.262		
UK	0.568	0.823	0.436	0.490	0.392	0.287	0.531	0.449	0.323	0.180	0.158	0.578	0.184	0.215	0.407	
US	0.399	0.593	0.332	0.346	0.296	0.186	0.391	0.296	0.243	0.184	0.181	0.400	0.166	0.216	0.312	0.625

Note: Correlation is calculated between each series in the sample for each sub-period. The correlation is positive for each pair in any given period, indicating a positive relationship. The correlation is generally higher during the crisis period, suggesting stronger returns co-movement in this period. Correlation between China's share markets and other countries is highest for HK, implying that Chinese equities are more related to HK than other countries in the sample. AS and BS are, however, more synchronised with each other than with other countries. Some pairs are observed to have a significantly high correlation, which is very close to one indicating robust market dependence; for example, SZA-SHA (pre-GFC 0.936, during crisis 0.92), and HS-HK (during crisis 0.96, post-crisis 0.932).

2.3.7. Conclusion

The preliminary analysis for the daily stock returns in the sample showed that these time series were not normally distributed and were prone to negative skewness and fat tails. The time series also exhibited serial correlation and heteroskedasticity particular to an ARCH effect. This finding is consistent with the existing literature on financial time series of stock returns. A simple correlation matrix suggested that the time series of these stocks were related to each other. The relation was higher over time and especially increased during the GFC and possibly the extended-crisis period. Among China's share markets, HS exhibited the highest regional interaction, whereas AS and BS were more isolated and related at a national level. Based on these properties, a GARCH model is one of the most effective models designed to account for these properties adequately, and provides a parsimonious approach to test the simultaneous spillover in means and volatility between these countries with China's share markets.

Chapter 3 Dependence analysis using univariate GARCH and EGARCH

This chapter examines the asymmetry in the volatility of the marginal distribution of each market and volatility spillover from and to each of China's markets using a GARCH and an EGARCH model. This addresses two research questions for each of the four sub-periods formulated in section 1.5, namely:

1. Is there evidence of leverage effect in the distributional volatility of each market in the sample?
2. Is there evidence of volatility spillover between each of China's markets and other markets in the sample?

A combination of Chapter 3 and Chapter 4 has been published in *The North American Journal of Economics and Finance*, which as mentioned in the Publications and Conference listing on page vi.

The design of this chapter is as follows. Section 3.1 introduces the background for this thesis. Section 3.2 discusses the main findings in the existing literature in this field. Section 3.3 describes the data used in this chapter. Sections 3.4 and 3.5 present the GARCH and EGARCH models respectively. The model hypotheses for this chapter are presented in section 3.6. Section 3.7 reports the empirical results. The robustness tests are shown in section 3.8, while section 3.9 discusses the main findings from these results. Section 3.10 concludes.

3.1. Introduction

Higher market integration results in increased market interdependence, which reduces diversification benefits and introduces higher external exposures for many global markets such as ASEAN-5, the US and other markets (Forbes & Rigobon, 2002; Royfaizal, Lee, & Azali, 2009). For this reason, cross-market linkages have been well explored in the empirical literature.

Market interdependence is usually modelled at two levels: the first moment (price return) and the second moment (volatility of price or return). Some measures which have been used abundantly for the first approach include return correlation (Becker, Finnerty, & Gupta, 1990; Junior & Franca, 2012), linear co-integration (Janor & Ali, 2007) and causality (Bessler & Yang, 2003) or Granger causality (Ajayi, Friedman, & Mehdian, 1998; Kwon, 2018).

These are among the most fundamental measures of price and returns co-movement. However, linkages at the first moment are found to be incomprehensive in describing the relationship among markets, especially during heightened volatility periods, which can lead to misleading inferences when assessing downside risk in joint distributions. The occurrence of the two financial crises, namely the AFC 1997 and the GFC 2008, which caused tremendous deterioration in global wealth led to the exploration of two striking findings. Firstly, cross-market return correlation is regime-dependent, which has been found to increase during crises and is often referred to as 'contagion' or, strictly speaking, 'correlation contagion' – that is, a significant increase in price co-movement across markets during a crisis (Białkowski & Serwa, 2005; Dungey & Gajurel, 2014; Glick & Hutchison, 2013). Furthermore, markets with low return correlation before the crisis have a joint probability of recession that is as high as markets with high correlation, suggesting that a co-crash probability is not related to the degree of pre-GFC correlation between two markets (Hu, 2006). This finding implies that the degree of return correlation has little to no role in explaining the joint distribution of volatility, especially during an economic downturn. Besides, the estimation errors of correlation coefficients are higher during crises, suggesting that return correlation is not a reliable indicator of extreme risk in the context of market interdependence (Chiang et al., 2007). Fry-McKibbin, Hsiao, and Tang (2014) have researched the contagion channels, including the return correlation and covolatility in nine crises ranging from the AFC 1997 to the European debt crisis 2010-2013, and confirmed that correlation contagion was not sufficient to describe the transmission of shocks in a crisis. Thus, correlation at the first moment can generate a misleading indication of correlation at the second moment.

These findings have spurred a large body of literature on the modelling of the second-moment structure of stock returns; that is, volatility and the dynamics of volatility from the view of market interdependencies (Bhuyan, Elian, Bagnied, & Al-Deehani, 2015; Hong, Yoon, & Chang, 2014; Palamalai et al., 2013). This approach provides crucial explanations and interpretations for a cross-market spreading effect during extreme volatility periods, including the AFC and the GFC (Li & Giles, 2015; Liow, 2015). Yu, Fang, Sun, and Du (2018) found that China's stock market has been a significant risk factor for major global markets in the period after 2010. The volatility of stock returns can also exhibit asymmetry; that is, the unequal impact of bad news and good news, where leverage effect refers to the event that the impact of negative innovations is greater than that of positive innovations of the same size (Black, 1976). This phenomenon has been documented in many markets (Baruník, Kočenda, & Vácha, 2016; Carr & Wu, 2017; Chelley-Steeley & Steeley, 2005; Naik & Padhi, 2015), suggesting that sign is as important as the size of the innovations. Therefore, studying this area brings knowledge to the dynamic behaviour of the volatility of a stock market and its relation to other markets.

Following this branch of literature, this chapter aims to investigate the relationship between three major share types in China (AS, BS and HS) – an area which has received little attention in the existing literature – and the major stock markets in this thesis including the US, UK, Japan, HK, Germany, Australia, NZ and the ASEAN-5 countries which are also major trading partners of China. There are two key research questions that will be addressed in this chapter: 1) whether there is leverage effect in each stock market, and 2) whether there is evidence of volatility spillover between each of China's markets and other markets in the sample.

Since China has become the world's second-largest economy, studying cross-linkages between China and a wide range of emerging and advanced markets is extremely necessary in the current context. The occurrence of two global stock crashes in August 2015 and late 2017, due to China's stock market turbulence, raises the critical question of whether China's stock markets have a significant impact on the volatility of other global markets. However, only a few previous studies have explored the cross-border relations of the three major share types in China's markets – A-, B- and HS – and these are mostly focused on neighbouring markets in Asia, or examine the first moment of return using Granger causality tests and stochastic discount factors (Sun, 2014; Yao, Ma, & He, 2014; Yao, He, Chen, & Ou, 2018). These papers studied market integration at the price level and did not scrutinise the interdependence at the volatility level. This is one of the primary motivations for this chapter. In addition, the study of Tam (2014) examines regional integration of China during the AFC 1997, and the GFC 2008 found that China is the key driver of regional linkages among East Asian countries, providing further motivation for this thesis. This chapter expands the literature by further exploring cross-equity linkages of China to not only emerging, but also advanced markets in and out of the GFC period, which includes the extended-crisis period after the GFC; namely the European debt crisis 2010-2012, the global stock crashes in August 2015 and late 2017, and the post-crisis period up to 2017. Hence, the findings of this chapter will benefit global investors and risk managers, as discussed in section 1.6.1.

Apart from the fact that the selected markets are global financial centres, they are also major trading partners of China. Bekaert et al. (2014) pointed out that globalisation could be a prominent explanation for increased volatility dependence, particularly for instantaneous risk transmission from one market to another (i.e. volatility spillover) through economic and financial linkages. This phenomenon has been discussed in section 1.4.3.

There are a number of ways to measure volatility of stock prices, including the volatility implied by the GARCH process proposed by Bollerslev (1986), which has been well covered in the existing literature, thanks to the simplicity of the model specification and the interpretability of the estimated coefficients (Ezzati, 2013; Li & Giles, 2015). The GARCH framework models the conditional mean and the conditional variance of a stock. The conditional mean is specified by past stock returns (known observations) and an error term (unknown observations), also called the residual factor. The error term is governed by a variance process that is explained by past variances and past innovations. The specification of a GARCH model implies that the current stock return and variance at time t are driven by the information up to time $t-1$, providing an intuitive approach to measure stock returns and variations.

This thesis adopts two models to address the research questions: the symmetric GARCH model and the EGARCH model – an asymmetric GARCH model to measure the leverage effect in each stock market and the volatility spillover between each of China's markets and other markets in the sample.

These GARCH models are selected because they can address the two prominent distributional features of stock returns effectively – heteroskedasticity and serial correlation. Failure to account for heteroskedasticity can distort the parameters and lead to misleading conclusions, as demonstrated in the study of Forbes and Rigobon (2002). Also, serial correlation or volatility clustering is routinely found in most stock markets (Engle, 2004). Hence, a practical model should account for these attributes. Finally, an EGARCH model uses natural logarithms to capture the asymmetry in volatility. Hence, it does not impose the positiveness restriction on the variances, allowing natural decaying behaviour in this factor. In addition, an EGARCH model can overcome the computational issue when the number of factors is increasing, providing a parsimonious model which is suitable to the sample size of 17 variables as found in this chapter.

The contribution of this chapter is threefold. Firstly, it examines the asymmetry in the volatility of global stock markets and extends the study of volatility spillover between major financial centres to include three different Chinese equities, which have received minimal attention in empirical studies. Secondly, this chapter covers a broader sample of countries than is usually studied in the literature, including global financial centres from different geographic locations, providing useful insights about the impact on the volatility of these markets from each type of China's equities and vice versa. Thirdly, this thesis covers a long period before, during and after the GFC over the past 15 years that includes the European debt crisis 2010-2012 and the short-term global stock crashes of August 2015 and late 2017 which can provide an essential understanding of volatility and shock transmission behaviour in crisis and non-crisis periods. This could be extremely useful to policymakers and global investors who are interested in China's stock markets and their impact on other global markets. The findings of this chapter contribute to the existing knowledge of volatility spillover between China and other global stock markets and the distributional asymmetry of the volatility of these stock markets.

3.2. Literature review

3.2.1. What is volatility?

Volatility is an important and significant topic for studying major financial markets such as equity markets. Before exploring why this is important and what the salient features of distributional volatility of stock returns are, one should understand what volatility is. Volatility was mentioned as early as the 1950s but was defined by Jones and Wilson (1989) and Schwert (1990) as changes in absolute value or percentage in stock returns, implying the uncertainty of the 'possible' or 'expected' movements in stock prices around the mean; that is, average value over a period. One of the most fundamental ways to value an asset is to determine the discounted future value of the benefits generated from holding the asset (Kaplan & Ruback, 1995; Koller & Goedhart, 2015; Ruback, 2002). The discounted rate, indeed, accounts for the uncertainty in future cash flows. An option is priced based on the risk of the changes in the underlying asset price (Kou, 2002; Liu, Chen, & Ralescu, 2015; Merton, 1973). Hence, there is no doubt that studying volatility provides important implications in financial modelling and asset valuation.

Regardless, volatility is not directly observable like prices or returns, but it is based on auxiliary assumptions of how it should be calculated. Under a GARCH process, volatility is the residual factors that explain the unknown variables in the current level of stock returns which cannot be explained by past returns. The specification of a GARCH process permits past volatilities and innovations to explain the current level of volatility. Hence, the interpretation of the estimated coefficients can draw useful information about the short-term dynamic behaviour of the volatility of a stock market. Due to this specification, a GARCH model is a popular approach to measure the volatility of the returns of many financial markets, as discussed in sections 3.2 and 3.4. A related concept in measuring volatility is realised volatility, capturing the quadratic variation in stock prices, which is usually derived from realised variance. This measure was introduced by Barndorff-Nielsen and Shephard (2002), and a similar concept was discussed by Andersen, Bollerslev, Diebold, and Ebens (2001). It is a relatively new, rising concept which has been tested in many studies (Andersen, Bollerslev, Diebold, & Labys, 2003; Audrino & Knaus, 2016; Bollerslev, Meddahi, & Nyawa, 2019; Corsi, 2009). However, it is found that the performance of realised volatility is improved when the sampling frequency increases, suggesting that this measure is sensitive to the frequency of data and is better fitted to intraday data rather than daily data (Hansen & Huang, 2015). Hence, the traditional approach is preferred, and therefore volatility extracted from a GARCH process is implemented in this chapter.

3.2.2. Asymmetric volatility response to news

The previous section showed that the relationship between returns and volatility is an important topic. Related to this, trade-off theory is a fundamental theory in traditional financial theory and a routinely used assumption in financial modelling and applications. This theory refers to the positive relationship between the return and risk of an asset which is usually measured by the standard deviation (total risk), whereby averse investors require additional units of return when bearing additional units of risk. In practice, higher volatility does not always lead to higher returns, which violates the trade-off theory. This phenomenon was first discovered by Black (1976), who found a reverse relationship between risk and return when taking into account the financial leverage of a company. A leverage effect is not only found at a firm level, but also at an aggregate level, as well as in the context of cross-market dependencies. Stock return correlations were found with asymmetry, whereby the probability of a co-crash in a highly volatile period is higher than the co-movement in market upswings (Kenourgios et al., 2011). These findings open wide the research of asymmetric volatility in responding to past news, in which the EGARCH Asymmetric volatility refers to an uneven impact of good news and bad news on the degree of volatility of stock returns. The asymmetry increases significantly during periods of high volatility, which was found in many countries such as Taiwan (Lin & Chen) and the US, Germany, Japan, China and Thailand using asymmetric fractionally integrated exponential GARCH-in-Mean –

FIEGARCH-M – models (Christensen, Nielsen, & Zhu, 2015). Asymmetric volatility in China's markets measured by an EGARCH model was also evident (Naik & Padhi, 2015). In exploring the reasons for this observation, it was found that the asymmetry in the volatility of macro-economic variables could be responsible, whereby volatility of these variables was higher during financial crises (Schwert, 1989). For example, a fall in stock prices could be induced by a reduction in GDP, leading to higher volatility in a period of low GDP growth. Schwert (1989) found that there was a significant and positive relationship between the aggregate level of financial leverage (debt/equity ratio) and volatility during recessions.

What determines the skewness of the volatility of stock return distribution remains an open question. There are numerous hypotheses that attempt to explain this particular property, but none are found to fully account for volatility responses. The most common hypotheses are financial leverage and volatility feedback effect. The former theory is associated with the event that bad news has more impact than the good news of the same size, which was named following the findings of Black (1976). Black (1976) argued that a falling stock price tends to increase a firm's financial leverage, which leads to higher idiosyncratic risks in business, hence moving the volatility of stock returns upward. This hypothesis is supported by a positive relationship between a firm's idiosyncratic volatility and leverage (Dennis & Strickland, 2004; Patton & Sheppard, 2015), and has been documented in many advanced stock markets; for example, the US, Brazil, China, South African markets (Mensi, Hammoudeh, Nguyen, & Kang, 2016) and the UK (Chelley-Steeley & Steeley, 2005).

It has also been found that leverage effect is responsible for volatility levels in the long-term, due to the accumulative and prolonged effect induced from leverage effect (Ericsson, Huang, & Mazzotta, 2016). However, the effect of financial leverage has been questioned and challenged in other empirical studies. For example, it has been found that leverage effect only accounted for a small part of the asymmetric volatility. Hence, labelling the phenomenon of adverse shocks increasing volatility more than positive shocks as a leverage effect is a misnomer (Bekaert & Wu, 2000). In addition, Duffee (1995) argued that the negative correlation between risk and changes in volatility induced by the financial leverage effect was through the negative correlations between return and *future* volatility, not through the correlations between returns and *current* volatility. Therefore a leverage effect cannot be used to explain the contemporaneous correlations of risk-return. Furthermore, an important finding regarding the financial leverage effect is that it might be responsible for the risk–return relationship, but it is not responsible for the inverse relationship of risk-return (Hasanhodzic & Lo, 2011), and therefore nullifies its impact on the asymmetry in volatility in responding to past information. Nevertheless, the financial leverage effect is one of the most common hypotheses explaining asymmetric volatility, such that leverage effects have become synonymous with asymmetric volatility.

The second theory attempting to explain the asymmetry in volatility is the 'volatility feedback effect', also known as the time-varying risk premium, whereby volatility and stock price are negatively causal, and which is possibly attributable to asymmetry in the volatility of stock returns. This theory suggests that if volatility can be priced, an expected rise in volatility leads to an instant fall in the stock price. Evidence supporting this theory was found in many empirical studies (Ericsson et al., 2016; Mo, Liu, & Yang, 2016). However, its impact was underestimated when ignoring the variation in leverage effect and capitalisation at the firm level (Conrad, Gultekin, & Kaul, 1991). The volatility feedback effect was found to explain some parts of the negative skewness and excess kurtosis of the US stock market residuals estimated by an asymmetric quadratic GARCH (QGARCH), especially during high volatility periods, from 10% to 25%, indicating that volatility feedback effect could be one of the reasons, but not the major one (Campbell & Hentschel, 1992).

On the other hand, Wu (2001) found that the volatility feedback effect and leverage effect were both critical determinants of asymmetries in the weekly and monthly volatility of the US stock market during 1962 to 1997 using a panel model. In agreement with this finding, Bekaert and Wu (2000) also found that the volatility feedback effect played an essential role in explaining the asymmetry in volatility when taking into account different leverages at the firm level. This theory explains that changes in returns are driven by volatility innovations, whereas leverage effect implies an inverse relationship. Even though the two hypotheses of financial leverage effect and the risk-return premium are a 'chicken and egg' debate, the latter is regarded as a crucial explanation of asymmetric volatility during crisis periods, as this theory explains the phenomenon of the higher risk–lower price relationship during these high volatility periods.

Another tempting explanation of asymmetries in volatility is the asymmetry in the rate of information flow. Since volatility is directly linked to the rate of information flow (Ross, 1989), asymmetry in the rate of information flow between large and small firms leads to asymmetry in volatility. This theory holds that innovations are not reflected at the same rate in large and small firms. They are reflected in large firms first, and then small firms. Similar results were found for the Tokyo Stock Exchange (Reyes, 2001).

Behavioural finance, which explains the irrationality of traders, is another possible cause of this asymmetric phenomenon. Noise traders theory argues against the efficient market hypothesis – a traditional explanation for the asymmetric response of volatility – highlighting that not all traders will make rational investment decisions, which in turn introduces asymmetries (Black, 1986). These investors do not trade on the information, but the noise. Black (1986) found that the reaction of those investors to the information could not be entirely captured in a rational model. This is clarified by the prospect theory, where a person weighs losses and gains differently, confirming the irrationality in making investment decisions (Kahneman & Tversky, 1979; Kahneman & Tversky, 2013). Specifically, the value function for loss is more concave and steeper than the value function for gains. Put simply, a person responds differently in regard to the same amount of uncertainty of gain and loss. That theory explains why volatility was found to be higher when prices are falling than when they are increasing because higher volatility (whether caused by a price fall or not) leads to fear of losses, which in turn could induce a sell-off, further depressing stock prices. This is contrary to the trade-off theory, which explains that the investors require (or expect) an asset to perform better when there is higher risk. Trade-off theory refers to the investors' expectations, whereas prospect theory describes the actual reactions of investors. However, not many empirical studies explore this area. Hibbert, Daigler, and Dupoyet (2008) are among the few who attempted to assess behavioural finance in explaining the negative asymmetric return-risk relationship. They found that neither the leverage effect nor volatility feedback hypotheses are the primary explanations for this phenomenon. Instead, several behavioural biases found in traders, including representativeness, and extrapolation biases are significant sources of the negative and asymmetric relationship. In a related study, Park (2011) revealed that, in contrast to the traditional belief system, both financial leverage effect and volatility feedback could not explain the asymmetry in the volatility of stock returns adequately, but the asymmetric herding effect appeared to be a primary determinant of the asymmetric volatility of stock returns.

Given mixed results in the existing literature, this chapter uses an EGARCH model to assess the return-risk relationship and to detect the presence of the asymmetric property. Evidence supporting the intuition of a positive relationship between return and, strictly speaking, anticipated volatility, is plentiful in traditional finance modelling (French, Schwert, & Stambaugh, 1987), yet a negative relationship between return and unexpected volatility is also widely documented, as aforementioned. If an asymmetric volatility response to stock returns in these global stock markets is found to be significant, the market intuition of a positive relationship between risk-return that is implied by the trade-off theory will be challenged. Studying asymmetric volatility in different periods provides useful insight into the time-varying dynamics of this property in the crisis (GFC 2008, extended-crisis 2012) and non-crisis periods (the periods before and after these crises).

3.2.3. Volatility spillover

From the simultaneous and uniform fall of many markets during crises in a long history of global equities, from the stock market crash of AFC 1997 to the GFC 2008 and most recently the stock crash in August 2018, the topic of international market dependence has attracted a vast amount of academic attention. This section focuses on the phenomenal regularity during crises – volatility spillover – an instantaneous change measured at the daily level in the volatility of one market in responding to the innovations in the returns of another market. A detailed discussion and definition of volatility spillover can be found in section 1.4.3.

Some studies suggest that increased financial market integration results in a higher correlation between returns and volatility of equity markets across borders because portfolio managers are more responsive to the news in foreign countries. Hamao et al. (1990) is among the first studies that documented an 'international bear market contagion' in the daily returns among global equity markets including the US, Japan and the UK using the two-stage GARCH-M model during heightened volatility periods. Other examples of key studies in this field include King and Wadhwani (1990), who found evidence of contagion in daily market returns between New York and London stock markets, and Lin, Engle, and Ito (1994), who used the two-stage GARCH-M model to assess the contagion by intraday returns between Tokyo and New York stock exchanges. Yu, Fung, and Tam (2010) found higher market integration since 2002 implied by an increased daily return correlation across Asian markets including Mainland China (SHA, SHB, SZA, SZB and HS), HK, ASEAN-5 and Japan using a DCC-GARCH model. Li and Rose (2008) revealed that market integration at both local and regional levels was responsible for the extreme movement of stock market returns in APEC countries. Apart from that, deregulation could also be the reason. Li (2012) found that China's liberalised capital policies also have an impact on volatility spillover from China to other global stock markets, including the US, Korea and Japan.

Even though conventional wisdom claims that volatility is transmitted from advanced to emerging markets, findings from empirical studies are inconclusive. Koutmos and Booth (1995) found evidence of volatility spillover among New York, Tokyo and London stock exchanges using an EGARCH model on open-to-close daily market returns. Volatility spillover from China to the US market was also documented using the GARCH-M and Glosten Jagannathan and Runkle (GJR)-GARCH-M models from 1999 to 2005 (Moon & Yu, 2010). In an extended study, HK and Mainland China markets (Shanghai and Shenzhen markets) received volatility from the US market from 2001 to 2013 but not vice versa (Mohammadi & Tan, 2015). In addition, volatility spillover was also recorded between Germany and the UK from 1984 to 1993 using an EGARCH model (Kanas, 1998).

Worthington and Higgs (2004) studied volatility spillover among nine Asian emerging and advanced markets (HK, Japan, Singapore, Indonesia, Korea, Malaysia, the Philippines, Taiwan and Thailand) using a multivariate GARCH model and found that these markets were highly integrated in terms of returns and volatility between 1988 and 2000. This chapter found that the spillover from these advanced markets to emerging markets was not homogenous. No volatility spillover was found between Shanghai and Japan markets in high-frequency data (intraday) from January 2013 to March 2014, while one-way market return spillover from China to Japan was evident using a BEKK-GARCH model (Nishimura, Tsutsui, & Hirayama, 2016). On the other hand, it was found that larger markets had more influence on smaller markets when examining return and volatility spillover among Australia, China, Japan, HK and NZ (Sazali, Krishna, & Chun, 2014).

Moreover, many studies found that volatility spillover is more substantial during financial distress. It was found that volatility was transmitted from the US to Japan and some Asian markets including China, India, Indonesia, Malaysia, the Philippines and Thailand from 1993 to 2012, and that bidirectional spillover between the US and these markets appeared stronger during the Asian financial crisis (Li & Giles, 2015). Yilmaz (2010) examined the crisis and non-crisis behaviour or volatility spillover indices of 10 major Asian-Pacific stock markets (HK, Indonesia, Japan, Korea, Malaysia, the

Philippines, Singapore, Taiwan, Thailand and Australia) from 1992 to 2009 and found that, indeed, there is a burst in volatility spillover during major crises (policy failure in Japan 1994, Mexican crisis 1994-1995, AFC 1997, Russian crisis 1998, Brazilian crisis 1999, increased US market tension due to technology stocks 2000-2001, 9/11 terrorist attack in US 2001, US market stock crash mid-2002, Iraq war 2003 and GFC 2008).

Studying volatility spillover between China and its trading partners can potentially have important implications, not only for financial investment decisions such as hedging and portfolio construction, but also for financial investment regulations designed to maintain stability for a market's long-term growth. Understanding the dynamic behaviours of market volatility transmission can support regulators and policymakers in forming risk management frameworks and controlling systems to minimise the risk from economic integration (Plummer, 2009). Sun (2014) is one of the few studies which examined cross-equity relationships between the three different share types in China and other countries. However, that study only focused on the cointegration for a short period after the GFC. Even though this is an important topic, not many studies have investigated volatility spillover between each of the three major share types in China's stock markets and other global markets over a long horizon that sufficiently covers the period before and after the GFC. Therefore, this chapter contributes to the existing literature in the field by filling this gap.

3.2.4. Methodology for the asymmetric volatility and volatility spillover

Earlier studies used the moving average of volatility to measure the asymmetric volatility of stock returns, while GARCH models were predominantly used in more recent work. The GARCH model was developed by Bollerslev (1986), based on the ARCH framework of Engle (1982). The GARCH family is the most popular approach to model the stochastic behaviour of returns and volatility in financial time series (Hamao et al., 1990; Lin et al., 1994). It allows the degree of volatility to be described by past news and lag conditional variances and accounts for the common properties in financial time series of stock returns, that is heteroskedasticity and volatility clustering. A less common method is the Bayesian approach to model stock volatility, but this model is useful in valuing stock choices by incorporating new information regarding the volatility (Karolyi, 1993).

However, the 'first-generation' GARCH model, also known as symmetric GARCH, focuses on the size of the shocks while ignoring the sign. The existing literature, as previously discussed in sections 3.2.1 and 3.2.2, highlighted the importance and existence of asymmetries in distributional volatility. Asymmetries in financial time series can stem from two sources: the skewness of the marginal distribution; and the cross-sectional asymmetric response of volatility from a joint distribution (Patton, 2004). Both of these properties are quite prominent in financial time series. For the former, the preliminary tests, as presented in section 2.3.2, revealed that all stock markets in the sample exhibit negative skewness. For the latter, many studies found evidence of a higher chance for stock markets to crash together than to boom together, and evidence of a leverage effect in volatility in responding to past news of another market (Chiang et al., 2007; Hansen & Huang, 2015; Olugbode, El-Masry, & Pointon, 2014). Thus, methods that assume equal weights to all observations regardless of the sign may underestimate the probability of return and volatility co-movements, especially during turbulence, if the joint distribution has significant asymmetric tail dependence (Ergen, 2014). This created a strong motivation for the development and use of asymmetric GARCH models in recent literature, of which EGARCH is representative.

Therefore, despite several extended models, one of the main limitations of the symmetric GARCH model lies in the assumption of symmetric distribution, which is not flexible to practical settings of financial time series. Many extensions of the GARCH model have been developed to address these issues, but they are far from perfect. First, Bollerslev (1986) included conditionally t-distributed errors to solve the conditional excess kurtosis in financial time series but did not account for time-varying conditional skewness. Moreover, this method assumes a thicker tail and symmetric distribution, thus failing to address the asymmetric properties. BEKK-GARCH is a good candidate for cross-sectional dependencies and has been applied in various empirical studies (Mohammadi & Tan, 2015; Nishimura et al., 2016). However, this model has an over-parametrisation issue (a fully parameterised model with k variables has $2.5k^2 + 0.5k$ parameters) which makes it practically impossible for a large dimensional data over 10 (Caporin & McAleer, 2012). Bollerslev (1990) later developed the CCC-GARCH model to resolve the negative skewness in return distributions. However, this model does not allow for spillover effect and time-varying conditional correlation (Ezzati, 2013). Kroner and Ng (1998) later extended the GARCH model to account for the asymmetric property of the time-varying variance; however, it failed to account for non-stationary characteristics in stock returns. More importantly, a fully integrated model requires a large number of parameters similar to BEKK-GARCH, which makes a large-scale, cross-sectional dimension unfeasible (Laurent, Rombouts, & Violante, 2012). In addition, the interpretation of individual coefficients is challenging (Engle & Sheppard, 2001; Mohammadi & Tan, 2015). The dynamic conditional correlation DCC-GARCH model was later developed by Engle (2002) to deal with excess kurtosis and to capture the movement in volatility effects without arbitrarily subdividing the period (Chiang et al., 2007). Even though the DCC-GARCH model has a computational advantage over prior GARCH models such as the BEKK model, it is sensitive to omitted variable bias (Wang et al., 2013), and the replication of asymmetries in asymptotic tail dependence has not been incorporated in the model (Boubaker & Sghaier, 2013).

Traditionally, empirical studies applied GARCH-type models to capture volatility in stock time series. The Nelson (1991) EGARCH model is selected for this chapter for three main reasons. First, it is designed to explicitly model asymmetry in the marginal distribution of the volatility of stock returns without having to impose positiveness of the coefficients parameters because it models the log of conditional variance. Other comparable models such as QGARCH, asymmetric power arch (APARCH) and GJR-GARCH are restricted to the positiveness of the variances (Hentschel, 1995; Sentana, 1995).

Second, the empirical literature has often found that a GARCH model that accounts for asymmetry in the impact of news on volatility outperforms a standard symmetric GARCH model and even APARCH and GJR-GARCH models (Alberg, Shalit, & Yosef, 2008; Kambouroudis, McMillan, & Tsakou, 2016).

Third, the condition for stationary variance for an EGARCH model is a GARCH coefficient of lower than one, which is easy to interpret and monitor. On the other hand, for comparable models such as QGARCH, threshold GARCH (TGARCH) and GJR-GARCH, the stationary condition is more complicated and challenging to interpret. An EGARCH model also accounts for two common properties in stock returns effectively: heteroskedasticity and volatility clustering (Choy, Chen, & Lin, 2014; Ezzati, 2013), and was found to be robust for equity markets (Huo & Ahmed, 2017). Hence, EGARCH provides a parsimonious model to investigate the asymmetries in volatility and to examine volatility spillover between China and other markets in the sample.

The EGARCH model, developed by Nelson (1991), is well known for modelling asymmetric volatility dependence in financial modelling. EGARCH has been widely applied in the existing literature in different capital markets with high-frequency data; for example, mortgage-backed securities (Poon & Fung, 2000), foreign exchange markets (Hsieh, 1989), exchange rates and commodities (Ghosh, 2011), exchange rates and currencies (Akçay, Alper, & Karasulu, 1997) and derivatives such as spot and futures markets in Australia (Bhar, 2001). It is also a commonly used method to assess the asymmetry in volatility for equity markets. For example, Kanas (1998) used EGARCH to evaluate the asymmetry in volatility of daily returns among European stock markets. Olugbode et al. (2014) examined the asymmetric relationship between the UK stock returns of 31 non-financial industries and the exchange rate and interest rate from 1990 to 2006 using an EGARCH-in-mean (EGARCH-M) model. Zhang and Chen (2011) used the Autoregressive Conditional Jump Intensity (ARJI) EGARCH model to identify the asymmetric distribution of linkages between the oil price on China's stock returns. Yu, Fang, et al. (2018) use asymmetric DCC (ADCC)-EGARCH with skewed *t*-distribution to model the time-varying asymmetric cross-market dependence between China and other stock markets, including the US, UK, Germany and Japan. Other related studies use an EGARCH model to examine the asymmetric property of the joint dependence between stock volatility and macro-economic and political variables volatility (Li & Born, 2006; Oseni & Nwosa, 2011).

Some studies also used the realised EGARCH model by introducing realised measures to the models (Hansen & Huang, 2015; Kambouroudis et al., 2016). These models claim to be more adaptive to sudden changes in volatility than standard models. However, the coefficients are more sensitive to noises, which in turn makes the model very responsive to outliers such as short trading days, crises and stock crashes. Therefore, this model is not suitable for a long study horizon that includes multiple catastrophic events like this thesis.

In this section, the aim is to study the asymmetric behaviour of the volatility of each stock market, which is part of the fundamental diagnostic tests to the distributional properties of each market in the sample. Chapter 4 will provide a bivariate and multivariate test to detect volatility spillover of each pair in the view of cross-market linkages while accounting for tail dependencies. The results of this chapter, therefore, establish an understanding of the characteristics of each stock return, which provides a solid foundation for developing the multivariate modelling in the next chapter.

3.3. Data

The daily closing prices are downloaded from Bloomberg for each market, and then converted to first difference natural logarithm to make each time series stationary. The data is sub-divided into four sub-periods as follows:

1. Pre-GFC period: from 1 May 2002 to 26 February 2007 (871 observations).
2. GFC period: from 27 February 2007 to 29 May 2009 (410 observations).
3. Extended-crisis period: from 30 May 2009 to 6 June 2012 (539 observations).
4. Post-crisis period: from 7 June 2012 to 31 July 2017 (912 observations).

More detail is provided in sections 2.1 and 2.2.

3.4. Univariate GARCH

3.4.1. Model description

The correlation matrix presented in section 2.3.6 suggests that the returns of each market in the sample are positively and linearly related to each other. It is well known that measuring the dependence between two markets by the return correlation coefficient as a square root of covariances is too relaxed in the real world, as it fails to account for some of the most common properties of a financial time series; that is, autocorrelation and heteroskedasticity in financial time series (Forbes & Rigobon, 2002; Lamoureux & Lastrapes, 1990). The GARCH models, as mentioned in section 3.2, have been extensively used in financial modelling, as they can account for the distributional properties of stock returns, as discussed in section 2.3. In this section, each time series is tested with a univariate GARCH model to examine if the current return is dependent on its lags.

A GARCH model was developed by Bollerslev (1986) from the Engle (1982) ARCH model that allowed the capture of heteroskedasticity and autocorrelation. The application of GARCH models in high-frequency data such as daily stock returns has been discussed in section 3.2.

Suppose $\mathrm{y_t}$ is the conditional mean of the return of market *i* at time *t*, and $\mathrm{E_{t-1}(y_t)}$ is the previous return at time *t – 1*. The conditional mean is given as:

$$y_t = E_{t-1}(y_t) + \varepsilon_t \ , \varepsilon_t | I_{t-1} \sim N(0, H_t) \qquad (3.1)$$

Equation (3.1) assumes that the conditional mean of the return of one market is explained by its previous lag and other factors, also known as error term, ε_t. Hence, the mean is conditional to all the information up to time $t - k$. The error term, also called the residual factors, is governed by the process:

$$H_t^2 = \omega + \sum_{i=1}^{k} a_k \epsilon_{t-k}^2 + \sum_{i=1}^{k} b_k H_{t-k}^2 \qquad (3.2)$$

ω is a constant. ϵ_{t-k}^2 is the squared residual factor measured from **(3.2)** at time $t - 1$, which represents the innovation in volatility, also known as the ARCH term. A positive a_k indicates the presence of volatility clustering. H_{t-k}^2 is the past covariance of returns at time $t - k$, also known as the GARCH term, which measures the persistence of past volatility. a and b are coefficient parameters. If a and b are significant, the time series exhibits both ARCH and GARCH effects. The sum of ARCH and GARCH effects is usually interpreted as a simple measure of the persistence of stock volatility. A sum of less than one specifies a mean-reverting process and validates the variance stationarity. If the sum has values close to one, the volatility has a long memory. So, if the sum is close to one, it indicates that even though the volatility process is highly persistent, it returns to mean. The parameter vector $\Theta = (\omega, a_k, b_k)$ is estimated using the maximum likelihood aka. Quasi-Maximum Likelihood Estimation (QMLE) under the assumption that the error term ϵ_t follows a GED. The application of QMLE in estimating GARCH parameters is extensive in the empirical studies of the financial modelling and forecasting (Angelidis, Benos, & Degiannakis, 2004; Bollerslev & Wooldridge, 1992; El Ghourabi, Francq, & Telmoudi, 2016; Mapa, 2003). Kraicová and Baruník (2017) examined various estimation models including QMLE, Fourier-based Whittle Estimator, and two Wavelet estimation techniques for the Fractionally Integrated E-GARCH model and found that QMLE outperformed in terms of efficiency for both empirical modelling and forecasting. Since stock returns are not normally distributed and are characterised with leptokurtic, fat tails and negative skewness, as shown in section 2.3.1, using a Gaussian distribution will underestimate the error terms.

3.4.2. Best lag length

Table 3-1 shows that the best lag length for each univariate GARCH model is within five lags, based on the AIC for the entire period under review. The results reveal that one lag is the best length for most markets except for SHA, SHB, SZB, Thailand and the US. A further test to check the AIC pattern of these markets to ensure the result is not biased by overfitting with the results of the AIC for each model from one to five lags is recorded in **Table 3-2**. The results show that for SHA, Japan and Germany, two, four and three lags, respectively, have the lowest AIC for each corresponding market without overfitting bias. For SZB, the AIC drops at two lags and then increases when more lags are added to the model, indicating a presence of overfitting. A similar pattern is recorded for Japan and the US, in which the best lag should be one lag and two lags respectively. Therefore, the maximum lag of these markets is three lags recorded for only one market; that is, Germany. Other uncommon cases are two lags for SHA, SZB and the US. The best lag length found in this chapter is short-lived, and most die out within the first day. Thus, adding more lags will compromise the model's efficiency, while not necessarily increasing the accuracy of the estimated parameters. Also, the existing literature confirms the appropriateness and sufficiency of the GARCH(1,1) model compared with higher lags GARCH models to financial markets (Hansen & Lunde, 2005; Katsiampa, 2017). A GARCH(1,1) model has also been used in many studies based on AIC, which found that the one lag is optimal for many developed and emerging markets such as China and the US (Hansen & Lunde, 2005; Syriopoulos, Makram, & Boubaker, 2015). In addition, Engle (2004) found that GARCH(1,1) is an intuitive approach that is sufficient to describe the dynamics of volatility in most markets, and the tests on the autocorrelation in this chapter together with the empirical studies have also confirmed this. The results from the lag-length test from this thesis are consistent with that finding in the literature. Hence, if one lag is already sufficient, adding more lags will complicate the model specification but might not necessarily generate a better result. It is also important to use a uniform lag model across all markets. This is to serve the comparison purpose of interpreting the parameters without comprising the efficiency and simplicity in the testing procedure. Therefore, this thesis adopts GARCH (1,1) to model the distribution of each time series for the studied sample.

Table 3-1. Summary of the lag length that has the lowest AIC and the AIC value for the corresponding lag for each market index using a univariate GARCH (p, q) from 1 to 5 lags – full sample

	Lag length	AIC
HS	1	-7.44624
SHA	2	-7.09167
SHB	1	-6.97755
SZA	1	-6.76537
SZB	5 (2)	-7.06069
Indonesia	1	-7.06706
Malaysia	1	-8.10757
Philippines	1	-7.26595
Thailand	2	-7.38182
Australia	4	-7.26277
HK	1	-6.83653
Japan	4 (1)	-7.2368
NZ	1	-7.70021
Singapore	1	-7.6801

US	5 (2)	-7.94456
Germany	3	-7.12495
UK	1	-7.52651

Note: A univariate GARCH-GED model is run for each time series from 1 to 5 lags. The best lag length that has the lowest AIC among 5 lags is reported in this table. Conditional mean equation: $R_t = c + \mu_t + \beta R_{(t-k)} + \epsilon_t$ with k = 1 to 5. For example, a two-lag model for HS is given as: $R_{Hs} = c + \mu_t + \beta R_{(t-1)} + \beta' R_{(t-2)} + \epsilon_t$. The best lag length after adjusting for overfitting issue is reported in the brackets.

Table 3-2. Summary of the AIC for each GARCH (p,q) model from 1 to 5 lags for selected stock markets

	1 lag	2 lags	3 lags	4 lags	5 lags
SHA	-7.091	-7.092	-7.091	-7.090	-7.091
SZB	-7.060	-7.061	-7.059	-7.059	-7.061
Australia	-7.263	-7.261	-7.262	-7.263	-7.262
Japan	-7.237	-7.236	-7.236	-7.237	-7.237
US	-7.944	-7.944	-7.944	-7.944	-7.945
Germany	-7.125	-7.124	-7.125	-6.368	-7.123

Note: The AIC for each GARCH-GED (1, k) with k from 1 to 5 lags is reported in this table. Only markets that have the best lag length of more than one lag from **Table 3-1** were tested, i.e. SHA, SZB, Australia, Japan, the US and Germany. The AIC for each model from 1 to 5 lags for each of these markets is reported in this table.

3.5. Univariate E-GARCH

3.5.1. Model description

An E-GARCH model introduced by Nelson (1991) is capable of capturing asymmetric relations of volatility across different markets and accounts for volatility clustering, as discussed in section 3.2.3. The model incorporates a threshold into the general GARCH model to capture the leverage effect. Similar to the approach of Xu and Hamori (2012), a univariate EGARCH model is applied for China's markets and each equity index in the sample with a conditional mean equation given by:

$$y_t = \mu_t + \varphi y_{t-1} + \varepsilon_t \ , \varepsilon_t | I_{t-1} \sim N(0, \sigma_t^2) \tag{3.3}$$

μ_t is a constant coefficient which represents the mean of returns in **(3.3)**. y_t is the expected stock return at time *t* and is regressed by $E_{t-1}(y_t)$, its previous lag at time *t* – 1, with φ being the coefficient that measures the impact of lagged returns. ε_t is the residual factor of the expected stock return at time *t* which has a mean of 0 and a variance of σ_t^2 which is governed by:

$$h_t = \ln(\sigma_t^2) = \omega_t + \sum_{j=1}^{k} \alpha_t f(z_{j,t-1}) + \beta^* h_{t-1} \tag{3.4}$$

$$f(z_{t-1}) = [|z_{t-1}| - E(|z_{t-1}|)] + \gamma_t z_{t-1} \tag{3.5}$$

The conditional variance σ_t^2 of the residual factors as given by (3.1) is an exponential function of past own (i.e. GARCH) effect measured by β^* and past standardised innovations; that is, $z_t = \frac{\varepsilon_t}{\sigma_t}$.

$f(z_{t-1})$ as given by (3.4) is a zero-mean, i.i.d. random sequence. The asymmetry effect is measured by γ. A significant negative γ indicates a leverage effect; that is, bad news has a larger impact on the volatility of a market than good news. The magnitude effect in the GARCH model – ARCH effect – is measured by α. A significant positive α implies the existence of volatility clustering, thus, an EGARCH model is more practical in financial modelling (Wang & Wang, 2011). The sum of the ARCH and GARCH effect is typically interpreted as a simple measure of the persistence of stock volatility. $\alpha + \beta^* < 1$ specifies a mean-reverting process, validating variance stationarity. If the sum has a value close to one, the volatility has a long memory and is mean-reverting. GED is used for the errors to account for non-normal distributions and fat tails in daily stock returns, while ensuring the plausibility of stationary of the conditional variances (Straumann & Mikosch, 2006). Regardless the discrepancy in the estimation of GARCH parameters using different computational software (which is beyond the scope of this thesis) (Brooks, Burke, & Persand, 2001), it is universally agreed in the existing literature that a GED or Student's *t*-distribution is more appropriate for financial returns than a Gaussian distribution (Pedersen & Rahbek, 2014; Troster, Tiwari, Shahbaz, & Macedo, 2019). Bampinas, Ladopoulos, and Panagiotidis (2018) found that an EGARCH model with GED errors was the best fit model to the individual stocks in the S&P1500 universe with stationarity constraint. A GED model also has lower AIC than a comparable Student's *t*-distribution model for the studied dataset in general.

To capture the volatility spillover effect on and from China's markets, an auxiliary term is added to (3.4), which is similar to Allen et al. (2012) and Hamao et al. (1990). For simplicity, the spillover equation is written for a univariate EGARCH(1,1) model as follows:

$$\mathrm{h}_{\mathrm{i,t}} = \ln\left(\sigma_{\mathrm{i,t}}^2\right) = \omega_{\mathrm{i,t}} + \alpha_1 \mathrm{f}_{\mathrm{i,t}}\left(\mathrm{z}_{\mathrm{i,t-1}}\right) + \beta_{\mathrm{j}}^* \mathrm{h}_{\mathrm{i,t-1}} + \alpha_{2,\mathrm{j}} \varepsilon_{\mathrm{j,t}}^2 \tag{3.6}$$

In (3.6), the volatility spillover effect on market *i* from market *j* is captured by the coefficient $\alpha_{2,j}$.

3.5.2. Model specification

The EGARCH model is estimated with an auxiliary term added to capture spillover effects:

$$h_{CH,t} = ln\left(\sigma_{CH,t}^2\right) = \omega_t + \alpha_1([|z_{j,t-1}| - E(|z_{j,t-1}|)] + \delta_j z_{j,t-1}) + \beta_j^* \mathrm{h}_{CH,t-1} + \alpha_2 \varepsilon_{Aus,t}^2 \tag{3.7}$$

$h_{CH,t}$ is the conditional variance of China's market as an illustration. α_1, δ_j and β_j^* measure the magnitude effect, sign effect and own lagged GARCH effect respectively. The null hypothesis for each parameter is that the coefficient is equal to zero. α_2 captures the effect of lag-squared residuals of an EGARCH(1,1). This coefficient measures the volatility spillover effect from the Australian market to the Chinese market. The null hypothesis of no spillover effect is rejected when α_2 is significantly different from zero, indicating there is no spillover effect from the Australian market to China's market.

The EGARCH (1,1) model is tested for the sample data because one lag is the best lag length, as shown in the preliminary tests. In addition, an EGARCH (1,1) is strongly supported by a vast majority of the existing literature because it is sufficient to capture the instantaneous transmission in daily stock returns (Arouri, Jouini, & Nguyen, 2011; Chang, McAleer, & Tansuchat, 2013; Karolyi, 1995; Miyakoshi, 2003). Robustness tests are performed for the standardised residuals of these models, including the heteroskedasticity test and ARCH test.

3.5.3. Best lag length

In order to determine the best lag length for the conditional mean equation, each market index is run with an EGARCH model from one to five lags, and the best lag is the one that has the smallest AIC. **Table 3-3** presents the best lag length for each market for the full sample of markets. It shows that the best lag length for most markets is one lag, with some exceptions. Notably, two lags appear to be the best lag length for SHA, Thailand and the US, and five lags for SHB and SZB. A further test is undertaken for SHB and SZB markets to ensure that there is not overfitting. **Table 3-4** shows that the AIC of SHB increases when more lags are added to the EGARCH (1,1) model. In addition, the AIC at one lag is slightly higher than at five lags, giving a clear indication of overfitting. Hence, the EGARCH (1,1) model should be the most appropriate for SHB. A similar pattern is found for the AIC of SZB, where the lowest point is two lags. In addition to the reasons for selecting one lag, which has been discussed in section 3.4.2, many studies also found that the EGARCH (1,1) model is sufficient to model the stochastic behaviour of stock return innovations adequately, confirming the efficiency of this model for stock markets (Anyfantaki & Demos, 2016; Dungey & Gajurel, 2015; Hansen & Huang, 2015). For this reason, EGARCH (1,1) is used for the whole sample, as the results show that one lag is sufficient for most markets.

Table 3-3. Summary of the lag length that has the lowest AIC and the AIC value for the corresponding lag for each market index using a univariate EGARCH (p, q) from 1 to 5 lags – full sample

	Lag length	AIC
HS	1	-7.45329
SHA	2	-7.09603
SHB	5 (1)	-6.97913
SZA	1	-6.77236
SZB	5 (2)	-7.05973
Indonesia	1	-7.07464
Malaysia	1	-8.1153
Philippines	1	-7.27855
Thailand	2	-7.39099
Australia	1	-7.27047
HK	1	-6.83637

Japan	1	-7.25345
NZ	1	-7.70409
Singapore	1	-7.6893
US	2	-7.97987
Germany	1	-7.14328
UK	1	-7.55131

Note: a univariate EGARCH model is run for each time series from 1 to 5 lags. The best lag length that has the lowest AIC among five lags is reported in this table. Conditional mean equation: $R_t = c + \mu_t + \beta R_{(t-k)} + \epsilon_t$ with k = 1 to 5. For example, a two-lag model for HS is given as: $R_{Hs} = c + \mu_t + \beta R_{(t-1)} + \beta' R_{(t-2)} + \epsilon_t$. The best lag length after adjusting for overfitting is reported in the brackets.

Table 3-4. AIC of a univariate EGARCH model from 1 to 5 lags for SHB and SZB – full sample

	1 lag	2 lags	3 lags	4 lags	5 lags
SHB	-6.979	-6.978	-6.977	-6.977	-6.979
SZB	-7.059	-7.059	-7.058	-7.058	-7.060

Note: a univariate EGARCH model is run for each time series from 1 to 5 lags. Conditional mean equation: $R_t = c + \mu_t + \beta R_{(t-k)} + \epsilon_t$ with k = 1 to 5. SHB stands for Shanghai B-shares, and SZB represents Shenzhen B-shares.

3.6. Hypotheses

As noted, this chapter deals with the first and second research questions, which examine the leverage effect and volatility spillover between China's stock market and other markets in the sample. Hypotheses relating to cross-equity linkages are:

Research question 1: Is there evidence of leverage effect in the distributional volatility of each market in the sample?

- **H_0**: There is no evidence of leverage effect in the marginal distribution of volatility of each market.
- **H_1**: There is evidence of leverage effect in the marginal distribution of volatility of each market.

If the gamma coefficient, γ_k in the **(3.5)** is not significant, the null hypothesis of no leverage effect in the stock return of a market is rejected. In contrast, a significant and positive coefficient suggests the existence of asymmetric volatility structure in stock returns. A significant and negative coefficient suggests the existence of the leverage effect.

Research question 2: Is there evidence of volatility spillover between China's markets and other markets in the sample?

- **H_0**: There is no evidence of volatility spillover.
- **H_1**: There is evidence of volatility spillover.

If α_2, in the **(3.7)** is significant, the null hypothesis of no spillover effect is rejected, suggesting the existence of volatility spillover from one market to another.

3.7. Empirical results

3.7.1. Univariate GARCH model

Empirical studies found that the residual factors of the selected equity markets are not normally distributed and negatively skewed (Alexander, 2008; Mohammadi & Tan, 2015; Wang, Miao, & Li, 2013). Thus, the assumption of normal distribution could be too restrictive in an empirical setting. Based on the AIC, GED is favourable for GARCH models in this chapter when compared to a Student-t distribution in a univariate model. This chapter reports and analyses the results from a univariate GARCH model assuming GED distribution for the error term.

The results of mean and variance equations for each time series over the four sub-periods are presented in **Table 3-5**. Since the sample includes 17 different markets, the table reports the results for all markets. However, the discussion focuses on China, as it is the target of this chapter.

The results for the full sample from 8 May 2002 to 31 July 2017 show that, in the mean equation, the constant was significant for most markets except for SHA. The impact of past returns on current market returns, on the other hand, was not evident for any of China's markets. The impact of past returns on current market returns, however, was evident for Indonesia, Malaysia, the Philippines, Thailand, Australia, HK, Japan, NZ and the US. All the variables in the variance equations were significant for all markets, indicating that the current volatility of daily returns of all markets could be explained by a constant ARCH effect (past innovations in volatility) and GARCH effect (past variance). The results for the full sample are reported in **Table 3-5**.

Over the period under review, the constant term, α, in the conditional mean equations was significant in some markets, however, these values were found to be close to zero, which does not imply any economic meaning. Therefore, they are usually omitted from reporting in existing literature (Doornik & Ooms, 2008).

The impact of past returns on current returns was not significant for any of China's markets over the four sub-periods indicating that the daily returns of Chinese equities could not be explained by their past returns in any given period. In other markets, the effect of past returns varied with markets and periods. Impacts of past returns were evident in Indonesia (0.123), Malaysia (0.105), the Philippines (0.055), Thailand (0.115), HK (0.090), Japan (-0.061), Germany (-0.067) and the UK (-0.074) in the pre-GFC period. There was a major change in both values (with mixed direction) and number of markets that were found with significant past returns during the GFC. Those markets are Thailand (0.078), Japan (-0.212) and the US (-0.164). The explanatory power of past returns in current returns for Thailand was weaker, while it was stronger for Japan. There was no evidence of past returns impacting on current returns in the US before the GFC, while it was evident during the GFC. In the extended-crisis period, evidence of past returns impacting current returns remained in Japan's market (-0.175). No evidence of past returns impacting current returns was found in two new markets in this period, including Australia (0.074) and NZ (0.080). In the post-crisis period, Malaysia (0.118), Thailand (0.065), Australia (0.063) and Japan (-0.162) were found with significant parameters of past returns. This implies that the influence of past returns on the current return changes with time. Less evidence of past returns was found in the high volatility periods, while the explanatory power of past returns on current stock returns was more evident in the low volatility periods. In general, the impact of past returns was evident in some markets, but the degree of influence is moderate. For those markets that have evidence of past returns impacting on current returns consistently from non-crisis periods to crisis periods or vice versa, there was not enough evidence to conclude a common trend in the degree of the effect of past returns during the crisis periods.

In the variance equations, many markets, including China, were found with a significant constant at the 1% level; however, the values were minimal, which does not have any economic meaning. The results are reported in **Table 3-5**.

Strong evidence of an ARCH effect was found in many of the studied time series over the four periods, even though the impact was trivial in some cases. In the pre-GFC period, all of China's markets had significant ARCH coefficients, from the smallest to highest order including HS (-0.029), SHA (0.082), SZA (0.090), SZB (0.110) and SHB (0.164). During the GFC, the parameters were significantly higher. However, only two markets were found to have significant coefficients including HS (0.130, up by 349%) and SHB (0.307, up by 241%). In the extended-crisis period, apart from SZB, all ARCH coefficients in China's other markets were significant, with considerable falls in the values of the parameters, which were even lower than the pre-GFC period – HS (0.053), SHA (0.055), SHB (0.064) and SZA (0.062). In the post-crisis period, apart from HS, an ARCH effect was evident with a slight increase in the ARCH effect in China's other markets, namely SHA (0.057), SZA (0.060), SZB (0.895) and SHB (0.111). The results show that there was a dramatic increase in the ARCH effect during the GFC, but not during the extended-crisis period. Therefore, it is not clear if a high-volatility period could drive the ARCH effect in the current volatility of daily stock returns for Chinese equities.

The ARCH effect was significant for all emerging markets in the pre-GFC period: Indonesia (0.147), Malaysia (0.090), the Philippines (0.026) and Thailand (0.132). Malaysia dropped out of the list during the GFC, leaving Indonesia (0.173, up by 92%), the Philippines (0.149, up by 13%) and Thailand (0.077, down by 42%) in the list of countries that were detected with ARCH presence in daily returns. In the extended-crisis period, the ARCH effect was evident in all emerging markets, with a mixed trend in the values of the parameters: Indonesia (0.152, down by 12%), Malaysia (0.072), the Philippines (0.110, down by 26%) and Thailand (0.153, up by 99%). A mixed trend was documented for emerging markets for the ARCH effect over the four sub-periods, with no clear trend in the GFC. In general, the current volatility of daily returns was impacted by past innovations in volatility, yet the effect was weak in some cases.

In the pre-GFC period, apart from Australia and NZ, other advanced markets had significant ARCH coefficients, with the absolute values ranging from 0.030 (Japan) to 0.079 (Germany), and an average of 0.044. Since the GFC, the presence of the ARCH effect was detected in all advanced markets over the remaining sub-periods (GFC, extended-crisis, post-crisis periods). During the GFC, the values varied in a larger band compared to the preceding period, from 0.064 (NZ) to 0.133 (HK), with an average of 0.11, indicating an increase in ARCH effect during this period compared to the pre-GFC period. The extended-crisis period had a similar band to the GFC in general, with a minimum value of 0.047 (UK), a maximum value of 0.196 (Japan) and an average of 0.093. This period had a higher upper bound value and a smaller lower bound value, indicating that the ARCH effect in the advanced markets had a more extensive variation during the extended-crisis period. In the post-crisis period, the lowest value of (negative) 0.038 was attributed to NZ, while the highest value of 0.240 was attributed to the US being an extreme case in this post-crisis period. The lower bound value for the ARCH effect in this period was quite similar to other periods. However, the upper bound value was much higher. An average value for this period was 0.088, implying a slight fall in the ARCH effect. In general, the ARCH effect was highest during the GFC period based on the average value, followed by the extended-crisis period, post-crisis period and, finally, by the pre-GFC period. Similar to China's markets and emerging markets, the effect was weak in many cases.

In brief, strong evidence of an ARCH effect was found in many markets including China, and other emerging and advanced markets in each sub-period; however, the effect was weak in some cases, especially during the non-crisis period. The effect increased significantly during the GFC in some of the emerging and advanced markets. This finding indicates the presence of volatility clustering in these markets. This phenomenon was documented abundantly in the existing literature (Cont, 2007; Friedmann & Sanddorf-Köhle, 2002; Lux & Marchesi, 2000; Niu & Wang, 2013). The remarkable similarity in volatility dynamics was observed in many stock markets, due to new information arrival, since an asset was priced based on the future information of the expected cash flow generated from holding the asset (Engle, 2004). Volatility clustering could be, in other words, due to clustering of information arrivals and is a generic feature of financial markets (Challet, Marsili, & Zhang, 2001). Engle (2004) also explained that the intuitive reason that a higher frequency of volatility clustering (higher ARCH effect) was observed during the GFC for many markets was that, given everything else being equal, typically, market reactions for a news event could be greater in a recession than in a boom period (Ning, Xu, & Wirjanto, 2015; Tseng & Li, 2011). This could be due to the financial leverage effect and herding behaviour (Schmitt & Westerhoff, 2017; Thurner, Farmer, & Geanakoplos, 2012), as discussed in section 3.2.2. This is consistent with the fact that left skewness and fat tails were routinely found as salient distributional features of many stock markets (more extreme values around the left tail than in the middle and right tail), as discussed in section 2.3.2.

The GARCH coefficient is the last parameter in the variance equation, and the results are reported in **Table 3-5**. The results suggest that the GARCH effect – past variance – played a major role in explaining the current volatility of daily stock returns compared to other variables in the variance equation. The results show that the GARCH coefficient was significant in most markets over the entire period under review and in each sub-period. The parameters for the GARCH effect were very high in many markets, ranging from 0.5 to close to 1, implying that a major part of the current volatility was attributable to the variation in own past volatility.

In the pre-GFC period, the average GARCH coefficient was 0.889 for AS and 0.806 for BS. During the GFC, the average GARCH coefficient was 0.941 for AS and 0.706 for BS. The extended-crisis period recorded the same average value of 0.880 for both AS and BS, whereas it was 0.934 and 0.881 for AS and BS respectively in the post-crisis period. These results show that the GARCH effect was generally more potent in the AS markets than in the BS markets. Among all of China's markets, HS was the only market where the GARCH effect was not detected in the pre-GFC and post-crisis periods. In other words, evidence of the GARCH effect could only be found in HS during market turbulence. There were changes in the GARCH effect for these markets from one period to another. However, the changes were not substantial. The GARCH coefficient of HS remained constant at 0.91 in both the GFC and extended-crisis periods. Regardless of the changes, the GARCH coefficients in any given period for Chinese equities were close to one, indicating that past volatility could have a substantial impact on the current volatility of daily stock returns.

The discussion now turns to other markets in the sample rather than China's markets. Evidence of the GARCH effect was not found for Australia in the pre-GFC period. In this period, the values of the GARCH coefficients in all other markets (that are found with a significant GARCH coefficient) ranged from 0.728 (Thailand) to 0.960 (Japan), with an average of 0.847. In the GFC period, all markets were detected with the presence of a GARCH effect within a very similar band and an average of 0.844. Similar results were also found in the extended-crisis period. The average value for this period was 0.809, a slight decrease compared to the GFC period. In the post-crisis period, evidence of the GARCH effect was found in all these markets, with an average value of 0.858, slightly increased from the prior period. There are two implications from these results. Firstly, the current volatility of daily stock returns was mainly driven by their past volatility at the one-day lag. Secondly, this result was documented consistently in both crisis and non-crisis periods, hence there was no clear evidence of material changes in the GARCH effect from one period to another in all markets in the sample. This is an interesting observation because the GARCH effect did not follow an upward pattern with their peak at the GFC like other variables such as the ARCH effect or past return effect, as discussed at the beginning of this section.

Apart from HS during the GFC, the sum of the ARCH and GARCH effects in all markets in any given period was close to one, which validates the appropriateness of the model. HS had a sum of the ARCH and GARCH coefficients of one during the GFC, implying a non-decaying behaviour. The reason could be the brevity of the period (there are only 410 observations during the GFC period). When the period is short, it could 'fool' the model to suggest a trend in the volatility, hence the model assumes that there will be no full decay (Zhong & Samaranayake, 2016; Zivot, 2009).

An intuitive approach to calculate the persistence in the volatility process is calculating the half-life period (HLP) of a shock on the process; that is, the duration that the volatility (generated by the innovation process) takes to decompose (Koutmos & Saidi, 1995). HLP is calculated using the formula $HLP = \log(0.5)/[\log(a + b)]$. The HLP will be infinity when the sum of the ARCH and GARCH coefficient equals one. In the pre-GFC period, there were variations in the persistence duration of each of China's markets. China's equities have an HLP of 16 days on average, in which HS took one day and SHA, SHB and SZA took 24, 20 and 26 days respectively, while SZB took eight days. During the GFC period, the average duration for Chinese equities was shortened to 14 days HLP (SHA took 25 days, SHB took 12 days, SZA took 15 days, and SZB took five days). This duration was the same as in the extended-crisis period. In the post-crisis period, it increased to 51 days HLP. This shows that the volatility of China's markets during the market turbulence was decaying faster than in the non-crisis period. The opposite was observed for other markets in the sample.

In brief, there are two key findings from the results of the univariate GARCH (1,1) model for the sample data. Firstly, past returns did not seem to explain the current returns of Chinese equities. In other markets, the effect was feeble and there was no clear trend in the effect of past returns during the crisis periods for these markets, which recorded significant past returns coefficients. Secondly, the current volatility of daily returns in many markets, including China, was driven strongly by its past volatility, with consistent findings throughout the entire period under review. Even though there were changes in the effect of this factor from one period to another, the changes were not significant, and the effect was found to be quite high in any given period. These findings also indicate that volatility was highly persistent in many markets. Apart from that, ARCH effects were evident in some markets, but only at a moderate level in many cases. The ARCH effect increased significantly during the GFC period for some cases but not all. These findings indicate a presence of long memory, which was discussed in section 3.7.1. They confirm the appropriateness of the GARCH model in describing the marginal distribution of the volatility of daily returns in many markets, which is consistent with the existing literature, as mentioned in sections 3.2.

A limitation of a general GARCH model, as has been presented in this section, is that it assumes that negative and positive shocks have an equal impact on the volatility of stock returns, and hence fails to account for the sign of the shocks. In the next section, this possibility is explored by introducing a threshold into the GARCH models, which allows capturing asymmetries in the distributional volatility of stock returns as a result of negative and positive shocks.

Table 3-5. Summary of the results for conditional mean and variance equations of the univariate GARCH(1,1) for each time series

	AU	GER	HK	HS	INDO	JAPAN	MALAY	NZ	PHIL	SING	SHA	SHB	SZA	SZB	THAI	UK	US
Panel A: Pre-GFC period																	
Conditional mean equation																	
Constant-mean	0.0003***	0.0002	0.0002***	0.0004***	0.0005***	0.0005***	0.0001**	0.0004***	0.0004***	0.0004***	0.0004***	0.0003***	0.0004***	0.0003***	0.0004***	0.0005***	0.0003***
Past return	-0.0034	-0.0055	0.0045	0.0263	-0.0051	0.0527***	0.0832***	0.0419**	0.0742***	0.0342*	0.0464**	-0.1257***	0.0404**	-0.0010	-0.0440**	-0.0257	-0.0252
Conditional variance equation																	
Constant	0.0000***	0.0000**	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***
ARCH	0.0618***	0.0605***	0.1297***	0.0664***	0.0741***	0.1444***	0.0793***	0.0788***	0.1217***	0.0538***	0.0690***	0.0809***	0.0392***	0.0795***	0.1034***	0.0774***	0.0890***
GARCH	0.9278***	0.9349***	0.8626***	0.9253***	0.9208***	0.8257***	0.9082***	0.8860***	0.8584***	0.9335***	0.9189***	0.8918***	0.9444***	0.9127***	0.8862***	0.9129***	0.9025***
Panel B: GFC period																	
Conditional mean equation																	
Constant-mean	0.0002*	0.0000	-0.0006***	0.0000	0.0001	0.0007***	0.0001	0.0002	0.0004**	0.0006***	0.0007***	0.0004**	0.0006***	0.0004	0.0004***	0.0007***	0.0004***
Past return	-0.0416	0.0105	0.0034	0.0363	-0.0008	0.1231***	0.1053***	0.0553**	0.1149***	0.0094	0.0899***	-0.0610**	0.0098	0.0428	-0.0480	-0.0666**	-0.0740**
Conditional variance equation																	
Constant	0.0000	0.0000*	0.0000***	0.0000*	0.0000**	0.0000***	0.0000**	0.0000*	0.0000***	0.0000	0.0000**	0.0000	0.0000	0.0000	0.0000*	0.0000*	0.0000**
ARCH	-0.0293***	0.0815***	0.1638***	0.0904***	0.1099***	0.1471***	0.0896***	0.0256*	0.1318***	-0.0121	0.0727***	0.0295**	0.0164	-0.0563***	0.0602***	0.0785***	0.0777***
GARCH	0.5729	0.8900***	0.8016***	0.8831***	0.8104***	0.7322***	0.8607***	0.9175***	0.7279***	0.3540	0.8976***	0.9604***	0.8954***	0.5905*	0.9284***	0.9133***	0.9006***
Panel C: Extended-crisis period																	
Conditional mean equation																	
Constant-mean	0.0001	0.0002	0.0010***	0.0009***	0.0006***	0.0010***	0.0005***	0.0007***	0.0010***	0.0003	0.0000	0.0002	0.0004*	0.0005**	0.0006***	0.0003	0.0003
Past return	0.0313	-0.0156	-0.0208	0.0470	0.0145	0.0286	0.0461	0.0330	0.0464	0.0736*	0.0101	-0.1754***	0.0794*	0.0506	-0.0321	-0.0178	-0.0257
Conditional variance equation																	
Constant	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000*	0.0000	0.0000	0.0000*	0.0000	0.0000	0.0000***	0.0000*	0.0000	0.0000*	0.0000	0.0000
ARCH	0.0534*	0.0545*	0.0640*	0.0617*	0.0496	0.1520***	0.0716**	0.1100**	0.1528***	0.0538**	0.0591**	0.1957***	0.1229*	0.0710**	0.1246***	0.0663**	0.0472**

GARCH	0.9147***	0.9036***	0.8782***	0.8759***	0.8973***	0.7964***	0.8586***	0.7464***	0.6955***	0.9030***	0.9087***	0.4240***	0.4267	0.8829***	0.8421***	0.9038***	0.8971***
Panel D: Post-crisis period																	
Conditional mean equation																	
Constant-mean	0.0003**	0.0002	0.0004***	0.0006***	0.0006***	0.0002*	0.0000	0.0004***	0.0004***	0.0001	0.0001	0.0005***	0.0002	0.0001	0.0003***	0.0005***	0.0002**
Past return	-0.0256	0.0155	0.0034	0.0015	-0.0389	-0.0072	0.1179***	0.0187	0.0645**	0.0630**	0.0256	-0.1621***	0.0427	0.0027	-0.0042	-0.0018	0.0452
Conditional variance equation																	
Constant	0.0000**	0.0000	0.0000***	0.0000**	0.0000***	0.0000**	0.0000*	0.0000***	0.0000	0.0000	0.0000	0.0000***	0.0000	0.0000**	0.0000***	0.0000**	0.0000***
ARCH	-0.0070	0.0568***	0.1113***	0.0597***	0.0848***	0.0556***	0.0565***	0.0892***	0.0702***	0.0413***	0.0330***	0.1281***	-0.0380***	0.0576***	0.2397***	0.0967***	0.1450***
GARCH	-0.6373	0.9365***	0.8671***	0.9321***	0.8948***	0.9275***	0.9330***	0.8753***	0.9219***	0.9468***	0.9596***	0.7460***	0.5866*	0.9231***	0.6532***	0.8287***	0.8027***

Note*:* *, ** and *** indicate significance at 10%, 5% and 1% levels respectively. Null hypothesis: the parameter equals zero. The results for data in the four sub-periods are presented in Panel A (pre-GFC), B (during the crisis period) and C (post-crisis period). In the conditional mean equations, the parameters for constant and past return effects are presented. The conditional variance equations have three parameters including constant, ARCH and GARCH effects, which are reported in the table. The values of the constant parameters in both equations are quite trivial, which does not have much economic meaning. Past returns have a moderate explanatory effect in the current returns in some emerging and advanced markets, even though those effects disappear in many markets during and after the crisis period. The constants in the conditional variances equation for most markets are statistically significant at the 1% level; however, the values are close to zero, which does not indicate any significant economic meaning. The ARCH effect has a moderate impact on the current volatility in many markets, while the GARCH effect is strongly evident with values close to one.

3.7.2. Univariate EGARCH model without volatility spillover

This section first applied a univariate EGARCH(1,1) model for each series in the sample, under each of the four sub-periods using **(3.3)** and **(3.4)**. The results for constants, past returns, ARCH effect, GARCH effect and leverage effect are presented in **Table 3-6.**

Similar to the symmetric GARCH model, the constant coefficient was found very small (close to zero) for the studied markets in the entire period, indicating that a linear constant was not evident in the daily mean of these stock markets.

It was also found that past returns coefficients were not significant for any of China's markets in any given period, implying that current returns were not explained by past returns at a one-day lag. This is consistent with the results from the GARCH model, as shown in section 3.7.1. The coefficient β for all Chinese markets was not statistically significant, indicating that the current return was independent of its past values over the entire sample period.

In the covariance equation, similar to the results found in the GARCH models in section 3.7.1, the constant coefficients were significant for all Chinese markets (and most other markets) in every sub-period. This reflects the decaying behaviour in stock return volatility, which is reasonable. The difference is that the parameters were negative, and the values were quite noteworthy. In the pre-GFC period, the constant coefficients for Chinese equities varied from -1.154 (SZB) to -0.433 (SHA). This shows that the decaying rate in SZB was fastest among China's stock markets. In the GFC period, the coefficients were increasing in value in most of China's markets. SZA increased significantly from -0.478 to -13.719, SZB from -1.154 to -1.854 and SHA from -0.433 to -0.769. Only HS fell, from -0.560 to -0.383. This result shows that the daily volatility in HS and SHA was more short-lived than in other markets, while the daily volatility in the HS market behaved oppositely. This is consistent with the fact that Shenzhen markets recovered quickly during the GFC, while the HS were heavily impacted by the crisis. In the extended-crisis period, the decaying rates in these markets were lower, except for SHB. SHB was also the market that had the fastest decaying rate among other markets in the sample during this period (-4.543). SZB was the second-fastest decaying market among China's equities (-2.933), followed by SZA (-1.912), SHA (-0.700) and HS (-0.362). The coefficients for each of the Chinese markets in the post-crisis period returned to the pre-GFC levels. The decaying rate ranged from -0.377 (SHB) to -0.138 (SHA). This shows that the daily volatility in Shenzhen markets during the GFC decayed faster than in China's other markets. Thus, it reflects a quick recovery, which could be the result of a shift in investors' preferences for Shenzhen markets as an alternative asset during the crisis. Therefore, volatility was more short-lived.

In contrast to the results from the GARCH models, the ARCH effect, denoted by θ_k ,was not evident in any of China's markets in the crisis period. In the non-crisis periods (pre-GFC and post-crisis), ARCH was evident for all of China's markets, with the values ranging from 0.1800 (SHA) to 0.320 (SHB) in the pre-GFC period, and ranging from 0.066 (HS) to 0.237 (SHB) in the post-crisis period. During the GFC, evidence of ARCH was found for HS (0.228), SHB (0.351) and SZB (0.188). In the extended-crisis period, ARCH was present in HS (0.085) and SHA (0.126). This suggests that the volatility of these markets was responsive to the innovations in the past residuals. In terms of magnitude, the ARCH effect, in general, had a more substantial impact on the volatility level in Chinese equities during the crisis period as compared to the non-crisis period.

Negative γ_k implies a leverage effect, which refers to the event where negative news has more impact than positive news of the same size. The results of the parameters for the leverage effect are reported in **Table 3-6**. Following is the summary of the findings.

In the pre-GFC period, this study rejected the hypothesis of no evidence of leverage effect for HS at the confidence level of 10%; and for Indonesia, Thailand, Australia, Japan, NZ, Singapore, the US, Germany and the UK at the 5% confidence level.

In the GFC period, the hypothesis of no evidence of leverage effect was rejected at the 10% confidence level for SHA, and at the 5% confidence level for HS, SZA, SZB, Indonesia, Malaysia, the Philippines, Australia, HK, Japan, NZ, Singapore, the US, Germany and the UK.

In the extended-crisis period, the hypothesis of no evidence of leverage was rejected at the confidence level of 5% for all markets, except for SHA, where the result failed to reject the hypothesis of no evidence of leverage effect. This finding suggests that the leverage effect was not statistically significant for only SHA in this period, whereas the leverage effect was evident in all other markets.

In the post-crisis period, this study rejected the hypothesis of no evidence of leverage effect at the confidence level of 10% for Malaysia and HK, and at the confidence level of 5% for HS, Indonesia, the Philippines, Thailand, Japan, Singapore, US, Germany and the UK.

As shown in **Table 3-7**, the evidence of leverage effect was abundant in each sub-period, predominantly at the 5% level of confidence. Leverage effect was consistenly evident for some emerging markets, including HS and Indonesia, and some advanced markets including Japan, Singapore, US, Germany and the UK, in all four sub-periods. Other markets exhibited the leverage effect in at least one sub-period such as SHA during the GFC and SHB during the extended-crisis period.

In terms of value, the coefficients of the leverage effect for HS were small and relatively stable, at around -0.06 to -0.07, as shown in **Table 3-6**. Similarly, the degree of leverage effect in SHA during the GFC was quite weak (-0.086), while it was much more robust in SHB (-0.292). The degree of leverage effect in Shenzhen markets was relatively moderate, increasing from -0.193 on average in the GFC period to -0.242 in the extended-crisis period.

Table 3-6. Summary of the results for the conditional mean and variance equations of the univariate EGARCH(1,1) for each pair

Panel A – Pre-GFC period

	Constant[1] μ	Past return φ	Constant[2] ω	ARCH α	Leverage γ	GARCH β^{*}
HS	0.0004**	-0.0057	-0.5596*	0.0766**	-0.0649*	0.9525***
SHA	0.0000	0.0132	-0.4326**	0.1800***	0.0076	0.9697***
SHB	-0.0006***	0.0047	-0.8637***	0.3199***	-0.0297	0.9332***
SZA	-0.0001	0.0358	-0.4757**	0.2036***	0.0017	0.9671***
SZB	0.0000	-0.0042	-1.1537**	0.2187***	0.0077	0.8958***
Indonesia	0.0007***	0.1201***	-1.7877***	0.2855***	-0.0952**	0.8373***
Malaysia	0.0001	0.1037***	-0.9364**	0.2071***	-0.0473	0.9300***
Philippines	0.0002	0.0548*	-0.9366*	0.1112**	-0.0006	0.9149***
Thailand	0.0004*	0.1145***	-2.3544***	0.2893***	-0.1506***	0.7872***
Australia	0.0006***	0.0115	-2.6325**	-0.0575	-0.1577***	0.7470***
HK	0.0007***	0.0845***	-0.6826***	0.2001***	-0.0445	0.9449***
Japan	0.0003	-0.0436	-0.7967***	0.1381**	-0.1094***	0.9306***
NZ	0.0006***	0.0103	-1.6736*	0.0035	-0.0960**	0.8445***
Singapore	0.0005***	-0.0310	-0.6249***	0.1536***	-0.0641**	0.9514***
US	0.0002***	-0.0326	-0.0245**	-0.0129	-0.0890***	0.9972***
Germany	0.0006***	-0.0614*	-0.2836***	0.1485***	-0.0753***	0.9831***
UK	0.0003**	-0.0638*	-0.5041***	0.1810***	-0.0843***	0.9655***

Panel B – GFC period

	Constant[1] μ	Past return φ	Constant[2] ω	ARCH α	Leverage γ	GARCH β^{*}
HS	0.0003	-0.0554	-0.3827**	0.2281***	-0.0596**	0.9766***
SHA	0.0011**	-0.0599	-0.7686***	-0.0223	-0.0858*	0.9110***
SHB	0.0007	-0.0211	-1.4823**	0.3510***	-0.0813	0.8559***
SZA	0.0010	0.0338	-13.7193***	0.0745	-0.2097**	-0.5944***
SZB	0.0006	0.0096	-1.8540*	0.1882*	-0.1771**	0.8073***
Indonesia	0.0004	0.0649	-1.4111***	0.4202***	-0.2431***	0.8763***
Malaysia	-0.0001	0.0330	-1.6212*	0.1726*	-0.1339**	0.8490***
Philippines	-0.0004	0.0507	-1.2871**	0.1328	-0.2054***	0.8716***
Thailand	-0.0001	0.0749*	-0.6056**	0.1684**	-0.0574	0.9483***
Australia	0.0006	-0.0251	-0.3429***	0.1557***	-0.1048***	0.9755***
HK	0.0009	-0.0007	-0.4479***	0.1852***	-0.0812***	0.9640***
Japan	-0.0006*	-0.2134***	-0.3114***	0.1695***	-0.1236***	0.9811***
NZ	-0.0001	0.0653	-0.3562**	0.1282**	-0.0842**	0.9731***
Singapore	0.0001	-0.0689	-0.3827**	0.2028***	-0.0777**	0.9749***
US	0.0000	-0.1581***	-0.2985***	0.1154**	-0.1228***	0.9788***
Germany	0.0003	-0.0115	-0.3468***	0.1692**	-0.1095***	0.9770***
UK	-0.0002	-0.0386	-0.3312***	0.1413**	-0.1529***	0.9767***

Panel C – Extended-crisis period

	Constant[1] μ	Past return φ	Constant[2] ω	ARCH α	Leverage γ	GARCH β^*
HS	0.0000	0.0333	-0.3620*	0.0847*	-0.0611**	0.9708***
SHA	0.0002	-0.0145	-0.6996*	0.1261**	-0.0461	0.9388***
SHB	0.0011***	-0.0431	-4.5429***	0.1272	-0.2922***	0.5441***
SZA	0.0009***	0.0500	-1.9124***	0.0167	-0.2456***	0.8031***
SZB	0.0007***	0.0203	-2.9330**	0.0558	-0.2377***	0.7061***
Indonesia	0.0009***	0.0243	-1.1399***	0.2275***	-0.1754***	0.9033***
Malaysia	0.0004***	0.0322	-0.4446*	0.0735	-0.1110***	0.9638***
Philippines	0.0006**	0.0357	-2.0765*	0.2087**	-0.1400**	0.8084***
Thailand	0.0007***	0.0397	-2.2301**	0.2083***	-0.2048***	0.7938***
Australia	0.0002	0.0718*	-0.4233**	0.0624	-0.1180***	0.9613***
HK	-0.0001	0.0158	-0.2923*	0.0869*	-0.0620**	0.9767***
Japan	0.0001	-0.1831***	-2.6353***	0.3552***	-0.0961**	0.7677***
NZ	0.0004*	0.0865**	-0.8707**	0.0784	-0.0724**	0.9222***
Singapore	0.0004*	0.0582	-0.6289**	0.1278**	-0.0829**	0.9487***
US	0.0005***	-0.0302	-0.7207***	0.1217**	-0.2358***	0.9407***
Germany	0.0000	-0.0018	-0.2746***	0.0554	-0.1275***	0.9755***
UK	-0.0002	-0.0157	-0.1858***	-0.0795***	-0.1398***	0.9747***

Panel D – Post-crisis period

	Constant[1] μ	Past return φ	Constant[2] ω	ARCH α	Leverage γ	GARCH β^*
HS	0.0003**	-0.0219	-0.2727**	0.0666**	-0.0702***	0.9791***
SHA	0.0002	0.0100	-0.1383***	0.1251***	0.0139	0.9955***
SHB	0.0004***	-0.0029	-0.3770***	0.2374***	0.0054	0.9789***
SZA	0.0006***	0.0032	-0.1738***	0.1320***	-0.0025	0.9923***
SZB	0.0006***	-0.0388	-0.3515***	0.1990***	-0.0033	0.9796***
Indonesia	0.0001	-0.0032	-0.4230***	0.1316***	-0.1009***	0.9686***
Malaysia	0.0000	0.1119***	-0.2634***	0.1397***	-0.0379*	0.9853***
Philippines	0.0003*	0.0189	-0.6713***	0.1742***	-0.1109***	0.9490***
Thailand	0.0003***	0.0637**	-0.4021***	0.1517***	-0.0988***	0.9735***
Australia	0.0001	0.0509**	-10.2680	0.0100	0.0100	0.0100
HK	0.0000	0.0179	-0.2109**	0.0834***	-0.0336*	0.9852***
Japan	0.0003*	-0.1388***	-1.1334***	0.1721***	-0.1429***	0.9033***
NZ	0.0003**	0.0252	-0.0853	0.0523**	-0.0134	0.9959***
Singapore	0.0001	0.0030	-0.1807***	0.0734***	-0.0750***	0.9889***
US	0.0002**	0.0051	-0.9421***	0.1373***	-0.2590***	0.9261***
Germany	0.0004***	0.0022	-0.6625***	0.1378***	-0.1178***	0.9460***
UK	0.0001	0.0520*	-0.6377***	0.1555***	-0.1896***	0.9520***

Note: *, ** and *** represents 10%, 5% and 1% significance. [1]Constant of the conditional mean equation (3.3). [2]Constant of the conditional variance/covariance equation (3.4).

Table 3-7. Summary of the findings of the leverage effect for each market in the sample, in the four sub-periods

Markets	Pre-GFC	GFC	Extended-crisis	Post-crisis
HS	*	**	**	*
SHA		*		
SHB			**	
SZA		**	**	
SZB		**	**	
Indonesia	**	**	**	**
Malaysia		**	**	*
Philippines		**	**	**
Thailand	**		**	**
Australia	**	**	**	
HK		**	**	*
Japan	**	**	**	**
NZ	**	**	**	
Singapore	**	**	**	**
US	**	**	**	**
Germany	**	**	**	**
UK	**	**	**	**

Note: *, ** and *** represent the null hypothesis of no evidence of leverage effect is rejected at the confidence levels of 10%, 5% and 1% respectively.

The final variable in the variance equation of an EGARCH model is the GARCH coefficient, denoted by α_k. Similar results were found from EGARCH models and GARCH models. GARCH coefficients were strongly significant for all markets in all sub-periods, except for HK in the post-crisis period. The values of these coefficients were close to one, which suggests that the majority of variation in the current level of volatility was caused by past shocks, indicating long memory. Similar results were also found for other markets in the sample. This result supports a vast number of studies that investigated long memory in the volatility of stock returns. So (2000) adopted semiparametric tests on the S&P 500 and DJIA index and revealed strong evidence of long-range dependence in volatility from 1962 to 1996. Similar evidence was found for Singapore, Japan and China using symmetric and asymmetric GARCH models on conditional and realised volatility (Duppati, Kumar, Scrimgeour, & Li, 2017).

The results of this chapter also show that the sum of the ARCH and GARCH coefficients was close to one, which is similar to the GARCH models, and was well documented in financial literature that has applied GARCH family models to high-frequency data (Aktan, Korsakienė, & Smaliukiene, 2010; Oberholzer & Venter, 2015; Zivot, 2009).

3.7.3. Univariate EGARCH model with volatility spillover

The volatility spillover factor is added to the variance equations of the univariate EGARCH(1,1) model, while the conditional mean equations are the same as the univariate EGARCH (1,1) without the spillover factors. Therefore, this section only reports the results of the parameters in the variance equations (3.5) and (3.6). The results of the constant coefficients and ARCH coefficients are reported in **Table 3-8**. The results of GARCH coefficients are reported in **Table 3-9**. The results of the volatility spillover coefficients are reported in **Table 3-10**.

Volatility equilibrium

The parameters of the constant coefficients were found to be significant and negative over the entire period under review for all market pairs, with various degrees depending on the market. The negative sign indicates a decaying behaviour in daily volatility in these stock markets, which is consistent with the existing literature. To avoid over-reporting, **Table 3-8** only reports the average values of the constant coefficients, since the results of the constants for this model are similar to the results for the constants without the added auxiliary term of volatility spillover.

In the pre-GFC period, the constant coefficient for SZB was highest at -1.207, followed by SHA (-0.653), SHB (-0.886), HS (-0.698) and SZA (-0.459). During the GFC, there was a big jump in the size of the constant coefficients of all of China's markets except for HS. In particular, SZA increased by more than 20 times to -13.956, followed by SHA (-3.146), SZB (-2.793) and SHB (-1.582). HS are the only one of China's markets in the sample that went backwards, falling by more than 40% to -0.384. These results imply that the decaying rates of AS and BS were much faster than HS during the GFC. The anomaly observed in SZA disappeared during the extended-crisis period. It was quite similar to SHA, bringing the average constant for AS to -2.234. BS constants were highest, with SHB and SZB increasing to -3.022 and -4.494 respectively. HS was the lowest, at -1.475. The post-crisis period was characterised by much lower constant parameters, with an average of -0.168, -0.308 and -0.371 for AS, BS and HS respectively.

It appeared that daily volatility died out quickest during the GFC. In general, the decaying behaviour was faster in the crisis period than in non-crisis periods.

ARCH and GARCH effect

Table 3-8 and **Table 3-9** present strong evidence of ARCH and GARCH effects, denoted by θ_k and α_k, for each time series which were found in EGARCH with the spillover factor, similar to the findings from the symmetric GARCH and EGARCH models, as presented in sections 3.7.1 and 3.7.2. GARCH coefficients were high, indicating a long memory property in the daily volatility of each stock market.

The sum of these coefficients was close to one, implying a mean-reverting behaviour which confirmed the robustness of the model.

Volatility spillover

Table 3-10 displays the results for the volatility spillover coefficients τ_i in equations (3.5) and (3.6). Significant coefficients validate the existence of volatility spillover from one market to another. A positive (negative) coefficient indicates a positive (negative) relationship between two markets, meaning a shock from one market can increase volatility in another market.

Since there are 140 pairs of markets (between each of China's markets and other markets only) for each period, it is not feasible to report the detailed hypothesis conclusion for each of the market pairs. Therefore, a colour map which illustrates statistically significant volatility spillover between each of China's markets and other markets in the sample is shown in **Figure 3-1** and **Figure 3-2**. These maps highlight the pairs where volatility spillover is found to be statistically significant; that is, a null hypothesis of no volatility spillover is rejected. The shade of the colour represents the confidence level at which the null hypothesis is rejected. The darkest shade represents the null hypothesis of no volatility spillover rejected at a 1% confidence level, and the lightest shade presents the null hypothesis of no volatility spillover rejected at a 10% level. The confidence level of 5% is presented by the middle shade.

Note: The map highlights the pairs that are found with volatility spillover and the null hypothesis of no volatility spillover is rejected. The shade of the colour represents the confidence level for 1%, 5% and 10%. represents1% confidence level. represents 5% confidence level. represents 10% confidence level. For example, in the pre-GFC period, the null hypothesis of no volatility spillover between HS and SHB is rejected at the 5% confidence level.

Figure 3-1. Colour map of volatility spillover from each of China's markets to other markets in the sample

Among China's markets

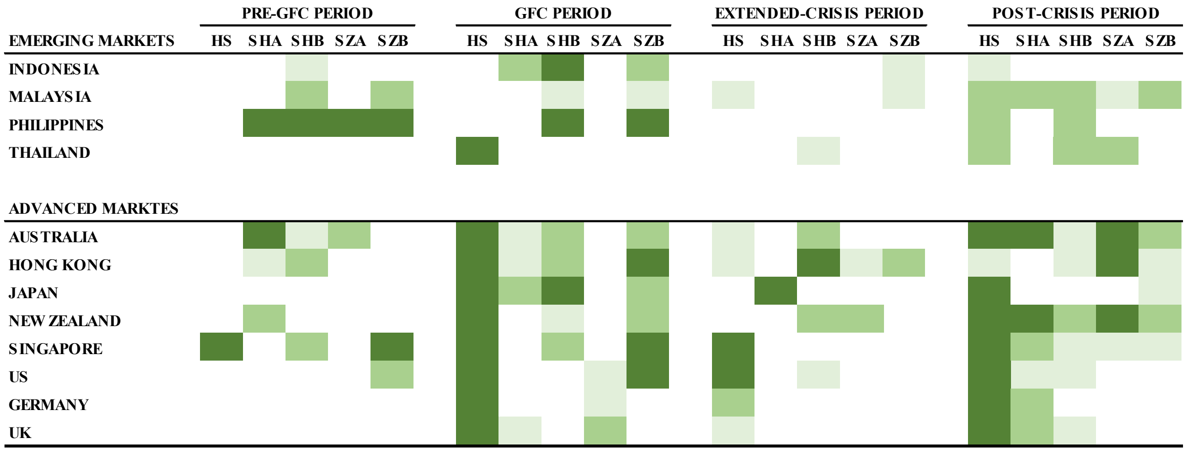
There is a change in shock transmission among China's markets from non-crisis periods (pre-GFC and post-crisis periods) to the crisis periods (GFC and extended-crisis periods) and vice versa.

In the pre-GFC period, there exists a unidirectional spillover from SZB to HS, and HS to SHB. Two-way volatility spillover between one of China's markets and another market in the sample is evident when both $\tau_{i,R}$ in equation (3.3) and $\tau_{i,C}$ in equation (3.4) are statistically significant at a minimum of the 10% level. The results show that bidirectional volatility spillover is strongly evident between AS and BS, and between HK, SHA and SHB. The impact is moderate for some pairs such as SZB to SHB (0.18) and SHA to B-share markets (0.15), while the spillover degree is very weak for others.

During the GFC, the daily volatility of the HS market is not impacted by shocks from China's other markets, whereas shocks from the HS market spread to SHA, SHB and SZB. AS and BS continue to show bidirectional volatility spillover at a higher level during the GFC. Bidirectional volatility spillover is evident between HK and SHA, SHB and SZB, while unidirectional spillover is evident from HS to HK. Evidence of spillover from AS to HS is found during the extended-crisis period. Bidirectional spillover between AS and BS is also higher (increased from 0.12 to 0.26 on average in absolute value) during the extended-crisis period. On the other hand, HK receives volatility from SZA and B-share markets while it transmits volatility to SHA. There is also two-way spillover between HK and HS during this period.

In the post-crisis period, evidence of bidirectional volatility spillover is found for more pairs among China's markets, indicating stronger synchronisation in daily volatility between these markets. Strong evidence of volatility spillover between AS and BS throughout the entire study period can be explained by the herding behaviour in AS and BS, as aforementioned. The impact of shocks from other markets is generally stronger during the GFC and extended-crisis periods than the pre-GFC and post-crisis periods, which is consistent with the empirical literature (Li & Giles, 2015).

The results also show that the spillover effect between HK and each of China's markets is stronger during the post-crisis period. In addition, there is more evidence of volatility in the HK market through innovations in AS and BS during the post-crisis period compared to the pre-GFC period, even though the impact is quite weak and decreases over time. This is opposite to the findings of Huo and Ahmed (2017), who suggest that volatility spillover from Shanghai to HK strengthened after the SH-HK Stock Connect program in 2014, which allows Chinese investors to trade securities in each other's market using their home exchange's trading and clearing facility. Before the post-crisis period, HK only interacts with some of China's markets, but during this period, volatility spillover is significant with all of China's markets. This study's results show that the interaction level between HK and China's other markets in the sample, after the program introduction, is more established in the way that HK is responsive to China's AS and BS, yet the relationship is weak. This indicates that the program has some impact on integration coverage between HK and China's other markets, but that the impact on the strength of these linkages is not significant.



Note: The map highlights the pairs that are found with volatility spillover and the null hypothesis of no volatility spillover is rejected. The shade of the colour represents the confidence level for 1%, 5% and 10%. represents 1% confidence level. represents 5% confidence level. represents10% confidence level. For example, in the pre-GFC period, the null hypothesis of no volatility spillover between Indonesia and SHB was rejected at the 5% confidence level, implying the existence of volatility spillover between these two markets.

Figure 3-2. Colour map of volatility spillover from other markets in the sample to each of China's markets

China versus other emerging markets

In general, regional integration between China and other emerging markets in the sample (Indonesia, Malaysia, the Philippines and Thailand) is evident throughout the study period. During the GFC period, regional segmentation exists between AS and emerging markets, in contrast to conventional wisdom (that there is higher volatility interdependence during the GFC and extended-crisis periods), whereas regional association still holds in B-share markets. In the extended-crisis period, regional integration is re-established unequally. For example, Indonesia and Malaysia are exposed to shocks from all of China's markets, while Thailand is only exposed to shocks from SHB, and the Philippines is segmented with all of China's markets. In the post-crisis period, the shock transmission from China's markets is more evident than for the reverse direction. Government intervention during the GFC and extended-crisis periods, which aims to ease the market and prevent the market from major capital loss, might make the A-share market appear to be 'insusceptible' to regional factors, and the movement of this stock does not seem to be in line with the regional context during market downturns. The B-share market, on the other hand, is still responsive because it is accessible to foreign investors. In the post-crisis period, regional (weak) impact from China's markets increases. Therefore, shocks from China's markets do not have a significant impact on the volatility of the emerging markets in the sample.

China's market is a 'policy market' (Wang, Li, & Kang, 2003) and policy factors as one of the drivers of the Chinese stock markets are worth considering. As part of various capital liberalisation policies that were imposed since 2002, in an attempt to grow regional integration, the Chinese government implemented two major projects during 2013 to 2015, which could be a plausible explanation for wider but not stronger regional integration during the post-crisis period. The first project is the China Belt and Road Initiative in 2013, which aims to increase Asian-Pacific cooperation mainly through financing and building infrastructure projects across Eurasia, and to strengthen regional political cooperation, unimpeded trade, financial integration and people-to-people exchanges. The second project is the establishment of the New Development Bank and the Asian Infrastructure Development Bank in late 2015 to provide funding options to infrastructure projects in Asia. The findings on the regional integration over these periods might reflect this. This study indicates that, prior to 2015, Indonesia, the Philippines, Malaysia and Thailand were not significantly exposed to volatility from China's equities. However, since 2015, during the post-crisis period, all four countries were exposed to HS, HK and SHB markets. Moreover, strong economic ties through import-exports and capital flows through investment could also lead to higher market integration among these markets (Pula, 2014). In addition, this study's findings of weak transmission may indicate that these activities, together with other 'opening-up' policies in capital flows, even though they have increased regional integration in terms of coverage (that is, integrated with more countries), have had little impact on the strength of the regional integration of China's equities. This finding is consistent with empirical literature that liberalisation policies might increase the integration between China and other countries, yet the impact is not significant (Yao et al., 2018).

China versus developed markets

Evidence of spillover from advanced markets to Chinese equities is abundant in the post-crisis period. In the pre-crisis period, the volatility spillover term $\alpha_{2,j}$ on HS from Australia, Japan and NZ is significant at the 5% level or lower, indicating strong evidence of volatility spillover from these markets to HS. There is unidirectional spillover from HS to Singapore at the 1% significance level. There is either unidirectional or bidirectional spillover between A- and B-share markets (SHA, SHB, SZA, SZB) and Australia, NZ, Singapore, HK, Germany, the UK and US at the 5% significance level or lower.

In the GFC period, there is bidirectional spillover between HS and Australia, HK, Japan, NZ, Germany and the UK at a 5% significance level or lower. There is unidirectional spillover from HS to Singapore and the US at the 1% significance level. On the other hand, spillover to SHA, SHB, SZA and SZB from many developed markets disappeared. There is bidirectional volatility spillover between HK and Japan and SHA, SHB and SZB at a 5% significance level or lower. There is unidirectional spillover from SZA to the UK at a 5% significance level and from SZB to Singapore and US at the 1% significance level, and from Australia to SZB at a 5% significance level, indicating China's AS and BS experienced global segmentation during this period.

In the extended-crisis period, at a 5% significance level or lower, there is bidirectional volatility spillover between HS and Australia, HK, Singapore and the UK. There is unidirectional spillover from NZ to HS and unidirectional spillover from HS to US and Germany. There is unidirectional spillover to SHA from HK, NZ and Singapore at the 5% significance level and unidirectional spillover from SHA to Japan at the 1% significance level. SHB and SZB received shocks from Singapore at the 1% significance level, while shock transmitted from SHB to Australia, HK and Japan at the 5% significance level or lower, and unidirectional spillover from SZB to HK is significant at a 5% level. There is bidirectional spillover between SZA and NZ at a 5% level.

In the post-crisis period, bidirectional volatility spillover between HS and all the developed markets is significant at a 5% significance level or lower. There is bivariate spillover between Australia, HK, Japan and NZ and SHA and SHB at a 5% significance level or lower. There is unidirectional volatility spillover from SHB to Singapore, the US and UK, and from SZA and SZB to Singapore at a 10% significance level or lower. At a 10% significance level, there is unidirectional volatility spillover from Germany and the UK to SHA.

These findings indicate that market segmentation was more prevalent in A- and B-share markets during the GFC and extended-crisis periods compared to pre-GFC and post-crisis periods. Moreover, there is more evidence of volatility spillover between Chinese equities and advanced Asian-Pacific countries including HK, Japan, Australia and Singapore than between Chinese equities and the UK, US and Germany, despite the size of the US economy. The established integration between Australia and China has been documented abundantly in empirical literature, due to the fact that China consumed a minimum of one-third of Australian total goods and services each year from 2013 to 2017 according to the data published by the OECD (2017). Regardless, the magnitude of volatility spillover effect from developed markets to Chinese equities is quite small.

Volatility spillover from China's equities to some developed markets such as Singapore, the US, Japan and NZ disappeared in the GFC and extended-crisis periods, and reappeared in the post-crisis period. Australia has been impacted by AS and BS listed on the SHSE since the pre-GFC period. Other countries such as Singapore, the US, Germany and UK are only impacted by HS, possibly due to the strong link between the HS and HK markets, and the established integration in terms of volatility between these markets and HK that is evident throughout the entire period. Increased, yet weak global integration could be a result of various capitalisation policies; for example, the economic reform in 2003 (Li, 2012), the China Belt and Road Initiative in 2013, and especially the launch of foreign accessibility to short AS by the SH-HK Stock Connect program in March 2015 (Wang, Tsai, & Li, 2017). Finally, there is not enough evidence to conclude that the impact from China's markets is stronger during the GFC and extended-crisis periods compared to the pre-GFC and post-crisis periods.

To test for the robustness of the model, the squared standardised residuals from models (3.3) and (3.4) are tested with serial correlations and heteroskedasticity using the Engle (1982) Lagrange multiplier ARCH test and White (1980) heteroskedasticity test at five lags. The key results are summarised here. The null hypothesis of these tests is that there is no serial correlation / heteroskedasticity in the residuals. The results show that serial correlation is not detected for most pairs of HS, SHA, SHB, SZA and SZB. In addition, heteroskedasticity is not detected for all pairs with Chinese markets at any time over the four sub-periods except for HK and HS in the post-crisis period. However, there is evidence that serial correlation existed in the HK and HS pairs over the four sub-periods, indicating that a higher number of lags is recommended for these markets. These results provide a strong indication that EGARCH(1,1) is a good fit for modelling the volatility spillover of these markets.

Some key findings are summarised below, and the discussions for these findings are presented in section 3.9.

Chinese equities, in general, were prone to shocks from local markets at any given time; however, they were more responsive to shocks from local markets during crisis periods (GFC and extended-crisis period) than non-crisis periods. Moreover, HS became more integrated with AS and BS in the post-crisis period. The volatility in AS and BS was driven by shocks from HS and vice versa, even though the impact from AS and BS on HS was weak.

Shock transmission between Chinese equities and emerging markets was found. However, the impact was weak except for the spillover to SHB. SHB was more responsive to external shocks from emerging markets compared to other of China's markets, and the impact was moderate. In addition, while emerging markets appeared to be less influenced by the shocks from Chinese equities in the post-crisis period, an opposite finding was recorded in Chinese equities. China's share markets were vulnerable to shocks from emerging markets, even though the effect was not significant.

Evidence of spillover from advanced markets is abundant in the post-crisis period. On the other hand, the influence from Chinese equities was observed in only a few countries, and the degree of the impact was weak throughout the period under review. However, in the post-crisis period, it was documented that more countries were responsive to shocks from Chinese equities, such as Australia, HK, Japan and NZ. Other countries such as Singapore, the US, Germany and the UK were only impacted by HS. There was not enough evidence to conclude that the impact of China's markets was more substantial during the crisis periods compared to non-crisis periods.

What the study observed is that despite the fears arising from public news that China could create another global crisis, the data shows otherwise in relation to spillover to the studied markets. Even though there was some evidence of spillover from China to emerging and advanced markets, the impact was not significant.

Table 3-8. Summary of the constant coefficients ω, and ARCH coefficients γ_k, in the variance equations in the univariate EGARCH(1,1) with a spillover factor for each pair of countries

Panel A: Pre-GFC period

	HS	SHA	SHB	SZA	SZB	INDO	MALAY	PHIL	THAI	AU	HK	JP	NZ	SING	US	GER	UK
Constant[1]	-0.6982	-0.9833	-0.8862	-0.4595	-1.2069	-1.8062	-0.9067	-2.0597	-2.3324	-2.3650	-0.6712	-0.7175	-5.1235	-0.5807	-0.0645	-0.2707	-0.4757
HS	0.0772*	0.1786***	0.3183***	0.2009***	0.2226***	0.2855***	0.2304***	0.1308**	0.2926***	-0.0473	0.1927***	0.1233***	-0.0040	0.1531***	0.0519**	0.1485***	0.1805***
SHA	0.0720**	0.1106***	0.2991***	0.1894***	0.2315***	0.2799***	0.2012***	0.1025**	0.2856***	-0.0619	0.1888***	0.1338**	0.0548	0.1361***	0.0443**	0.1439***	0.1717***
SHB	0.0701**	0.1861***	0.2625***	0.2115***	0.1973***	0.2877***	0.2047***	0.1078**	0.2874***	-0.0576	0.1952***	0.1376**	0.0217	0.1307***	-0.0148	0.1416***	0.1725***
SZA	0.0719**	0.1700***	0.2949***	0.1721***	0.2193***	0.2838***	0.2040***	0.0944**	0.2878***	-0.0607	0.1949***	0.1319**	0.0071	0.1361***	0.0556**	0.1385***	0.1627***
SZB	0.0534*	0.1851***	0.2744***	0.2131***	0.1959***	0.3013***	0.1997***	0.1038**	0.2790***	-0.0570	0.1827***	0.1406**	0.0807	0.0872**	-0.0160	0.1351***	0.1692***
INDO	0.0764*	0.1759***	0.3212***	0.1989***	0.2276***	0.2993***	0.2065***	0.1098**	0.2949***	-0.0561	0.2006***	0.1384**	0.1171	0.1551***	0.0520**	0.1517***	0.1804***
MALAY	0.0696*	0.1777***	0.3183***	0.2003***	0.2545***	0.2774***	0.2057***	0.1432	0.2866***	-0.0569	0.1981***	0.1232**	0.0084	0.1496***	-0.0160	0.1491***	0.1815***
PHIL	0.0758*	0.1725***	0.3130***	0.1897***	0.2295***	0.2852***	0.2263***	0.0927	0.2911***	-0.0516	0.2006***	0.1350**	-0.0026	0.1540***	-0.0185	0.1305***	0.1884***
THAI	0.0737*	0.1804***	0.3181***	0.2036***	0.2195***	0.2896***	0.2087***	0.1124**	0.2786***	-0.0441	0.1984***	0.1326**	0.0038	0.1509***	-0.0215	0.1433***	0.1774***
AU	0.0770*	0.1608***	0.3113***	0.1816***	0.2326***	0.2888***	0.2046***	0.1125**	0.2893***	-0.0397	0.1994***	0.1296***	0.0191	0.1517***	0.0277*	0.1458***	0.1786***
HK	0.0766*	0.2605**	0.3099***	0.2051***	0.2376***	0.2861***	0.2083***	0.1185**	0.2867***	-0.0572	0.1846***	0.1369**	-0.0005	0.1472***	-0.0161	0.1410***	0.1847***
JP	0.0754*	0.1786***	0.3245***	0.2023***	0.2223***	0.2806***	0.2224***	0.1152**	0.2890***	-0.0617	0.1998***	0.1441**	0.0035	0.1531***	0.0433**	0.1476***	0.1823***
NZ	0.0707*	0.1621***	0.3136***	0.1909***	0.2203***	0.2965***	0.1812***	0.1051	0.2741***	-0.0422	0.1997***	0.1306***	0.0096	0.1405***	-0.0147	0.1484***	0.1786***
SING	-0.0350	0.1792***	0.3174***	0.2030***	0.2605***	0.2870***	0.2363***	0.1460**	0.2896***	-0.0490	0.1998***	0.1246**	-0.0024	0.1503***	-0.0140	0.1492***	0.1926***
US	0.0816*	0.1787***	0.3219***	0.2070***	0.2056***	0.2666***	0.2075***	0.1257**	0.2891***	-0.0065	0.1962***	0.1059***	-0.0002	0.1478***	0.0703***	0.1381***	0.1667***
GER	0.0764**	0.1789***	0.3159***	0.2059***	0.2177***	0.2857***	0.2149***	0.1348**	0.2901***	-0.0469	0.2007***	0.1364***	0.0056	0.1537***	-0.0105	0.1502***	0.1817***
UK	0.0729*	0.1748***	0.3197***	0.2005***	0.2115***	0.2830***	0.2151***	0.1435**	0.2899***	-0.0485	0.2002***	0.1345***	0.0093	0.1538***	-0.0081	0.1472***	0.1684***

Panel B: GFC period

	HS	SHA	SHB	SZA	SZB	INDO	MALAY	PHIL	THAI	AU	HK	JP	NZ	SING	US	GER	UK
Constant[1]	-0.3946	-2.4369	-1.5537	-12.4498	-2.5476	-1.4341	-2.6174	-1.3996	-0.6480	-0.4586	-0.5336	-0.3538	-0.3669	-0.3689	-0.2934	-0.3249	-0.3247
HS	0.2329***	-0.0247	0.3633***	0.0589	0.1768*	0.4208***	0.1726*	0.1465	0.1789**	0.2327***	0.2452***	0.2072***	0.1700***	0.1983***	0.1213**	0.1824***	0.1832***
SHA	0.2457***	-0.1306***	0.3560***	0.1214	0.2092*	0.4010***	0.1743*	0.1731*	0.1708**	0.1658**	0.2563***	0.2010***	0.1284**	0.1856***	0.1055*	0.1483**	0.0914
SHB	0.2373***	-0.0225	0.3623***	0.0843	0.2116*	0.3990***	0.1701*	0.2051**	0.1724**	0.1678***	0.2288***	0.1805***	0.1281**	0.2050***	0.1119**	0.1581**	0.1266**
SZA	0.2335***	-0.0236	0.3426***	0.1358	0.2109*	0.3865***	0.1688*	0.1419*	0.1685**	0.1599***	0.2222***	0.1806***	0.1304**	0.1917***	0.1116**	0.1372*	0.1223**

SZB	0.2249***	-0.0126	0.3641***	0.0779	0.2051*	0.4077***	0.1683*	0.1984**	0.1717**	0.1846***	0.2056***	0.1829***	0.1323**	0.2084***	0.1125**	0.1753**	0.1435**
INDO	0.2356***	-0.0539	0.3636***	0.0599	0.1814*	0.4005***	0.1716*	0.1380	0.1485**	0.2359***	0.2087***	0.2071***	0.1537**	0.0288	0.1113**	0.2081***	0.1430**
MALAY	0.2420***	-0.0220	0.3765***	0.0628	0.2086*	0.4324***	0.1771*	0.1771*	0.1609**	0.2216***	0.2196***	0.2179***	0.1368**	0.1831***	0.1153**	0.1850**	0.1486**
PHIL	0.2427***	-0.0210	0.4064***	0.0541	0.2234**	0.4142***	0.1666*	0.0982	0.1634**	0.2191***	0.2035***	0.1798***	0.1491**	0.1915***	0.1154**	0.1795**	0.1652***
THAI	0.2160***	-0.0209	0.3626***	0.0721	0.1866*	0.4252***	0.1761*	0.1290	0.1685**	0.1869***	0.1950***	0.1767***	0.1481**	0.2045***	0.1132**	0.1940***	0.1606***
AU	0.1987***	-0.0177	0.3688***	0.0646	0.1915*	0.4718***	0.1757*	0.1470*	0.1869**	0.1369**	0.2093***	0.1956***	0.1069**	0.2031***	0.1154**	0.1811***	0.1566***
HK	0.2185***	-0.0241	0.3636***	0.0651	0.1577	0.4188***	0.1706*	0.1391	0.1751**	0.2291***	0.2115***	0.1946***	0.1614***	0.2095***	0.1268**	0.1843***	0.1837***
JP	0.1878***	-0.0084	0.3739***	0.1207	0.1760*	0.4984***	0.1487*	0.1428*	0.1803**	0.1785***	0.1523**	0.0770	0.1517**	0.2083***	0.1090**	0.1337**	0.1469***
NZ	0.2201***	-0.0183	0.3651***	0.0626	0.1860*	0.4639***	0.1752*	0.1402	0.1823**	0.2053***	0.1978***	0.1867***	0.1236**	0.1824***	0.1304**	0.2091***	0.1708***
SING	0.2007***	-0.0178	0.3531***	0.0557	0.1866*	0.4096***	0.1734*	0.1319	0.1785**	0.1568***	0.1922***	0.1685***	0.1090*	0.1929***	0.0920*	0.1135**	0.1509***
US	0.1859***	0.0010	0.3529***	0.0550	0.2256	0.4077***	0.1662*	0.1329	0.1762**	0.1584***	0.1667**	0.1571***	0.1158**	0.2047***	0.0628	0.1715***	0.1507***
GER	0.1770***	-0.0129	0.3560***	0.0656	0.1990*	0.4411***	0.1692*	0.1388	0.1795**	0.1472**	0.1818**	0.1583**	0.0948*	0.2090***	0.0945*	0.1348**	0.1350**
UK	0.1740***	-0.0686	0.3497***	0.0570	0.1907*	0.4277***	0.1680*	0.1335	0.1788**	0.1412**	0.1700**	0.1593***	0.0631	0.2081***	0.0984*	0.1498**	0.1384**

Panel C: Extended-crisis period

	HS	**SHA**	**SHB**	**SZA**	**SZB**	**INDO**	**MALAY**	**PHIL**	**THAI**	**AU**	**HK**	**JP**	**NZ**	**SING**	**US**	**GER**	**UK**
Constant[1]	-1.4732	-1.9375	-4.1245	-2.4656	-2.9865	-1.2325	-0.4560	-2.0532	-2.2433	-0.3617	-0.2933	-2.7938	-0.9940	-0.7255	-0.6746	-0.2550	-0.1964
HS	0.0813*	0.1317**	0.1423	0.0077	0.0843	0.2762***	0.0509	0.2117**	0.2042**	0.0314	0.0885**	0.3587***	0.0815*	0.0792*	0.1129**	0.0253	-0.0533***
SHA	-0.0381**	0.1143*	0.1066	0.0307	0.0656	0.2487***	0.0833*	0.2056**	0.2080**	0.0678	-0.0265	0.3596***	0.0828	0.1647**	0.1271**	0.0611	-0.0699***
SHB	0.0847*	0.1139	0.2074*	0.0112	0.0680	0.2407***	0.0849	0.2059**	0.2143***	0.0670	0.0969**	0.3598***	0.0834	0.1360**	0.1202**	0.0395	-0.0893***
SZA	-0.0252**	0.1051	0.1069	-0.0197	0.0349	0.2423***	0.0841	0.2048**	0.2071**	0.0678	0.0819*	0.3569***	0.0860	0.1408**	0.1267**	0.0537	-0.0786***
SZB	0.0855*	0.1135	0.1958*	0.0370	0.0703	0.2375***	0.0815	0.2040**	0.2094***	0.0604	0.0946**	0.3566***	0.0809	0.1263**	0.1129**	-0.0013	-0.0710***
INDO	0.0955*	0.1236**	0.1327	0.0167	0.0664	0.2514***	0.0942*	0.2234**	0.2188***	0.0704	0.0969**	0.3678***	0.0921	0.1710**	0.1213**	0.0560	-0.0723***
MALAY	0.0730	0.1335**	0.1214	0.0124	0.0543	0.2899***	0.0773*	0.2095**	0.2126***	0.0566	0.0836*	0.3580***	0.0778	0.1049**	0.1214**	0.0453	-0.0695***
PHIL	0.0877*	0.1264**	0.1293	0.0119	0.0570	0.2884***	0.0794	0.2181**	0.2329***	0.0618	0.0900*	0.3694***	0.1111	0.1698**	0.1129*	0.0610	-0.0727***
THAI	0.0845*	0.1261**	0.1167	0.0195	0.0547	0.2394***	0.0764	0.2088**	0.2058**	0.0615	0.0848*	0.3602***	0.0810	0.1254**	0.1076*	0.0535	-0.0725***
AU	0.1049**	0.1295**	0.1377	0.0159	0.0727	0.2747***	0.0783	0.2137**	0.1991**	0.0740*	0.1050**	0.3527***	0.0790*	0.1143*	0.1462**	0.0596	-0.0795***
HK	0.0830*	0.1330**	0.1379	0.0180	0.0839	0.2703***	0.0519	0.2127**	0.2085***	0.0372	0.0789**	0.3700***	0.0729*	0.1099**	0.1099*	0.0381	-0.0821***
JP	0.0900*	-0.0426	0.1337	0.0162	0.0590	0.2461***	0.0734	0.2069**	0.2109***	0.0490	0.0884*	0.1993**	0.0753	0.1299**	0.1154**	0.0429	-0.0739***
NZ	0.0937*	0.1253**	0.1268	-0.0059	0.0604	0.2715***	0.0675	0.2020**	0.2075***	0.0552	0.0981**	0.3640***	0.0739	0.1352**	0.1310**	0.0428	-0.0667***

SING	0.0869*	0.1267**	0.1244	0.0010	0.0682	0.2907***	0.0686	0.2240**	0.2250***	0.0544	0.1007**	0.3716***	0.0877*	0.0273	0.1122**	0.0253	-0.0713***
US	0.0208	0.1267**	0.1293	0.0078	0.0610	0.2599***	0.0750	0.2028**	0.1895**	-0.0714***	0.0924**	0.3670***	0.0764*	0.1341**	0.0752	0.0570	-0.0889***
GER	0.0853*	0.1303**	0.1317	0.0178	0.0607	0.2385***	0.0509	0.2087**	0.1973**	0.0182	0.0871**	0.3524***	0.0412	0.0803*	0.1406**	0.0210	-0.1036***
UK	0.0940*	0.1281**	0.1291	0.0121	0.0589	0.2464***	0.0511	0.2083**	0.2095***	0.0414	0.0972**	0.3630***	0.0618	0.0943*	0.1354**	0.0513	-0.0557***

Panel D: Post-crisis period

	HS	SHA	SHB	SZA	SZB	INDO	MALAY	PHIL	THAI	AU	HK	JP	NZ	SING	US	GER	UK
Constant[1]	-0.2264	-0.1522	-0.3874	-0.1925	-0.3660	-0.4377	-0.2838	-0.6743	-0.4218	-0.1157	-0.1717	-1.4696	-2.0003	-0.1883	-0.9305	-0.6794	-0.6554
HS	0.0642**	0.1100***	0.2307***	0.1177***	0.1786***	0.0961***	0.1248***	0.1680***	0.1501***	0.0470**	0.0737***	0.1941***	0.0466**	0.0653**	0.1170**	0.1319***	0.1696***
SHA	-0.0273**	0.1249***	0.2434***	0.1494***	0.2071***	0.1209***	0.1398***	0.1766***	0.1515***	0.0307*	0.0231	0.1854***	0.0474**	0.0736**	0.1408***	0.1445***	0.1564***
SHB	-0.0310***	0.1127***	0.2311***	0.1484***	0.2014***	0.1325***	0.1428***	0.1737***	0.1411***	-0.0172*	-0.0249**	0.1877***	0.0005	0.0732**	0.1307***	0.1354***	0.1540***
SZA	-0.0258***	0.1293***	0.2508***	0.0901***	0.2029***	0.1316***	0.1389***	0.1755***	0.1481***	0.0287*	-0.0189*	0.1894***	0.0003	0.0742***	0.1410***	0.1583***	0.1602***
SZB	-0.0289***	0.1193***	0.2460***	0.1448***	0.1904***	0.1307***	0.1381***	0.1770***	0.1327***	-0.0060	0.0113	0.1974***	0.0001	0.0733***	0.1371***	0.1403***	0.1620***
INDO	0.0672**	0.1188***	0.2259***	0.1259***	0.1940***	0.1589***	0.1776***	0.1898***	0.1749***	0.0357*	0.0672***	0.2009***	0.0466**	0.0914***	0.1361***	0.1391***	0.1689***
MALAY	0.0513**	0.1227***	0.2501***	0.1305***	0.2092***	0.1677***	0.1393***	0.1971***	0.1575***	0.0377*	0.0611***	0.2137***	0.0000	0.0954***	0.1378***	0.1388***	0.1798***
PHIL	0.0751**	0.1246***	0.2336***	0.1297***	0.1992***	0.1572***	0.1609***	0.1808***	0.1740***	-0.0162	0.0869***	0.2353***	0.0875	0.0910***	0.1547***	0.1411***	0.1656***
THAI	0.0593**	0.1187***	0.2192***	0.1195***	0.1917***	0.1757***	0.1606***	0.1864***	0.1432***	-0.0257***	0.0733***	0.2071***	0.1119*	0.0918***	0.1609***	0.1565***	0.1896***
AU	0.0094	0.1012***	0.2189***	0.1038***	0.1802***	0.1066***	0.0981***	0.1695***	0.1387***	-0.0073	0.0410**	0.1614***	-0.0833	0.0470**	0.1465***	0.1212***	0.1548***
HK	0.0766***	0.1098***	0.2327***	0.1168***	0.1850***	0.0882***	0.1298***	0.1716***	0.1515***	0.0501**	0.0781***	0.1990***	0.0513**	0.0632**	0.1351***	0.1311***	0.1596***
JP	0.1049***	0.1239***	0.2386***	0.1304***	0.2021***	0.1493***	0.1535***	0.1980***	0.1626***	0.0506**	0.0903***	0.1496***	0.0587**	0.0889***	0.1490***	0.1460***	0.1840***
NZ	0.0615**	0.1015***	0.2012***	0.1055***	0.1731***	0.1302***	0.1372***	0.1711***	0.1654***	0.0414**	0.0607***	0.1854***	-0.0565	0.0754***	0.1577***	0.1422***	0.1930***
SING	0.0448**	0.1169***	0.2422***	0.1239***	0.2051***	0.1018***	0.1330***	0.1734***	0.1403***	0.0508**	0.0534**	0.1978***	0.0139	0.0742***	0.1437***	0.1382***	0.1916***
US	0.0330	0.1204***	0.2121***	0.1254***	0.1873***	0.1294***	0.1346***	0.1768***	0.1572***	0.0229	0.0694***	0.1552***	0.0160	0.0758***	0.1695***	0.1406***	0.1649***
GER	0.0605**	0.1275***	0.2349***	0.1310***	0.1996***	0.1124***	0.1360***	0.1784***	0.1592***	0.0402**	0.0774***	0.1888***	0.0263	0.0702***	0.1684***	0.1069**	0.1901***
UK	0.0445*	0.1327***	0.2437***	0.1333***	0.2022***	0.1234***	0.1324***	0.1875***	0.1614***	0.0360*	0.0696***	0.1846***	0.0091	0.0672***	0.1513***	0.1160***	0.1035**

Note: *, ** and *** indicate significance at 10%, 5% and 1% level. Null hypothesis: the coefficient equals zero. Endogenous variables are in the first row. Each column presents the coefficients of the bivariate tests between that country (as the endogenous variable) and other countries (as the exogenous variables) in the sample. Equations for the spillover from China and to China are $H = \log(\sigma^2_{C,t}) = \omega + \sum_{i=1}^{q} \theta_j \left(\left|\frac{\epsilon_{t-1}}{\sigma_{t-1}}\right| - E\left|\frac{\epsilon_{t-1}}{\sigma_{t-1}}\right|\right) + \sum_{j=1}^{r} \gamma_k \frac{\epsilon_{t-1}}{\sigma_{t-1}} + \sum_{j=1}^{q} \alpha_j \log(\sigma^2_{C,t-1}) + \sum_{j=1}^{q} \tau_{i,R} \log(\sigma^2_{R,t})$ and $H = \log(\sigma^2_{R,t}) = \omega + \sum_{i=1}^{q} \theta_j \left(\left|\frac{\epsilon_{t-1}}{\sigma_{t-1}}\right| - E\left|\frac{\epsilon_{t-1}}{\sigma_{t-1}}\right|\right) + \sum_{j=1}^{r} \gamma_k \frac{\epsilon_{t-1}}{\sigma_{t-1}} + \sum_{j=1}^{q} \alpha_j \log(\sigma^2_{R,t-1}) + \sum_{j=1}^{q} \tau_{i,C} \log(\sigma^2_{C,t})$ respectively. $\tau_{i,R}$ and $\tau_{i,C}$ represent the spillover to and from China respectively. [1]Average of constants of each pair.

Table 3-9. Summary of the GARCH coefficients α_j in the variance equations in the univariate EGARCH(1,1) with a spillover factor for each pair of countries

Panel A: Pre-GFC period

	HS	SHA	SHB	SZA	SZB	INDO	MALAY	PHIL	THAI	AU	HK	JP	NZ	SING	US	GER	UK
HS	0.9529***	0.9710***	0.9286***	0.9692***	0.8941***	0.8373***	0.9283***	0.8942***	0.7950***	0.7602***	0.9528***	0.9567***	0.9134***	0.9521***	0.9910***	0.9834***	0.9654***
SHA	0.9637***	0.9687***	0.9219***	0.9685***	0.8548***	0.8412***	0.9290***	0.9248***	0.7839***	0.7806***	0.9438***	0.9307***	-0.2922	0.9613***	0.9941***	0.9856***	0.9706***
SHB	0.9653***	0.9670***	0.9347***	0.9653***	0.9037***	0.8358***	0.9298***	0.9229***	0.7909***	0.7467***	0.9487***	0.9294***	-0.3982	0.9657***	0.9969***	0.9861***	0.9703***
SZA	0.9629***	0.9595***	0.9178***	0.9671***	0.8599***	0.8275***	0.9260***	0.9315***	0.7856***	0.7911***	0.9411***	0.9291***	-0.5128**	0.9626***	0.9938***	0.9870***	0.9728***
SZB	0.9719***	0.9688***	0.9298***	0.9662***	0.9108***	0.8321***	0.9303***	0.9248***	0.7919***	0.7570***	0.9483***	0.9311***	-0.0466	0.9764***	0.9972***	0.9868***	0.9718***
INDO	0.9528***	0.9738***	0.9322***	0.9717***	0.8955***	0.8224***	0.9528***	0.9216***	0.7844***	0.7114***	0.9444***	0.9295***	0.0281	0.9490***	0.9922***	0.9832***	0.9690***
MALAY	0.9579***	0.9701***	0.9220***	0.9683***	0.8720***	0.8502***	0.9279***	0.0384	0.7921***	0.7360***	0.9472***	0.9443***	0.8656***	0.9503***	0.9978***	0.9824***	0.9657***
PHIL	0.9501***	0.9761***	0.9411***	0.9758***	0.9041***	0.8306***	0.9321***	0.9164***	0.7863***	0.7614***	0.9445***	0.9273***	0.8590***	0.9527***	0.9972***	0.9836***	0.9652***
THAI	0.9550***	0.9701***	0.9342***	0.9672***	0.8959***	0.8364***	0.9316***	0.9153***	0.7962***	0.7959***	0.9457***	0.9288***	0.8636***	0.9512***	0.9968***	0.9821***	0.9667***
AU	0.9524***	0.9753***	0.9322***	0.9753***	0.8955***	0.8306***	0.9456***	0.9214***	0.7872***	0.8104***	0.9456***	0.9373***	0.7168***	0.9521***	0.9950***	0.9830***	0.9677***
HK	0.9525***	0.0169	0.9315***	0.9676***	0.8885***	0.8379***	0.9357***	0.9107***	0.7885***	0.7524***	0.9407***	0.9343***	0.8518***	0.9517***	0.9964***	0.9851***	0.9691***
JP	0.9546***	0.9695***	0.9315***	0.9668***	0.8951***	0.8295***	0.9325***	0.9136***	0.7873***	0.7484***	0.9449***	0.9287***	0.7267***	0.9509***	0.9936***	0.9837***	0.9679***
NZ	0.9531***	0.9703***	0.9338***	0.9684***	0.9026***	0.8262***	0.9430***	-0.0201	0.8052***	0.7922***	0.9443***	0.9490***	0.8579***	0.9546***	0.9962***	0.9828***	0.9673***
SING	0.6909***	0.9707***	0.9285***	0.9680***	0.8812***	0.8357***	0.9242***	0.8777***	0.7862***	0.7747***	0.9452***	0.9452***	0.8677***	0.9456***	0.9983***	0.9833***	0.9664***
US	0.9548***	0.9707***	0.9327***	0.9646***	0.8950***	0.8563***	0.9314***	0.9040***	0.7892***	0.9096***	0.9508***	0.9701***	0.8910***	0.9578***	0.9891***	0.9853***	0.9693***
GER	0.9528***	0.9703***	0.9330***	0.9659***	0.8967***	0.8351***	0.9306***	0.8908***	0.7819***	0.7715***	0.9450***	0.9352***	0.8463***	0.9515***	0.9967***	0.9838***	0.9657***
UK	0.9503***	0.9724***	0.9328***	0.9687***	0.8991***	0.8412***	0.9285***	0.8842***	0.7871***	0.7423***	0.9461***	0.9413***	0.8744***	0.9506***	0.9973***	0.9824***	0.9656***

Panel B: GFC period

	HS	SHA	SHB	SZA	SZB	INDO	MALAY	PHIL	THAI	AU	HK	JP	NZ	SING	US	GER	UK
HS	0.9741***	0.9089***	0.8447***	-0.6705***	0.8160***	0.8761***	0.8426***	0.8727***	0.9427***	0.9601***	0.9541***	0.9772***	0.9687***	0.9752***	0.9793***	0.9828***	0.9795***
SHA	0.9708***	0.9166***	0.8532***	-0.5768***	0.7888***	0.8883***	0.8412***	0.8432***	0.9462***	0.9738***	0.9418***	0.9735***	0.9732***	0.9785***	0.9801***	0.9772***	0.9795***
SHB	0.9726***	0.9182***	0.8592***	0.8389***	0.7901***	0.8885***	0.8347***	0.8009***	0.9445***	0.9732***	0.9507***	0.9782***	0.9730***	0.9743***	0.9786***	0.9762***	0.9769***
SZA	0.9745***	0.9130***	0.8638***	-0.5447**	0.7809***	0.8949***	0.8613***	0.8648***	0.9484***	0.9749***	0.9536***	0.9788***	0.9724***	0.9764***	0.9786***	0.9753***	0.9774***
SZB	0.9743***	0.9087***	0.8635***	0.8519***	0.8087***	0.8797***	0.8419***	0.8067***	0.9461***	0.9684***	0.9559***	0.9792***	0.9728***	0.9737***	0.9782***	0.9777***	0.9767***

INDO	0.9755***	0.8979***	0.8527***	-0.6676***	0.8238***	0.8778***	0.8511***	0.8694***	0.9520***	0.9610***	0.9590***	0.9776***	0.9710***	0.9810***	0.9784***	0.9769***	0.9768***
MALAY	0.9744***	0.9074***	0.8348***	-0.6563***	0.7893***	0.8769***	0.8516***	0.8506***	0.9502***	0.9632***	0.9557***	0.9738***	0.9736***	0.9765***	0.9788***	0.9768***	0.9774***
PHIL	0.9736***	0.8982***	0.8245***	-0.6684***	0.7813***	0.8747***	0.8449***	0.8808***	0.9498***	0.9604***	0.9596***	0.9770***	0.9672***	0.9771***	0.9788***	0.9758***	0.9761***
THAI	0.9757***	0.9037***	0.8514***	-0.6047***	0.8174***	0.8789***	0.8466***	0.8744***	0.9476***	0.9661***	0.9581***	0.9782***	0.9684***	0.9748***	0.9787***	0.9803***	0.9770***
AU	0.9789***	0.8976***	0.8435***	-0.6321***	0.8089***	0.8578***	0.8426***	0.8747***	0.9368***	0.9670***	0.9578***	0.9813***	0.9823***	0.9749***	0.9825***	0.9844***	0.9800***
HK	0.9712***	0.9111***	0.8472***	-0.6422***	0.8286***	0.8765***	0.8393***	0.8757***	0.9424***	0.9583***	0.9559***	0.9779***	0.9706***	0.9740***	0.9789***	0.9822***	0.9779***
JP	0.9742***	0.8963***	0.8414***	-0.4699*	0.8129***	0.8397***	-0.8113***	0.8711***	0.9429***	0.9603***	0.9636***	0.9747***	0.9675***	0.9731***	0.9806***	0.9841***	0.9789***
NZ	0.9739***	0.8964***	0.8372***	-0.6097***	0.7903***	0.8551***	0.8307***	0.8673***	0.9418***	0.9570***	0.9554***	0.9784***	0.9708***	0.9778***	0.9776***	0.9758***	0.9760***
SING	0.9797***	0.8982***	0.8498***	-0.6755***	0.8140***	0.8756***	0.8495***	0.8679***	0.9451***	0.9718***	0.9622***	0.9839***	0.9802***	0.9737***	0.9839***	0.9876***	0.9819***
US	0.9754***	-0.5141	0.8576***	-0.5192**	-0.4532**	0.8764***	0.8502***	0.8672***	0.9408***	0.9663***	0.9583***	0.9799***	0.9695***	0.9743***	0.9716***	0.9769***	0.9779***
GER	0.9730***	0.9033***	0.8568***	-0.6710***	0.8010***	0.8657***	0.8454***	0.8679***	0.9362***	0.9605***	0.9516***	0.9747***	0.9718***	0.9706***	0.9771***	0.9780***	0.9777***
UK	0.9766***	-0.8160***	0.8590***	-0.6453***	0.8123***	0.8761***	0.8501***	0.8794***	0.9424***	0.9626***	0.9584***	0.9790***	0.9736***	0.9739***	0.9772***	0.9803***	0.9786***

Panel C: Extended-crisis period

	HS	SHA	SHB	SZA	SZB	INDO	MALAY	PHIL	THAI	AU	HK	JP	NZ	SING	US	GER	UK
HS	0.9745***	0.9406***	0.5675***	0.7007***	0.6734***	0.8937***	0.9754***	0.8077***	0.7940***	0.9797***	0.9780***	0.7635***	0.9461***	0.9664***	0.9493***	0.9807***	0.9824***
SHA	0.9852***	0.9344***	0.7169***	0.7358***	0.7519***	0.8965***	0.9570***	0.8264***	0.7934***	0.9602***	0.9923***	0.7761***	0.9064***	0.9172***	0.9438***	0.9739***	0.9760***
SHB	0.9708***	0.7868***	0.7204***	0.6830***	0.6879***	0.8891***	0.9434***	0.8185***	0.7933***	0.9559***	0.9728***	0.7656***	0.9021***	0.9280***	0.9425***	0.9753***	0.9733***
SZA	0.9922***	0.8694***	0.7355***	0.8040***	0.7270***	0.8947***	0.9562***	0.8231***	0.7876***	0.9571***	0.9783***	0.7705***	0.8886***	0.9341***	0.9415***	0.9739***	0.9719***
SZB	0.9704***	0.7657***	0.6697***	0.6832***	0.7214***	0.9031***	0.9517***	0.8335***	0.7995***	0.9641***	0.9737***	0.7668***	0.9196***	0.9368***	0.9485***	0.9823***	0.9750***
INDO	0.9667***	0.9404***	0.5527***	0.8000***	0.6792***	0.9042***	0.9552***	0.8008***	0.7836***	0.9589***	0.9734***	0.7486***	0.8502***	0.8981***	0.9430***	0.9756***	0.9775***
MALAY	0.9733***	0.9371***	0.5629***	0.7670***	0.7116***	0.8874***	0.9652***	0.8071***	0.7903***	0.9641***	0.9768***	0.7575***	0.8939***	0.9461***	0.9422***	0.9766***	0.9765***
PHIL	0.9693***	0.9382***	0.5349***	0.7894***	0.6923***	0.8801***	0.9602***	0.8055***	0.7706***	0.9621***	0.9754***	0.7463***	0.7298***	0.9012***	0.9468***	0.9749***	0.9746***
THAI	0.9725***	0.9388***	0.6277***	0.7934***	0.7239***	0.9024***	0.9621***	0.8084***	0.8112***	0.9616***	0.9787***	0.7651***	0.9159***	0.9448***	0.9459***	0.9756***	0.9734***
AU	0.9687***	0.9398***	0.4904***	0.7510***	0.6845***	0.9002***	0.9634***	0.8071***	0.8002***	0.9637***	0.9740***	0.7140***	0.9480***	0.9408***	0.9424***	0.9750***	0.9719***
HK	0.9757***	0.9456***	0.6141***	0.7241***	0.7103***	0.8964***	0.9775***	0.8123***	0.7938***	0.9784***	0.9817***	0.7541***	0.9523***	0.9588***	0.9524***	0.9788***	0.9716***
JP	0.9671***	-0.8088***	0.5612***	0.7936***	0.6970***	0.8978***	0.9634***	0.8067***	0.7936***	0.9664***	0.9760***	0.8448***	0.9301***	0.9375***	0.9386***	0.9759***	0.9741***
NZ	0.9675***	0.9391***	0.5071***	0.6564***	0.6885***	0.8840***	0.9646***	0.8165***	0.7942***	0.9632***	0.9716***	0.7037***	0.9143***	0.9346***	0.9366***	0.9778***	0.9770***
SING	0.9671***	0.9387***	0.5002***	0.7409***	0.6813***	0.8797***	0.9645***	0.7940***	0.7808***	0.9686***	0.9688***	0.7017***	0.9114***	0.9573***	0.9485***	0.9798***	0.9743***
US	-0.7390***	0.9389***	0.5626***	0.7334***	0.6991***	0.9064***	0.9643***	0.8039***	0.7932***	0.9775***	0.9769***	0.7354***	0.9421***	0.9409***	0.9527***	0.9770***	0.9687***

GER	0.9719***	0.9432***	0.5423***	0.7564***	0.7050***	0.9158***	0.9718***	0.8085***	0.8000***	0.9749***	0.9767***	0.7479***	0.9663***	0.9631***	0.9410***	0.9728***	0.9614***
UK	0.9692***	0.9401***	0.5386***	0.7673***	0.7013***	0.9124***	0.9725***	0.8068***	0.7942***	0.9763***	0.9747***	0.7267***	0.9611***	0.9554***	0.9470***	0.9783***	0.9816***

Panel D: Post-crisis period

	HS	**SHA**	**SHB**	**SZA**	**SZB**	**INDO**	**MALAY**	**PHIL**	**THAI**	**AU**	**HK**	**JP**	**NZ**	**SING**	**US**	**GER**	**UK**
HS	0.9786***	0.9930***	0.9772***	0.9894***	0.9798***	0.9758***	0.9862***	0.9452***	0.9722***	0.9888***	0.9875***	0.8709***	0.9923***	0.9896***	0.9343***	0.9461***	0.9534***
SHA	0.9928***	0.9954***	0.9743***	0.9836***	0.9688***	0.9677***	0.9855***	0.9392***	0.9739***	0.9926***	0.9965***	0.8602***	0.9978***	0.9878***	0.9246***	0.9357***	0.9498***
SHB	0.9897***	0.9936***	0.9808***	0.9912***	0.9795***	0.9685***	0.9844***	0.9504***	0.9750***	0.9948***	0.9866***	0.8731***	1.0016***	0.9894***	0.9275***	0.9483***	0.9525***
SZA	0.9933***	0.9958***	0.9748***	0.9816***	0.9749***	0.9690***	0.9852***	0.9448***	0.9722***	0.9927***	0.9939***	0.8772***	0.9995***	0.9878***	0.9246***	0.9329***	0.9506***
SZB	0.9930***	0.9955***	0.9765***	0.9902***	0.9807***	0.9674***	0.9857***	0.9449***	0.9778***	0.9963***	0.9909***	0.8570***	1.0019***	0.9889***	0.9261***	0.9434***	0.9490***
INDO	0.9746***	0.9946***	0.9782***	0.9920***	0.9793***	0.9615***	0.9764***	0.9477***	0.9632***	0.9913***	0.9850***	0.8654***	0.9945***	0.9868***	0.9310***	0.9503***	0.9553***
MALAY	0.9810***	0.9921***	0.9739***	0.9906***	0.9749***	0.9590***	0.9835***	0.9536***	0.9697***	0.9905***	0.9887***	0.8639***	0.9914***	0.9867***	0.9268***	0.9499***	0.9512***
PHIL	0.9680***	0.9946***	0.9777***	0.9919***	0.9788***	0.9511***	0.9802***	0.9496***	0.9644***	0.9944***	0.9787***	0.7700***	0.6360***	0.9851***	0.9257***	0.9456***	0.9511***
THAI	0.9740***	0.9940***	0.9798***	0.9911***	0.9804***	0.9534***	0.9784***	0.9500***	0.9645***	0.9927***	0.9830***	0.8452***	0.7665***	0.9860***	0.9248***	0.9379***	0.9434***
AU	0.9920***	0.9937***	0.9795***	0.9917***	0.9803***	0.9821***	0.9905***	0.9632***	0.9839***	0.9899***	0.9931***	0.9327***	-0.3322	0.9966***	0.9416***	0.9635***	0.9700***
HK	0.9758***	0.9938***	0.9769***	0.9882***	0.9787***	0.9776***	0.9861***	0.9437***	0.9731***	0.9876***	0.9853***	0.8531***	0.9926***	0.9892***	0.9271***	0.9422***	0.9522***
JP	0.9522***	0.9944***	0.9772***	0.9917***	0.9766***	0.9562***	0.9815***	0.9421***	0.9693***	0.9881***	0.9812***	0.9151***	0.9888***	0.9853***	0.9267***	0.9407***	0.9432***
NZ	0.9822***	0.9957***	0.9840***	0.9944***	0.9841***	0.9740***	0.9879***	0.9586***	0.9761***	0.9931***	0.9931***	0.8920***	-0.1050	0.9902***	0.9243***	0.9472***	0.9514***
SING	0.9777***	0.9909***	0.9740***	0.9896***	0.9742***	0.9718***	0.9781***	0.9523***	0.9716***	0.9869***	0.9855***	0.8560***	0.9900***	0.9881***	0.9291***	0.9481***	0.9488***
US	0.9786***	0.9927***	0.9809***	0.9903***	0.9800***	0.9698***	0.9830***	0.9579***	0.9726***	0.9887***	0.9818***	0.9404***	0.9880***	0.9876***	0.9329***	0.9414***	0.9506***
GER	0.9727***	0.9923***	0.9775***	0.9911***	0.9770***	0.9708***	0.9855***	0.9472***	0.9710***	0.9880***	0.9839***	0.8807***	0.9924***	0.9891***	0.9200***	0.9408***	0.9396***
UK	0.9731***	0.9911***	0.9759***	0.9907***	0.9773***	0.9674***	0.9828***	0.9471***	0.9708***	0.9849***	0.9825***	0.8815***	0.9844***	0.9882***	0.9253***	0.9418***	0.9585***

Note*:* *, ** and *** indicate significance at 10%, 5% and 1% level. Null hypothesis: the coefficient equals zero. Endogenous variables are in the first row. Each column presents the coefficients of the bivariate tests between that country (as the endogenous variable) and other countries (as the exogenous variables) in the sample. Equations for the spillover from China and to China are $H = \log(\sigma^2_{C,t}) = \omega + \sum_{i=1}^{q} \theta_j \left(\left| \frac{\epsilon_{t-1}}{\sigma_{t-1}} \right| - E \left| \frac{\epsilon_{t-1}}{\sigma_{t-1}} \right| \right) + \sum_{j=1}^{r} \gamma_k \frac{\epsilon_{t-1}}{\sigma_{t-1}} + \sum_{j=1}^{q} \alpha_j \log(\sigma^2_{C,t-1}) + \sum_{j=1}^{q} \tau_{i,R} \log(\sigma^2_{R,t})$ and $H = \log(\sigma^2_{R,t}) = \omega + \sum_{i=1}^{q} \theta_j \left(\left| \frac{\epsilon_{t-1}}{\sigma_{t-1}} \right| - E \left| \frac{\epsilon_{t-1}}{\sigma_{t-1}} \right| \right) + \sum_{j=1}^{r} \gamma_k \frac{\epsilon_{t-1}}{\sigma_{t-1}} + \sum_{j=1}^{q} \alpha_j \log(\sigma^2_{R,t-1}) + \sum_{j=1}^{q} \tau_{i,C} \log(\sigma^2_{C,t})$ respectively. $\tau_{i,R}$ and $\tau_{i,C}$ represent the spillover to and from China respectively.

Table 3-10. Summary of the volatility spillover coefficients $\tau_{i,R}$ and $\tau_{i,C}$ in the variance equations of the univariate EGARCH(1,1) with spillover factor for each pair of countries

Panel A: Pre-GFC period

	HS	SHA	SHB	SZA	SZB	INDO	MALAY	PHIL	THAI	AU	HK	JP	NZ	SING	US	GER	UK
HS		0.0109	0.0625*	0.0144	0.0075	-0.0003	0.0635***	0.0417	-0.0392	-0.0574***	-0.0289	-0.0512***	-0.0531**	-0.0026	-0.0057	0.0117	-0.0028
SHA	0.0259		0.1541***	0.1031***	0.1511***	0.0852***	0.0678**	0.0563***	0.0824**	0.0578**	0.0783***	-0.0122	0.0977**	0.0471**	0.0129	0.0317**	0.0392**
SHB	0.0272	0.0733***		0.0794***	0.1322***	0.0897***	0.0509**	0.0296	0.0476	-0.0009	0.0470**	-0.0034	0.0844	0.0509***	0.0121**	0.0284*	0.0290
SZA	0.0248	0.1344***	0.1490***		0.1469***	0.0833***	0.0694**	0.0417**	0.0724*	0.0573**	0.0707***	-0.0189	0.1239***	0.0491**	0.0214*	0.0403**	0.0419**
SZB	0.0440***	0.0992***	0.1844***	0.0811***		0.1237***	0.0874***	0.0345	0.0589	0.0414	0.0796***	0.0154	0.0606	0.0745***	0.0177***	0.0402**	0.0437**
INDO	0.0022	0.0272	0.0657*	0.0286	0.0198		0.0704***	0.0126	-0.0488	-0.0538***	0.0306	-0.0128	-0.1024***	-0.0100	0.0253	0.0362*	0.0308*
MALAY	0.0262	0.0156	0.0729**	0.0205	0.0646**	-0.0264		0.1530***	-0.0172	-0.0204	-0.0109	-0.0280*	-0.0317	0.0256	0.0271**	-0.0077	0.0024
PHIL	0.0221	0.0753***	0.1183***	0.0706***	0.1096***	-0.0524*	0.0781***		0.0130	-0.0340	0.0032	-0.0228	-0.0366**	0.0291	-0.0098	-0.0280	0.0141
THAI	0.0112	0.0032	0.0338	0.0003	0.0037	-0.0254	0.0156	0.0105		-0.0503*	0.0078	0.0183	-0.0274	0.0093	0.0137	0.0281	0.0232
AU	-0.0020	0.0769***	0.0726*	0.0699**	0.0568	-0.0185	0.0967***	0.0277	0.0043		-0.0150	-0.0718***	-0.0878***	0.0081	0.0491***	0.0256	0.0214
HK	-0.0001	0.0830*	0.0890**	0.0184	0.0457	0.0322	0.1088***	0.0146	0.0129	-0.0364		-0.0237	-0.0490*	0.0417*	0.0088	0.0330*	0.0429**
JP	0.0121	-0.0058	0.0261	-0.0071	0.0072	-0.0486*	0.0546*	0.0090	0.0200	-0.0972***	-0.0059		-0.0577*	-0.0351	0.0175	0.0094	0.0220
NZ	0.0244	0.0572**	0.0490	0.0405	0.0390	-0.0367*	0.0758***	-0.1583***	0.0592*	-0.0802***	0.0338	-0.0563***		0.0295	0.0218**	0.0092	0.0153
SING	0.0739***	0.0117	0.0800**	0.0081	0.0821***	-0.0384*	0.1102***	0.0823***	0.0031	-0.0529**	-0.0017	-0.0459**	-0.0624**		0.0248	0.0050	0.0333*
US	-0.0383	0.0053	-0.0070	-0.0124	-0.0634*	-0.0826***	0.0094	0.0320	-0.0093	-0.0927***	-0.0864***	-0.0814***	-0.0790***	-0.0452		-0.0997***	-0.0607**
GER	0.0022	0.0052	0.0171	-0.0094	-0.0039	-0.0116	0.0518	0.0546*	0.0303	-0.0322	-0.0094	-0.0482**	-0.0512*	-0.0020	0.0116		0.0142
UK	0.0149	0.0210	0.0071	0.0089	-0.0202	0.0125	0.0441*	0.1000***	-0.0062	-0.0424	-0.0078	-0.0439**	-0.0522**	0.0050	0.0183	0.0212	

Panel B: GFC period

	HS	SHA	SHB	SZA	SZB	INDO	MALAY	PHIL	THAI	AU	HK	JP	NZ	SING	US	GER	UK
HS		-0.0472*	-0.1067**	0.0471	-0.1312**	-0.0011	-0.0416	-0.0351	-0.0714*	-0.1809***	0.0000***	-0.1178***	-0.0905**	0.0092	-0.0319	-0.1439***	-0.0825**
SHA	-0.0413		-0.1572***	-0.1631***	-0.1154**	0.0457	-0.0184	-0.0558	-0.0110	-0.0128	-0.0860**	-0.0571*	0.0066	0.0299	0.0360	0.0449	0.0437
SHB	-0.0381	-0.0846***		-0.1293***	-0.0601	0.0425	-0.0220	-0.0802*	-0.0272	-0.0249	-0.0531*	-0.0442	0.0049	-0.0073	0.0181	0.0226	0.0183
SZA	-0.0264	-0.1108**	-0.1710***		-0.0905*	0.0884	0.0257	-0.0101	0.0003	-0.0074	-0.0532	-0.0331	0.0181	0.0395	0.0324	0.0597	0.0247

SZB	-0.0509	-0.0959***	-0.0831**	-0.1366***		0.0458	-0.0222	-0.1347***	-0.0198	-0.0706*	-0.0572*	-0.0701**	-0.0241	-0.0259	0.0212	-0.0129	-0.0032
INDO	-0.0204	-0.0671**	-0.1365***	0.0574	-0.1038**		0.0052	-0.0058	0.0424	-0.0978***	-0.0308	-0.0692***	-0.0468	0.1139***	0.0128	-0.0954***	-0.0020
MALAY	-0.0429	-0.0121	-0.1045*	0.0568	-0.1071*	-0.0375		-0.0655	0.0136	-0.0957**	-0.0388	-0.0921***	-0.0696*	0.0352	-0.0005	-0.0385	-0.0200
PHIL	-0.0430	-0.0379	-0.1716***	0.0799	-0.2061***	0.0245	-0.0614		0.0306	-0.1134***	-0.0244	-0.0644**	-0.0554	0.0244	-0.0001	-0.0341	-0.0436
THAI	-0.0780***	-0.0330	-0.0756	0.0186	-0.0794	-0.0191	-0.0298	-0.0263		-0.0951***	-0.0665**	-0.0805***	-0.0690**	-0.0070	-0.0350	-0.1031***	-0.0418
AU	-0.1276***	-0.0570*	-0.1434**	0.0318	-0.1583**	-0.0718*	-0.0524	-0.0464	-0.0907**		-0.1228***	-0.1394***	-0.1406***	-0.0008	-0.0639*	-0.1461***	-0.0534*
HK	-0.1553***	-0.0472*	-0.1165**	0.0296	-0.1658***	0.0031	-0.0579	-0.0221	-0.0646*	-0.1889***		-0.1115***	-0.0927**	-0.0176	-0.0453	-0.1227***	-0.0812**
JP	-0.1657***	-0.0914**	-0.2368***	-0.0907	-0.1835**	-0.1201**	-0.1469***	-0.0347	-0.0677	-0.1984***	-0.1372***		-0.1100***	-0.0626	-0.0487	-0.1741***	-0.0836**
NZ	-0.0829***	-0.0447	-0.1285	0.0653	-0.1673**	-0.0585	-0.0580	-0.0138	-0.0409	-0.1535***	-0.0756**	-0.1014***		0.0379	-0.0647**	-0.1073***	-0.0588**
SING	-0.0923***	-0.0525	-0.1441**	0.0558	-0.1489***	0.0200	-0.0151	0.0138	-0.0421	-0.1242***	-0.0865***	-0.0909***	-0.0841***		-0.0694**	-0.1928***	-0.0727**
US	-0.1074***	0.1007	-0.0196	0.1528	0.1895***	0.0400	-0.0327	0.0214	-0.0552	-0.1410***	-0.0929**	-0.1022***	-0.1219***	-0.0189		-0.1701***	-0.1030***
GER	-0.1230***	-0.0219	-0.0800	0.1063	-0.0872	-0.0329	-0.0296	-0.0122	-0.0668**	-0.1787***	-0.1035***	-0.1403***	-0.1283***	-0.0934**	-0.1387***		-0.1159***
UK	-0.1274***	0.1126*	-0.0449	0.1636**	-0.0607	-0.0253	-0.0451	-0.0523	-0.0489	-0.2223***	-0.1034***	-0.1343***	-0.1915***	-0.0753	-0.1709***	-0.1983***	

Panel C: Extended-crisis period

	HS	SHA	SHB	SZA	SZB	INDO	MALAY	PHIL	THAI	AU	HK	JP	NZ	SING	US	GER	UK
HS		-0.0248	-0.1523**	-0.1028	-0.1421**	-0.1175***	-0.1009***	-0.0107	0.0106	-0.0913***	-0.0798**	-0.0075	-0.0922***	-0.1523***	-0.0549	-0.0369	-0.0404**
SHA	0.0581***		-0.3469***	-0.2557***	-0.2769***	-0.1256***	-0.0620**	-0.0685	0.0018	-0.0406	0.0493***	-0.0411	-0.0700***	-0.0759**	-0.0521	-0.0306	-0.0065
SHB	-0.0001	-0.1916***		-0.2821***	-0.1273***	-0.0951***	-0.0893***	-0.0500	-0.0248	-0.0414	-0.0179	-0.0181	-0.0401	-0.0715***	-0.0479	-0.0332	0.0005
SZA	0.0448***	-0.2586***	-0.3938***		-0.3346***	-0.1056**	-0.0412	-0.0716	0.0199	-0.0289	0.0058	-0.0150	-0.0662**	-0.0473	-0.0434	-0.0269	-0.0003
SZB	-0.0015	-0.1825***	-0.2105***	-0.2815***		-0.0974***	-0.0969***	-0.0589	-0.0224	-0.0294	-0.0171	-0.0038	-0.0333	-0.0674**	-0.0525*	-0.0336**	-0.0100
INDO	-0.0276	0.0105	-0.1133	-0.0076	-0.1097*		-0.0651*	-0.1207***	-0.0250	-0.0367	-0.0212	-0.0597	-0.1054**	-0.1185***	-0.0312	0.0026	-0.0075
MALAY	-0.0544*	-0.0351	-0.0934	-0.0538	-0.0968*	-0.1127***		-0.0047	-0.0065	-0.0400	-0.0398	-0.0824	-0.1018**	-0.1150***	-0.0377	-0.0124	-0.0113
PHIL	-0.0089	-0.0025	-0.1105	-0.0356	-0.0726	-0.1822***	-0.0679**		-0.0531	-0.0128	-0.0077	-0.0492	-0.1201**	-0.1020***	-0.0373	0.0159	-0.0092
THAI	0.0198	-0.0003	-0.1095*	-0.0347	-0.0548	-0.0608	-0.0149	0.0042		-0.0035	0.0210	-0.0236	-0.0509	-0.0439	-0.0422	-0.0025	-0.0103
AU	-0.0561*	-0.0094	-0.1533**	-0.0541	-0.0831	-0.1350***	-0.0368	-0.0144	0.0156		-0.0426	-0.1502***	-0.1222***	-0.1318***	-0.0922**	-0.0146	-0.0028
HK	-0.0634*	-0.0496	-0.1769***	-0.1163*	-0.1525**	-0.1257***	-0.1041***	-0.0279	-0.0005	-0.0885***		-0.0344	-0.0984***	-0.1190***	-0.0602	-0.0328	-0.0404**
JP	-0.0306	-0.1762***	-0.0960	-0.0145	-0.0335	-0.0476	-0.0065	0.0125	-0.0140	-0.0754**	-0.0052		-0.0762**	-0.0778**	-0.0487	-0.0380	-0.0328
NZ	-0.0307	0.0027	-0.1529**	-0.1151**	-0.0951	-0.0949**	-0.0275	0.0211	0.0022	-0.0634*	-0.0324	-0.1157***		-0.1062***	-0.0548	0.0287	0.0022
SING	-0.0916***	-0.0025	-0.1069	-0.0515	-0.0788	-0.1333***	-0.1012***	-0.0778*	-0.0355	-0.0836***	-0.0849**	-0.0925*	-0.1009***		-0.0921**	-0.0399	-0.0188

US	0.1387***	-0.0026	-0.1157	-0.0655	-0.0293	-0.1113***	-0.0552	0.0300	0.0566	-0.1609***	-0.0317	-0.1323***	-0.1217***	-0.1215***		-0.1183***	-0.1118***
GER	-0.0659**	-0.0223	-0.0662	-0.0562	-0.0284	-0.1330***	-0.0687**	-0.0005	0.0287	-0.1116***	-0.0477	-0.1241***	-0.1194***	-0.1054***	-0.1464***		-0.1050***
UK	-0.0614*	-0.0113	-0.0570	-0.0409	-0.0190	-0.1477***	-0.1130***	0.0048	-0.0051	-0.1289***	-0.0569*	-0.1217***	-0.1244***	-0.1292***	-0.1189***	-0.0958***	

Panel D: Post-crisis period

	HS	**SHA**	**SHB**	**SZA**	**SZB**	**INDO**	**MALAY**	**PHIL**	**THAI**	**AU**	**HK**	**JP**	**NZ**	**SING**	**US**	**GER**	**UK**
HS		-0.0442**	-0.0376*	-0.0485**	-0.0457*	-0.0678***	-0.0288	-0.0677***	-0.0340	-0.0285**	-0.0547**	-0.1186***	-0.0285**	-0.0357**	-0.0567***	-0.0676***	-0.0874***
SHA	0.0229***		-0.0773***	-0.0867***	-0.1141***	-0.0326	0.0034	-0.0376*	0.0068	0.0045	0.0469***	-0.0649**	0.0068	-0.0085	-0.0104	-0.0326*	-0.0337*
SHB	0.0335***	0.0402*		-0.0385*	-0.0432**	0.0018	0.0294*	0.0055	0.0557***	0.0220***	0.0556***	-0.0571*	0.0331***	0.0071	0.0239	0.0126	0.0073
SZA	0.0319***	-0.0222	-0.1150***		-0.1277***	0.0060	0.0181	-0.0266	0.0280	0.0084	0.0442***	-0.0445	0.0312***	-0.0136	-0.0091	-0.0332	-0.0115
SZB	0.0309***	0.0185	-0.0458***	-0.0311*		-0.0107	0.0055	-0.0132	0.0336*	0.0172***	0.0498***	-0.0546*	0.0247***	0.0002	0.0006	-0.0075	-0.0150
INDO	-0.0336*	-0.0192	-0.0459	-0.0147	-0.0228		-0.0856***	-0.0831***	-0.1084***	0.0017	-0.0365**	-0.0617*	-0.0209	-0.0247	-0.0357	-0.0292	-0.0585**
MALAY	-0.0421**	-0.0426**	-0.0678**	-0.0300*	-0.0479**	-0.0979***		-0.0833***	-0.0794***	-0.0222*	-0.0347**	-0.0856***	-0.0527***	-0.0463**	-0.0052	-0.0443**	-0.0633***
PHIL	-0.0390**	-0.0221	-0.0479**	-0.0162	-0.0299	-0.1003***	-0.0341		-0.0685***	0.0344***	-0.0342*	-0.1765***	-0.1448***	-0.0314	-0.0421*	-0.0157	-0.0252
THAI	-0.0389**	-0.0266	-0.0591**	-0.0330**	-0.0333	-0.0961***	-0.0604***	-0.0638***		0.0393***	-0.0322**	-0.0734**	-0.1411***	-0.0440**	-0.0708***	-0.0648**	-0.1033***
AU	-0.0759***	-0.0599***	-0.0558*	-0.0609***	-0.0681**	-0.0863***	-0.0745***	-0.1123***	-0.0929***		-0.0730***	-0.1135***	-0.1183***	-0.0773***	-0.1048***	-0.0908***	-0.1259***
HK	-0.0383*	-0.0366*	-0.0391*	-0.0548***	-0.0418*	-0.0576***	-0.0131	-0.0469**	-0.0099	-0.0279**		-0.1256***	-0.0197	-0.0258*	-0.0232	-0.0537**	-0.0573***
JP	-0.0843***	-0.0293	-0.0360	-0.0170	-0.0576*	-0.1143***	-0.0506**	-0.1283***	-0.0412	-0.0236	-0.0202		-0.0413*	-0.0588**	-0.0792**	-0.1027***	-0.1649***
NZ	-0.0491***	-0.0494***	-0.0633**	-0.0451***	-0.0551**	-0.0363	-0.0329	-0.0718***	-0.0593**	-0.0238	-0.0487***	-0.0543*		-0.0148	-0.0385	-0.0189	-0.0772***
SING	-0.0762***	-0.0487**	-0.0562*	-0.0330*	-0.0484*	-0.1084***	-0.0987***	-0.1046***	-0.0831***	-0.0417**	-0.0640***	-0.1416***	-0.0550***		-0.0591**	-0.0583**	-0.1064***
US	-0.0919***	-0.0481*	-0.0637*	-0.0399	-0.0484	-0.1095***	-0.0717***	-0.1176***	-0.0643**	-0.0609***	-0.0624***	-0.1167***	-0.0764***	-0.0696***		-0.1480***	-0.1933***
GER	-0.0712***	-0.0421**	-0.0420	-0.0202	-0.0391	-0.0747***	-0.0110	-0.0465**	-0.0417*	-0.0396**	-0.0374*	-0.1023***	-0.0443**	-0.0485**	-0.1039***		-0.1559***
UK	-0.0982***	-0.0525**	-0.0587*	-0.0238	-0.0475	-0.0917***	-0.0537*	-0.0830***	-0.0673***	-0.0667***	-0.0651***	-0.1438***	-0.0788***	-0.0572**	-0.1304***	-0.1753***	

Note: *, ** and *** indicate significance at 10%, 5% and 1% level. Null hypothesis: the volatility spillover coefficient equals zero. Endogenous variables are in the first row. Each column presents the coefficients of the bivariate tests between that country (as the endogenous variable) and other countries (as the exogenous variables) in the sample. Equations for the spillover from China and to China are $H = \log(\sigma^2_{C,t}) = \omega + \sum_{i=1}^{q} \theta_j \left(\left|\frac{\epsilon_{t-1}}{\sigma_{t-1}}\right| - E\left|\frac{\epsilon_{t-1}}{\sigma_{t-1}}\right|\right) + \sum_{j=1}^{r} \gamma_k \frac{\epsilon_{t-1}}{\sigma_{t-1}} + \sum_{j=1}^{q} \alpha_j \log(\sigma^2_{C,t-1}) + \sum_{j=1}^{q} \tau_{i,R} \log(\sigma^2_{R,t})$ and $H = \log(\sigma^2_{R,t}) = \omega + \sum_{i=1}^{q} \theta_j \left(\left|\frac{\epsilon_{t-1}}{\sigma_{t-1}}\right| - E\left|\frac{\epsilon_{t-1}}{\sigma_{t-1}}\right|\right) + \sum_{j=1}^{r} \gamma_k \frac{\epsilon_{t-1}}{\sigma_{t-1}} + \sum_{j=1}^{q} \alpha_j \log(\sigma^2_{R,t-1}) + \sum_{j=1}^{q} \tau_{i,C} \log(\sigma^2_{C,t})$ respectively. $\tau_{i,R}$ and $\tau_{i,C}$ represent the spillover to and from China respectively.

3.8. Robustness tests

This section examines whether the squared standardised residuals from the estimated equations **(3.5)** and **(3.6)** still exhibit serial correlations and heteroskedasticity using serial correlation and White tests, as discussed in section 2.3.4 and section 2.3.5. All tests were conducted at five lags because all markets in the sample have autocorrelations within the first five lags, as discussed in section 2.3.4. The results from these tests, as presented **Table 3-11**, indicate the robustness of the model.

Serial correlations disappeared in the residuals of all Chinese equities and many other markets in the sample, in the pre-GFC period. During the GFC, serial correlations were still significant for HS-HK, HS-Singapore and between SHB and a number of other markets. However, in the extended-crisis period, none of China's markets were found with serial correlation. In the post-crisis period, SHB was the only market where serial correlation was found (at five lags). This indicates that EGARCH(1,1) might not be the best model to adequately account for serial correlations for SHB during the GFC and in the post-crisis period. So, the study ran the EGARCH model for SHB from one to five lags and found that the best lag length, based on the AIC for SHB in the pre-GFC period and extended-crisis period, is one, while it is four during the GFC and five in the post-crisis period. Hence, the study ran an EGARCH model at four lags and five lags for SHB in these periods respectively. The study found that the serial correlation of the residuals disappeared significantly, implying that the daily return volatility of SHB was impacted by not only the previous stock return at one lag, but also at four to five-day lags in some periods. With regards to heteroskedasticity, the result looks satisfactory, as heteroskedasticity was not detected in any of China's markets or in most other studied markets over the four sub-periods, reinforcing the robustness of the model. In conclusion, accepting the fact that there is no single perfect model for all markets, the results are reasonably favourable, implying that EGARCH (1,1) is a parsimonious model for describing the unobserved volatility of daily stock returns in these markets.

Table 3-11. Summary of t-statistics of serial correlation and White tests at 5 lags for the EGARCH (1,1) residuals for each market in the sample – full sample

Panel A: Pre-GFC period

	HS	SHA	SHB	SZA	SZB	INDO	MALAY	PHIL	THAI	AU	HK	JP	NZ	SING	US	GER	UK
HS	0.0009	0.1976	0.3313	0.0950	0.5429	0.5199	0.5962	1.1053	0.0932	0.2996	1.1341	0.0088	0.8785	0.0000	1.4596	0.6730	0.0246
SHA	1.0005	4.9885**	0.0552	1.9664	0.0198	0.0264	0.0129	0.0068	0.0053	0.7870	0.4057	0.2486	0.2280	0.3345	0.4628	0.8902	0.0000
SHB	0.1280	0.9100	3.7050*	0.0444	0.0475	0.0521	0.6771	0.0083	0.0139	0.8507	0.5452	0.3085	0.1812	0.4260	1.0714	0.9439	0.0167
SZA	2.5844	0.5946	0.1007	4.5577**	0.1160	0.0678	0.0004	0.0241	0.0104	0.8657	0.4102	0.2715	0.1715	0.3404	0.3413	0.8209	0.0074
SZB	0.1590	0.6203	3.7038*	0.3365	0.5211	0.0922	0.2721	0.0085	0.0080	0.6796	0.5743	0.4402	0.0073	0.2276	0.3563	0.7131	0.0188
INDO	0.7229	0.2468	0.2093	0.0918	0.8399	0.1923	0.8441	0.0490	0.0432	0.0004	0.7112	0.1872	0.0710	0.9420	1.2489	0.8667	0.0093
MALAY	0.1564	0.2488	0.4273	0.1672	0.7307	0.0914	0.8300	1.5428	0.0594	0.2287	0.4406	0.4044	0.1567	0.1238	0.5235	0.8155	0.0043
PHIL	0.2973	0.2968	0.2787	0.1357	0.4937	0.0529	0.3914	0.0089	0.0175	0.2061	0.4355	0.4809	0.0727	0.7014	1.1109	0.7487	0.0108
THAI	0.0443	0.1815	0.1951	0.1122	0.1311	0.0342	0.4445	0.0009	13.2455***	0.0667	0.4340	0.0039	0.5436	0.2299	0.5957	0.9115	0.0007
AU	0.1981	0.2091	0.3393	0.1212	0.6447	0.5758	0.6168	0.0621	0.1190	3.4949*	0.6287	0.1114	0.7930	0.9935	1.3621	0.8320	0.0922
HK	0.0967	0.1952	0.2965	0.1102	0.3635	0.0058	0.0231	1.4288	0.0275	0.1509	2.5124	0.3507	0.1378	0.3475	0.6179	0.7529	0.1028
JP	0.8719	0.2333	0.7189	0.1457	0.8703	0.5917	0.2444	0.5034	0.0323	0.4624	0.7000	5.4733**	0.4959	1.6075	1.1958	0.7898	0.0078
NZ	0.4366	0.3721	0.3506	0.2160	0.5144	0.3430	0.2634	2.2939	0.0640	0.1970	0.5316	1.1121	2.7200*	1.2849	1.1760	1.1405	0.0366
SING	0.5836	0.3227	0.3811	0.2062	1.0214	0.5370	0.0290	2.1020	0.0881	0.0330	0.1472	0.0111	0.0863	2.9854*	0.9876	0.4007	0.0014
US	0.3596	0.1750	0.3219	0.1417	0.3513	0.1119	0.1701	0.0317	0.0152	1.3919	0.8120	0.4890	0.2171	0.5337	42.0945***	1.1413	0.3296
GER	0.0126	0.3110	0.3056	0.1800	0.6970	0.0267	0.2058	0.0175	0.1025	0.3864	0.9608	1.0127	0.4622	0.4232	2.0235	21.5818***	0.2937
UK	0.1760	0.3117	0.3633	0.1698	0.8782	0.0263	0.0381	0.5288	0.1166	0.3480	1.1774	0.2984	0.6380	0.5054	1.7270	0.8369	36.0440***

Panel B: GFC period

	HS	SHA	SHB	SZA	SZB	INDO	MALAY	PHIL	THAI	AU	HK	JP	NZ	SING	US	GER	UK
HS	12.3531***	0.2160	0.1429	0.5464	0.0618	0.0398	0.4098	0.4388	0.0001	0.8371	6.3153**	0.0072	0.7693	0.2372	0.0230	0.8005	1.2043
SHA	0.5587	1.7628	3.0779*	1.2102	0.0000	0.1689	0.4215	0.0140	0.5219	0.1368	1.2864	0.4064	0.0333	0.8806	0.0010	0.6359	0.8742
SHB	0.4202	1.8713	0.0027	0.1710	0.1222	0.1888	0.0934	0.0286	0.5586	0.1065	0.6483	0.6205	0.0334	0.8851	0.0104	0.3771	0.8146
SZA	0.4451	0.3302	2.0412	1.8563	0.1021	0.1265	0.4132	0.0125	0.3167	0.0533	0.9948	0.5860	0.0357	1.7498	0.0277	0.3719	0.6105

SZB	0.5293	0.1956	1.1930	0.0206	0.6159	0.2335	0.3405	0.0101	0.6192	0.0963	0.9215	0.3372	0.0326	0.5794	0.0001	0.3858	0.8188
INDO	1.7308	0.9629	0.1324	0.3077	0.0348	0.0617	0.8222	0.1657	0.0906	0.2288	1.3793	0.0169	0.0100	1.4897	0.0246	1.0870	0.9115
MALAY	1.4631	0.6385	0.3918	0.1201	0.2779	0.0429	2.6484	0.3009	0.0045	1.0683	1.0556	0.3652	0.5480	0.6764	0.0068	0.4758	1.1167
PHIL	0.7280	0.3985	0.1793	0.0136	0.0680	0.4650	1.3239	0.3610	0.0070	0.0563	0.0329	0.0013	0.7926	0.5117	0.0130	0.9592	1.6535
THAI	2.3651	0.2990	0.2157	0.5332	0.0749	0.5169	0.0001	0.0784	10.6773***	0.0596	2.7556*	0.9408	0.9303	0.0241	0.0088	1.9363	1.8861
AU	1.7450	0.0631	0.1790	0.0592	0.2227	0.3739	2.1424	0.0448	0.6623	6.4876**	2.3459	0.8142	0.1295	0.2391	0.1510	2.1275	2.0372
HK	4.6930**	0.2992	0.0241	0.1837	0.0133	0.0757	0.1082	0.3918	0.0034	0.7856	16.9946***	0.0136	0.7012	0.0258	0.0032	0.8885	1.1554
JP	2.1340	0.0000	0.1602	0.6754	0.2229	0.2813	0.1889	0.0005	0.1220	1.3864	2.6453	15.7454***	1.1597	0.8316	0.2155	1.7981	1.3417
NZ	0.6112	0.2692	0.0880	0.0103	0.0250	0.3392	0.0009	0.2099	0.7221	0.0828	0.2599	0.4114	4.5462**	1.4019	0.0171	1.8252	1.9869
SING	1.7256	0.7798	0.1001	0.0529	0.1307	0.0004	0.2265	0.4824	0.0825	0.3179	2.0709	0.1192	0.6548	4.1911**	0.0632	0.9954	1.3577
US	0.5969	0.2892	0.0638	0.0629	0.0015	0.3284	0.2495	0.0013	0.0640	0.1640	0.6882	0.2723	0.0758	0.1135	6.4288**	1.9364	2.0162
GER	0.9530	0.4568	0.0567	0.0200	0.0138	0.1494	0.0024	0.0255	0.0008	0.4016	1.6392	0.8236	0.0115	0.4002	0.6363	4.0877**	2.3850
UK	1.1626	0.2227	0.0826	0.0033	0.0000	0.3421	0.0320	0.0581	0.1888	0.1653	0.9443	0.2195	0.8764	0.0817	0.1335	0.1882	2.9934*

Panel C: Extended-crisis period

	HS	SHA	SHB	SZA	SZB	INDO	MALAY	PHIL	THAI	AU	HK	JP	NZ	SING	US	GER	UK
HS	4.9684**	1.9217	0.2371	2.5311	0.7521	0.7126	0.5432	1.3908	0.5470	0.0011	3.1816*	0.4515	2.0524	0.1674	3.2427*	2.0912	2.5976
SHA	0.1407	2.3252	0.0647	1.0973	0.2628	0.4092	0.2211	0.6985	0.3484	0.2221	0.0118	0.0938	0.3669	0.7367	4.5860**	1.4615	0.8173
SHB	0.1184	0.2564	13.4579***	0.3497	0.0131	0.5096	0.2281	0.0751	0.2861	0.2709	0.7984	0.1666	1.2424	0.2863	4.4822**	1.0110	0.4480
SZA	0.1311	0.0017	0.0550	2.0229	0.2158	0.2008	0.2180	0.3891	0.6015	0.2580	0.0026	0.0175	1.6713	0.3042	4.2571**	1.1921	0.5786
SZB	0.1780	0.0000	0.0008	0.6104	1.7055	0.2907	0.2072	0.2891	0.2898	0.2849	0.0783	0.2184	1.4354	0.7323	4.5982**	1.1176	1.2731
INDO	1.0629	1.4890	0.2726	2.0422	0.6964	38.0207***	0.6328	0.5173	0.3549	0.1904	2.8735*	0.4694	0.4994	0.5409	4.8116**	2.2358	2.8482*
MALAY	0.1075	1.2468	0.2159	1.6789	0.4627	0.4908	8.0683***	0.0156	0.2476	0.3547	0.0868	0.8085	4.5865**	0.7375	4.7659**	1.6885	1.8823
PHIL	0.0179	1.9486	0.3283	2.1099	1.3190	0.9810	0.0399	0.3471	0.1575	0.2786	0.0492	0.2262	2.2977	1.0562	4.8247**	1.8904	0.5004
THAI	0.0000	2.0805	0.3112	1.8247	1.0149	0.5840	0.1508	1.9685	7.8144***	0.0139	0.1893	0.6166	2.2911	0.1544	4.4456**	1.8052	0.8756
AU	0.0918	1.8266	0.2932	1.9349	0.6212	0.4392	0.9057	1.0924	0.7225	4.1284**	0.3562	0.1156	13.8660***	0.1078	5.4191**	3.2241*	3.3940*
HK	1.7070	0.3174	0.1869	2.3821	0.4364	0.8520	1.0011	1.5568	0.1261	0.2069	5.9328**	0.5984	2.1170	1.9283	4.6813**	2.1635	2.3631
JP	0.7668	1.4026	0.2949	1.4893	0.3904	0.3053	0.0810	1.1351	0.1244	0.3382	0.3619	0.0003	2.0909	0.5853	4.9216**	1.9691	1.7203

NZ	1.2849	1.3385	0.3063	1.8338	0.9871	1.2534	0.0266	1.0808	0.0797	0.0496	0.2304	0.0171	1.3433	2.2825	5.2565**	0.0006	2.4973
SING	0.0046	1.5122	0.2681	1.7335	0.4664	1.2553	0.4288	0.7586	0.9261	0.5431	0.4427	0.2501	7.7026***	0.2024	5.7311**	3.0802*	2.7894*
US	0.6907	1.3887	0.2848	1.8260	0.6907	1.0274	0.0429	0.5859	0.2535	0.3374	0.0976	0.1414	1.5166	2.3857	3.8471**	0.1101	0.0560
GER	0.5621	1.4705	0.2441	1.5606	0.5778	1.1116	0.0266	0.6575	0.2106	0.1527	0.1958	0.0218	3.4751*	2.1506	5.7959**	12.4235***	0.0287
UK	1.2147	1.3654	0.2465	1.6514	0.6801	1.1863	0.1594	0.5534	0.3161	0.1475	0.5444	0.0204	3.2517*	0.3224	1.9759	0.6956	6.3782**

Panel D: Post-crisis period

	HS	SHA	SHB	SZA	SZB	INDO	MALAY	PHIL	THAI	AU	HK	JP	NZ	SING	US	GER	UK
HS	9.3476***	0.0761	0.0121	0.0167	0.3095	0.0011	0.0000	1.4731	0.2526	2.4606	0.0130	0.0125	0.5080	4.5840**	0.1145	0.0951	0.1040
SHA	1.3602	18.3130***	0.0100	2.3747	0.0001	0.0109	0.8054	1.3798	0.3058	0.3277	0.9197	0.0380	0.1345	1.1923	0.1274	0.0049	0.3027
SHB	1.1654	1.8623	8.2160***	3.1299*	5.3059**	0.0079	0.0376	1.1913	0.1475	0.2112	0.2286	0.0039	1.0182	0.8495	0.0001	0.0800	0.0894
SZA	1.1720	2.0771	0.0017	24.5152***	0.0002	0.0110	0.0661	1.2536	0.2745	0.4857	1.0760	0.0915	0.1035	0.8929	0.0258	0.0120	0.2861
SZB	1.9295	0.5224	0.0297	0.8713	8.4786***	0.0100	0.0449	1.2213	0.1007	0.0267	0.3168	0.0023	0.8038	0.9415	0.0072	0.0892	0.0923
INDO	0.1092	0.0259	0.8207	0.0615	0.5716	0.1266	0.4943	2.0359	0.6021	0.2194	0.2665	0.0059	0.2082	1.4526	0.0147	0.0225	0.1197
MALAY	0.3719	0.0001	0.8278	0.0352	0.0010	0.5611	8.9659***	1.4168	0.3361	0.3997	0.6191	0.1978	0.2613	1.3614	0.1632	0.0111	0.0897
PHIL	0.5348	0.0143	0.3841	0.0468	0.0287	0.7174	0.0903	16.9817***	0.7085	0.0632	0.7586	0.0276	0.1559	1.1150	0.2556	0.0861	0.0226
THAI	2.1867	0.0030	0.4049	0.0491	0.0837	0.7142	0.0002	1.7965	1.8141	0.0728	1.6713	0.0213	0.2134	1.5567	0.1154	0.0063	0.2372
AU	0.0831	0.0123	0.3422	0.0118	0.0001	0.2016	0.8581	1.2406	0.6562	1.2406	0.0197	0.5458	0.5695	1.5118	1.0543	0.1279	0.1801
HK	9.0535***	0.0969	0.0387	0.0104	0.3177	0.0014	0.0008	1.4196	0.2260	2.7586*	6.7204***	0.0079	0.3157	11.0514***	0.0895	0.0013	0.1376
JP	0.4829	0.0103	0.6189	0.0487	0.0746	0.0189	0.0311	1.3175	0.1036	0.1231	0.5612	4.8052**	0.8693	1.5172	0.0635	0.0242	0.1235
NZ	0.1830	0.0012	0.4917	0.0472	0.1575	0.0400	0.3262	1.1192	0.5684	0.3512	0.6300	0.0866	0.3118	1.1691	0.5890	0.4678	0.5763
SING	2.2023	0.0061	0.1528	0.0341	0.0015	0.6018	0.6061	1.4115	1.1447	0.3405	0.5797	0.0134	0.6904	7.9140***	0.7294	0.2351	0.2546
US	0.1587	0.0999	0.5128	0.0118	0.1046	0.0006	0.0728	1.1768	0.2117	0.0012	0.2551	0.0336	1.8939	1.4172	22.4635***	0.9203	2.1442
GER	0.0676	0.0140	0.3469	0.0087	0.0804	0.0123	0.1038	0.9659	0.4367	0.0464	0.3224	0.0695	0.2098	1.1683	0.8424	4.4855**	3.8210*
UK	0.1078	0.0435	0.3021	0.0010	0.0047	0.0050	0.3680	1.2330	0.7750	0.0898	0.5030	0.0660	0.6825	1.7664	1.6969	0.0723	26.5535***

Note: *, ** and *** represents 10%, 5% and 1% significance. White test is performed for the standardised residuals of each pair of markets at 5 lags. The null hypothesis is no heteroskedasticity. If p-value is less than 0.01, the null hypothesis is rejected, indicating there is evidence of heteroskedasticity. If p-value is more than 0.01, the null hypothesis cannot be rejected at the 1% significant level, implying there is no evidence of heteroskedasticity.

3.9. Discussion

An EGARCH model with spillover factors in the variance equations was used to answer two research questions: i) whether a leverage effect exists in China and other stock markets in the sample; and ii) whether volatility spillover is evident between China and other markets in the sample. Additionally, a univariate GARCH and EGARCH model also revealed other properties of the volatility of stock returns, including long memory and volatility persistence.

3.9.1. Long memory and volatility persistence

In the univariate GARCH model, there are two key findings. The first has to do with the impact of past returns on the current return and whether this reflects long memory. If a market's return is found to be impacted (significantly and economically) by its own past returns, its returns possess long-memory property. The second has to do with the results of the GARCH coefficients, which describe the volatility persistence of a stock market.

First, the results in section 3.7 show that past returns did not explain the current returns of Chinese equities. In other markets, the effect was feeble and there was no clear trend in the effect of past returns during the crisis periods for these markets that recorded significant past returns coefficients. These findings indicate that Chinse equities did not have long memory, whereas this property was weakly evident in other markets. In addition, the daily return in each market was linearly related to a constant, indicating the presence of a long-term mean. However, the values of these coefficients were trivial. When the returns do not have a long-term mean and cannot be predicted using its past values, they behave similar to a random walk process defined by Fama (1995). The random walk theory holds that successive price changes in a stock market should be independent, which means stock prices should not have memory (Fama, 1965). The results of this study did not confirm the random walk theory but are not entirely opposing. Since the long-term mean did not have any meaningful prediction on the future level, this suggests that the daily volatility of these series behaves more like a random walk. This is consistent with the existing literature which found the random walk in many markets such as HK, China and Singapore, especially when the model accounted for structural breaks (Araújo Lima & Tabak, 2004; Lim, Habibullah, & Hinich, 2009; Ngene, Tah, & Darrat, 2017). A stock market that displays behaviour similar to a random walk is more likely to be a mature and efficient market. A great deal of research has been devoted to rigorous testings and discussion on these hypotheses (Borges, 2010; Fama, 1965; Hamid, Suleman, Shah, & Akash, 2015; Lim, 2007; Norden & Weber, 2004; Rizvi, Dewandaru, Bacha, & Masih, 2014). However, as the primary focus of this chapter is to provide empirical implications of the nature of cross-equity linkages based on historical data, further exploration of this theory is out of scope.

Heterogeneity was also found for AS and BS listed on the SHSE, whereas homogeneity in the long memory behaviours was found in the Shenzhen markets. It was also found that these behaviours were different between the crisis periods and the non-crisis periods. This is consistent with the findings of Ngene et al. (2017), who found that many emerging markets, including China, were consistent with the random walk hypothesis when taking into account the structural breaks. It was also found that China's A- and B-share markets were different in terms of random walk and market efficiency hypotheses, due to the differences in liquidity and the market capitalisation between these markets. (Araújo Lima & Tabak, 2004).

The current volatility of daily returns in many markets (as shown in sections 3.7.1 and 3.7.2), including China, was found to be strongly driven by their own past volatility (GARCH effect) throughout the entire period under review. This implies the presence of volatility clustering, which was well documented in many equity markets in empirical studies (Cont, 2007; Friedmann & Sanddorf-Köhle, 2002; Lux & Marchesi, 2000; Niu & Wang, 2013). Volatility clustering is possibly caused by herding behaviour, where investors make decisions based on current market trends; that is, they sell when prices are low and buy when prices are high. Herding behaviour was well documented in China's stock markets, and it was most pronounced in large market swings (Fu, 2010; Lao & Singh, 2011). Even though stricter reporting regulations and associated capital policies were imposed in 2002, herding behaviour was still evident in A- and B-share markets from 1998 to 2008 and more profound during declining periods (Yao et al., 2014). In addition, herding behaviour was found to be more prominent in AS, while only weak evidence was found in BS during high volatility periods (Mahmud & Tiniç, 2015). This is consistent with the findings of GARCH effects in A- and B-share markets in this chapter. Generally, the GARCH effect was more robust in AS compared to BS, especially during crisis periods. This could be explained by the fact that BS are traded mostly by sophisticated foreign institutional investors, while AS are predominantly traded by domestic retail Chinese investors with less knowledge. China's stock markets are dominated by small and medium-size investors (account balance below \$10,000), who accounted for 90 million individual share accounts in 2015 – one of the world's highest retail investor participation rates in equity markets (Credit Suisse, 2015). Therefore, herding might be more influential in A-share markets, which in turn possibly causes a more substantial GARCH effect in the daily volatility of these markets compared to BS. In addition, Teng and Liu (2014) found that herding behaviour was prominent and contagious in Shanghai and Shenzhen markets during the GFC. This could explain why the evidence of a GARCH effect was always found in both Shanghai and Shenzhen markets in this study, regardless of the period.

Furthermore, weak ARCH effects were evident in China's markets pre-GFC and after the GFC in 2010, while different behaviour was documented during the GFC. The presence of an ARCH effect indicates that the current volatility of a market was driven by unobserved volatility (innovations in the returns). Another observation during the GFC was the disappearance of the ARCH effect in A-share markets and SZB. This effect only remained in HS and SHB markets. In those markets, the ARCH effect appeared to be considerably higher during the GFC compared to the pre-GFC and post-GFC periods. During the extended-crisis period, an ARCH effect appeared in all Chinese markets, excluding SZB. During the post-crisis period, only HS did not have an ARCH effect. This shows that the ARCH effect changed during the GFC. The fact that HS and BS are accessible by foreign investors while AS are traded by local investors could explain the finding that A-share investors ‘ignore’ the global factors and news, while HS and SHB are vulnerable.

Even though an ARCH effect was evident before and after the GFC, the effect was feeble, which could be explained by the fact that local activity is the main driver of AS during a crisis, as aforementioned. Another possible explanation for this phenomenon is the government’s intervention to stabilise the market during a catastrophic event such as the GFC, or a massive sell-off. Most stocks listed as AS are predominantly state-owned enterprises, where management is appointed by the government. Moreover, the government has also closely monitored the equity market. Throughout China’s market history, there has been repeated government intervention, especially in the Shanghai market during market downturns to help prop up or depress share prices, even though this is not publicly promoted. For example, initial public offerings (IPOs) were suspended after multiple record lows during 1993-1994; treasury bond futures were halted in May 1995 after a huge price rigging scandal; a 10% daily limit for share price movement was issued in 1996 to ease excessive speculation; IPOs were again suspended in 2005 to calm down market fears that too many shares would be issued as the government conducted reforms to sell state shares; the government purchased stock from state-owned banks and quietly suspended IPOs to halt the slide in the equity market from the GFC in 2008 (Reuters, 2010); and trading on some stocks was halted and large shareholders were prohibited from selling their stocks in 2015 after the stock market bubble burst. This intervention could lead to the heterogeneous behaviour of AS in responding to global factors, compared to other share types during declining markets that has been found over the study period.

As shown in section 3.7, daily volatility in China’s markets was less persistent during crisis periods (GFC and extended-crisis period) than the post-crisis period, even though the volatility level was still highly persistent overall. In the pre-GFC period, there were variations in the persistence duration of each of China’s markets. Shocks in the volatility of China’s equities took 16 days on average to decompose, in which HS took one day; SHA, SHB and SZA took 24, 20 and 26 days respectively; and SZB took eight days. During the GFC period, the average HLP duration for Chinese equities was shortened to 14 days (SHA took 25 days, SHB took 12 days, SZA took 15 days and SZB took five days). This duration was the same as the extended-crisis period. In the post-crisis period, it increased to 51 days. This shows that the volatility of China’s markets during the market turbulence was decaying faster in crisis periods than in non-crisis periods. Opposite behaviour was observed for other markets in the sample. It was found that trading volume, used as a proxy for information arrival time, was not only a dominant explanatory factor of the conditional variance of return, but was also positively correlated with the conditional variance of stock returns (Aragó & Nieto, 2005; Choi, Jiang, Kang, & Yoon, 2012;

Chuang, Kuan, & Lin, 2009; Lamoureux & Lastrapes, 1990) and persistence of return volatility of equities (Chandra Pati & Rajib, 2010; Salman, 2002). The significant and positive impact of the trading volume on the persistence of conditional variance measured by the GARCH effect was also documented in A- and B-share markets (Wang, Wang, & Liu, 2005). Fraser and Power (1997) and Girard and Biswas (2007) suggested that the analysis of the persistence of shocks to volatility and the influence of trading volume on volatility should be an individual country analysis, as the behaviour varied with countries, suggesting that reduced trading volume could lead to lower stock return volatility, and in turn reduce the persistence. As discussed previously, government intervention during the GFC period contributed to the reduced trading volume, in an attempt to stabilise the market by reducing the overheated market volatility. **Figure 3-3** presents the trading volume in Shanghai and Shenzhen markets from 2002 to 2017. It shows that the trading volume was meagre from 2007 to 2012 compared to the period after 2012. From 2012 to 2015, the trading volume increased significantly by more than triple, which could explain the significant increase in the volatility persistence during the post-crisis period (after 2012) compared to the crisis periods (from 2007 to 2012). Therefore, it is found that the persistence duration for the crisis periods was much shorter than for non-crisis periods, especially the post-crisis period.

Source: Bloomberg

Figure 3-3. Total trading volume in Shanghai and Shenzhen markets from 2002 to 2017

3.9.2. Asymmetric volatility response to news

Asymmetric volatility response to the news was examined using a univariate EGARCH model. The findings of this model answered the research question of whether there is evidence of a leverage effect in each market in the sample.

It was found that the leverage effect is quite different among China's markets. It was significant for HS in all sub-periods from the pre-GFC to the post-crisis period. On the other hand, AS and BS were more prone to bad news than good news only during market turbulence. In particular, leverage effect was significant in SHA only during the GFC, while in SHB only during the extended-crisis period. Both SZA and SZB exhibited leverage effects during the GFC and the extended-crisis period. For China's markets, only HS showed evidence of leverage effect throughout the entire period from non-crisis to crisis periods. Hence, there was insufficient evidence to conclude that there were changes in the leverage effect during the crisis.

A possible explanation of the leverage effect in AS and BS during the GFC is the volatility feedback trading hypothesis, also known as the time-varying risk premium, whereby volatility and stock price is negatively causal, which is possibly attributable to asymmetry in the volatility of stock returns. This theory suggests that if volatility can be priced, an expected rise in volatility leads to an instant fall in stock price. Evidence supporting this theory is abundant in empirical studies (Bohl & Siklos, 2008; Sutthisit et al., 2012; Zhang & Wang, 2012). Wu (2001) found that this effect and leverage effect were both crucial determinants of asymmetries in weekly and monthly volatility of the US stock market from 1962 to 1997 using a panel data model. In agreement with this finding, Bekaert and Wu (2000) also found that the volatility feedback effect plays a vital role in explaining the asymmetry in volatility. Negative feedback trading (buy low, sell high) was found in Shanghai markets, while positive feedback trading (buy high, sell low) was found in Shenzhen markets (Zhang & Wang, 2012). In a related study, positive feedback trading was found for SHA, SZA, SZB and HS, and the effect is stronger during a market downturn (Sutthisit et al., 2012). It shows that China's stock markets tend to sell more when the price falls, which puts further downward pressure on price, hence increasing volatility, which is attributable to the fact that the majority of Chinese investors are individuals and more likely to be market takers than makers. In addition, it was found that herding behaviour was significant and contagious among HK, Shanghai and Shenzhen markets during the GFC 2008 (Teng & Liu, 2014), while asymmetric volatility is attributed to asymmetric herding (Park, 2011). This might explain why AS, BS, HS and HK were prone to bad news during financial distress.

Government intervention could be the reason why the leverage effect disappeared in SHA during the extended-crisis period. Increased margin lending in stock purchases was legalised in 2010 to 2011, in addition to the monetary easing policy that is responsible for the significant rise in equity prices of SHA lasting until 2015 to 2016. Therefore, from the extended-crisis period (2010 to 2012) to the post-crisis period (2012 to 2017) there was no sign of a leverage effect in this market.

The trading behaviour of HS was similar to HK because these shares are traded on the same exchange. Therefore, a leverage effect was found in both these markets over the entire period under review. The finding of the leverage effect in HK and HS was consistent with findings in other advanced markets including the US, UK, Australia, Germany and Singapore. Strong evidence of a leverage effect over the entire period under review in these markets is consistent with the existing literature for advanced markets. Apart from volatility feedback trading, other common hypotheses that are attributable to leverage effect in these markets include Black (1976) financial leverage (Chelley-Steeley & Steeley, 2005; Chen, So, & Gerlach, 2005) and asymmetry in the rate of information flow (Reyes, 2001; Ross, 1989), as discussed in sections 3.2.1 and 3.2.2.

3.9.3. Volatility spillover

The findings of the EGARCH model with a spillover variable in the variance equation answered the research question about volatility spillover from China to other emerging and advanced markets in the sample and vice versa.

Among China's markets

Among China's markets, there was evidence of volatility spillover between AS and BS throughout the entire study period, which could be explained by substantial herding behaviour in these markets. In the post-crisis period (2015 to 2017), more evidence of bidirectional volatility spillover was found among China's markets, indicating a stronger synchronisation in daily volatility between these markets since 2015. The impact of shocks from other markets was generally more vigorous during the crisis period than the non-crisis periods, which is consistent with empirical literature that volatility spillover increased significantly during crisis periods (Li & Giles, 2015; Yilmaz, 2010).

HK was interconnected with China's other markets, with the strongest spillover between HK and all of China's share markets observed during the post-crisis period. In addition, there was more evidence that volatility in the HK market was prone to the innovations in A- and B-share markets during the post-crisis period than the previous periods, although the impact was quite weak and decreasing over time. This is opposite to the findings of Huo and Ahmed (2017), who suggested that volatility spillover from Shanghai to HK was strengthened after the SH-HK scheme was launched in 2014. Our results show that the interaction level increased between HK and all of China's A- and B-share markets after the program launch. Before the post-crisis period, HK interacted only with some of China's markets, but during this period, volatility spillover was significant with all of China's markets. This finding shows a change in the integration between HK and other of China's markets. While the parameters of volatility spillover were statistically significant, the size of these parameters were small, suggesting that the relationship was weak.

China versus emerging markets

In general, regional integration between China and other emerging markets in the sample (Indonesia, Malaysia, the Philippines and Thailand) was evident, with some exceptions. During the GFC, market separation existed between AS and emerging markets, in contrast to conventional wisdom (that there is higher volatility interdependence during crisis periods), whereas only BS (either SHB or SZB) still expressed regional integration with some countries. In the extended-crisis period, regional integration was re-established, but unequally. For example, Indonesia and Malaysia were exposed to shocks from all of China's markets, Thailand was only exposed to shocks from SHB, and the Philippines was totally disconnected. In the post-crisis period, transmission from China's markets was more evident than for the reverse direction. The regional dis-integration in the A-share market could be explained by government intervention and thin trading during the crisis periods. BS, on the other hand, were still responsive because they were accessible to foreign investors. In the post-crisis period, the regional impact from China's markets increased; however, the impact was weak. Overall, these findings suggested an integration between China and other emerging markets, but with a weak impact.

Various trade policies were introduced in China from 2002 to 2005, after joining the WTO in order to fulfil the liberalised trade policies. However, the study observed that those policies had little impact on the regional integration of China's equities. This finding is consistent with the empirical literature that liberalisation policies might increase the integration between China and other countries, but with low magnitude (Yao et al., 2018).

Similarly, two major policies introduced since 2013 could be a plausible explanation for higher regional integration during the post-crisis period. The first one is the China Belt and Road Initiative in 2013, which aimed to increase Asian-Pacific cooperation, but where the main focus was to finance and build infrastructure projects across Eurasia and to strengthen regional political cooperation, unimpeded trade, financial integration and people-to-people exchanges. In late 2015, China established the New Development Bank and the Asian Infrastructure Development Bank to fund infrastructure projects in Asia including US$692 million to fund infrastructure projects in Indonesia in 2016, and US$500 million to the Philippines flood project in 2017 (AIDB, 2017). The liberalisation policies in trade and capital markets issued during 2001 and 2011, and their impacts on the markets and economies of emerging countries in the region, might be reflected in the regional integration observed by this chapter over these periods. Prior to 2015, Indonesia, the Philippines, Malaysia and Thailand were not exposed to volatility from China's equities; however, since 2015, during the post-crisis period, all four countries were found to expose shocks in volatility in HS, HK and SHB markets. This major shift could be linked with the policies that were issued during this period.

There could be other reasons, or a combination of various reasons, that led to this change; for example, strong economic ties through import-exports and capital flows through investment (Dockery & Vergari, 2001; Pula, 2014), political issues, poor economic development, high unemployment rate, enormous government budget deficit, trade coordination policies, inequality in economic development and growth can also increase the exposure of a country to external risks from other countries (Chaudhry et al., 2012; Rafi & Lewis, 2012). This hypothesis might be questionable because there is a lack of clear evidence in the literature that these factors decelerated significantly after 2015. Hence, while they could be a contributory factor to the increased integration between China and these emerging markets, they do not seem to be the primary reasons.

China versus developed markets

The findings in section 3.9.3 showed abundant evidence of spillover from advanced markets to Chinese markets in the post-crisis period. On the other hand, the influence of Chinese equities was found in only a few countries and remained weak throughout the period under review. In the post-crisis period, it was found that all countries were responsive to shocks from at least one Chinese stock market. Australia was impacted by AS and BS listed on the SHSE since the pre-GFC period. This established integration has been documented abundantly in empirical literature, due to the fact that China was the top consumer of Australian exports, accounting for almost 30% of Australian total goods and services for the financial year 2016-2017, in the *Trade and Investment at a Glance* report in 2017 published by Department of Foreign Affairs and Trade (2017). Other countries such as Singapore, US, Germany and the UK were only impacted by HS due to the well-built link between HS and HK markets – thanks to the fact that these shares operate on the HKSE, and established volatility integration was found between HK and HS over the study period, as discussed in section 3.7.3. This implies that China's liberalisation policies may increase the integration of other major markets with China. However, they might not have a significant impact on the magnitude of these interactions, or in terms of volatility. This finding is consistent with empirical studies examining the impact of these policies on the regional integration of China in terms of volatility spillover. For example, the economic reform in 2003 was found to increase global integration with major stock markets (the US, Korean and Japan) and spillover from China during 2003 to 2010, but the impact is weak (Li, 2012).

This chapter has answered a question that interests many academics and investors globally; that is, if China's markets 'get a cold', would other major markets sneeze? Based on the EGARCH model, there is some evidence of a spillover from China to emerging and advanced markets, but the impact is not significant, and there is not enough evidence to conclude that the impact is more substantial during the crisis periods, even during the GFC or the recent market turbulence from 2010 to 2012. Chinese equities may impact the world market to a certain degree, but it is far from conclusive that there could be another global crisis due solely to the increased uncertainty in China's economy or its equity markets. In explaining a few global stock crashes in 2015 due to a massive sell-off in China's capital markets, overaction could be the reason. In fact, this phenomenon is not unusual in stock markets and is asymmetric (bigger for losers than winners) (De Bondt & Thaler, 1985). Conservatively, this theory could be a significant contributory factor during a crisis, as it may lead to a massive sell-off from investors, because a fear of increasing asset illiquidity and overreaction is asymmetric. How significant it is opens an exciting area for further research. In saying this, if the Chinese government's intervention remains a common expectation, a stock crash in China could become a golden opportunity for investing in Chinese shares at a discounted market price when the trend reverses.

3.10. Conclusion and recommendations

The first research question addressed by this chapter relates to the leverage effect and asymmetries in the distributional volatility of each market in the sample. The study found that the leverage effect differed among China's markets, while some similarities were found between AS and BS, which could possibly be explained by the volatility feedback trading hypothesis. Strong evidence of a leverage effect in many advanced markets was found, including the US, UK, Australia, Germany and Singapore, which is consistent with the existing literature. The changes of the leverage effect were not uniform over the four sub-periods, but they varied with markets.

The second research question examined evidence of volatility spillover between each of China's markets and the other markets in the sample. Chinese equities, in general, were found to be vulnerable to shocks from local markets and more responsive during crisis periods (the GFC and extended-crisis period) than non-crisis periods. In addition, HS became more integrated with AS and BS after the extended-crisis period. The volatility in A- and B-share markets was driven by shocks from HS and vice versa, even though the impact from AS and BS on HS was weak.

Shock transmission between Chinese equities and emerging markets was found. However, the impact was weak except for the spillover from the emerging markets to SHB. Compared to SZB, other of China's markets, including SHA, SHB and SZA, were more insulated to external shocks from emerging markets. The degree of the influence from the emerging market to SZB was non-trivial.

Evidence of spillover from advanced markets was abundant in the post-crisis period. On the other hand, the influence of Chinese equities was evident in only a few countries and was weak for most of the periods under review. However, in the post-crisis period, it was found that more countries were responsive to shocks from Chinese equities, including Australia, HK, Japan and NZ. Other countries such as Singapore, the US, Germany and the UK were only impacted by HS.

Despite speculation from public news that China's markets could create another global crisis, coupled with the evidence of increased spillover from China in the existing literature, the findings of this study do not support this view. First, while there was some evidence of spillover from China to emerging and advanced markets, the impact was not significant. The findings do not support the view that volatility spillover is stronger during the crisis periods as is commonly believed, or during the GFC or the market turbulence of 2010-2012. In addition, the study found increased volatility spillover from China to some emerging Asian markets including Indonesia, the Philippines, Malaysia and Thailand since 2015, which the literature reveals could be due to the 'cash pump' from China to those countries' major infrastructure projects via the two Chinese banks – New Development Bank and the Asian Infrastructure Development Bank. Even though the degree of market dependence between China and the studied emerging markets was small, the evidence pointed out some changes in volatility spillover with mixed direction since 2015. Moreover, while emerging markets appeared to be less influenced by shocks from Chinese equities in the post-crisis period, the reverse situation was observed in Chinese equities. China's stocks were more vulnerable to shocks from emerging markets, yet the effect was not material.

Based on the empirical findings, Chinese equities may impact the world markets at a certain level, but the impact is small overall. This finding is also consistent with the findings from the study of Bekaert et al. (2014). They found that exposure to external factors played no role in risk transmission during the GFC, whereas the critical factor that facilitated the transmission of risk is the internal factors or idiosyncratic risks of a country. For example, countries with weak economic fundamentals, poor sovereign ratings and high fiscal and current account deficits contribute to the transmission of risks from other countries. In addition, this chapter did not account for market sentiments, which could be a significant contributing factor in two recent global stock crashes in August 2015 and late 2017, following the massive sell-off in China's financial markets. A further study examining the impact of sentiment factors on volatility spillover between China and other global markets in the short term is a recommended area for further research.

Chapter 4 Dependence analysis using multivariate DCC-EGARCH

This chapter evaluates the time-varying and multivariate dependence between each of China's markets and other international markets in the sample, which has not been addressed in Chapter 3, in order to answer the following research questions:

1. Is volatility spillover under the multivariate context evident between China's markets and other emerging and advanced markets in the sample, especially for the A-share market, since it is a 'closed' market?
2. Is there evidence of time-varying correlation between each of China's markets and other markets in the sample?
3. Are the joint dependence structures in terms of return correlation and volatility spillover of A-, B- and H-share markets homogenous or heterogeneous?
4. Did China's equities experience market segmentation during the GFC and extended-crisis periods (decoupling effect), as found in the existing literature, or contagion effect?

The design of this chapter is as follows. Section 4.1 provides an introduction to this chapter, followed by a discussion of the key existing literature in this field in section 4.2. Section 4.3 presents data used in this chapter and the methodology. Section 4.4 describes the hypotheses for each research question. Section 4.5 reports the empirical results and the goodness-of-fit tests. Section 4.6 concludes.

4.1. Introduction

Chapter 3 has examined the return and volatility spillover between each of China's markets and the other markets in the sample using a univariate EGARCH model with an auxiliary term. This chapter further analyses the dynamic correlations and asymmetric spillover effect across markets under a multivariate joint dependence process that has not been addressed in Chapter 3, focusing on China's markets (AS, BS and HS) and the other advanced and emerging markets in the sample (using the same markets as for Chapter 3).

The findings from Chapter 3 highlight the differences in the joint dependence structure in both return and volatility levels regarding spillover for the major share types in China's equity markets. The following is a summary of some of the major findings from the analysis of volatility spillover in Chapter 3 using the univariate conditional volatility EGARCH model. Volatility spillover among China's markets (AS, BS and HS) is strongly evident and is higher in the GFC and extended-crisis periods compared to the pre-GFC and post-crisis periods. Chinese equities, especially AS and BS, are found to be more correlated with neighbouring markets in Asian areas such as Japan, Singapore and Australia, rather than with the US, UK, Germany and NZ. There are also major differences in volatility spillover between AS, BS and HS and other global markets. These findings endorse the necessity of modelling the market interdependencies of AS, BS and HS separately.

While many studies have examined shock transmissions and the volatility dependence of major stock markets in China; that is, Shanghai, Shenzhen and Taiwan, only a few studies have assessed the multivariate volatility spillover effect of A-, B- and H-share markets simultaneously (Ke, Wang, & Murray, 2010; Qiao, Qiao, & Wong, 2010; Sun, 2014). These studies either tested for linear dependence or constant correlations, whereas the existing literature has documented that the correlations of financial time series are time-varying. Thus, the assumption of constant correlations is not always suitable for empirical modelling of cross-market linkages (Allen et al., 2013; Engle, 2002; Tse & Tsui, 2002). Chapter 3 tested the studied data with a univariate GARCH model under the constant assumption. This chapter expands on Chapter 3 and examines the data under a multivariate context that allows for time-varying correlation. Moreover, these prior studies use data up to 2012, which does not account for the key capitalisation policies introduced in China from 2011 to 2016. Therefore, this chapter attempts to close these gaps by examining the dynamics of the conditional correlations of A-, B- and H-share markets with several major advanced and emerging markets from 2002 to 2017.

Financial volatilities have been found to move closely together over time across markets (Allen et al., 2013; Kanas, 2000; Koutmos & Booth, 1995). To establish whether this is the case for the markets in this study, this chapter examines the multivariate volatility and return spillover of three major share types in China with other global markets over the period 2002 to 2017, and to distinguish the behaviour of spillover and correlations among these three share types.

To answer the research questions, this chapter extends Chapter 3 by testing the data under a multivariate context which accounts for time-varying correlations and asymmetry in correlations using a multivariate DCC-EGARCH model. As with Chapter 3, to ensure a broad view of regional and global integration, this study includes the same 12 emerging and advanced markets which are neighbouring trading partners of China and which hold a significant economic position globally or regionally, including the ASEAN-5, Japan, HK, US, UK, Germany, Australia and NZ. In order to observe the possible changes in the volatility spillover effect in the periods before and after the GFC 2009, during the European debt crisis 2012 and during China's capital deregulation policies in the past five years, the sample covers the same periods used in Chapter 3 – from 1 May 2002 to 31 July 2017 divided into four sub-periods: 1) pre-GFC period from 1 May 2002 to 26 February 2007; 2) GFC period from 27 February 2007 to 28 May 2009; 3) extended-crisis period from 29 May 2009 to 6 June 2012; and, 4) post-crisis period from 7 June 2012 to 31 July 2017. More detail about these periods is provided in section 2.2.

Chapter 3 has discussed the importance of studying the three major share types in China separately and concurrently due to the differences in market accessibility and operational features. This, however, received limited attention from the existing literature regarding modelling dependence in both univariate contexts, as discussed in Chapter 3, and multivariate contexts (Li & Giles, 2015; Moon & Yu, 2010). The closest article to this multivariate study is Allen et al. (2013), which modelled the time-varying volatility spillover between Chinese stock markets and its major trading partners including Australia, HK, Taiwan, Singapore, Japan and the US. This chapter extends the sample size of the existing literature to 17 countries and the sample period to 2017, which includes the major market deregulation policies from 2011 to 2016 in China's equity markets, as aforementioned. In addition, this chapter examines the dynamic correlation of multivariate dependence structures, which has received limited attention in the existing literature regarding three major share types in China under a multivariate context. The findings of this study disinguish the behaviour associated with volatility and the return spillover of AS, BS and HS, so they help investors to form appropriate investment and hedging strategies for each of these share types. Moreover, asset correlation is critical in asset pricing as well as in financial risk management such as hedging. If the correlation is time-varying (as examined in this study), hedging ratios should be constantly adjusted to reflect this change. It is also found that a model which accounts for time-varying properties in conditional correlations can generate lower optimal portfolio variance and higher portfolio returns than a model which uses constant correlation (Billio et al., 2006).

This examination of dynamic correlation using the multivariate DCC-EGARCH model shows that the correlation of AS, BS and HS markets is indeed time-varying. Moreover, there are differences in regional and global correlations of AS, BS and HS markets, which reinforces the appropriateness of analysing these markets separately in the context of cross-linkages. In addition, the results of the DCC-EGARCH model present strong evidence of a significantly increased dynamic conditional correlation during the GFC and extended crisis periods compared to the pre-GFC and post-crisis periods for all of China's markets.

Overall, the findings of this chapter provide strong evidence of distinct behaviour in volatility spillover and dynamic correlations between AS, BS and HS, indicating that in these markets the degree and extent of regional and global integration in terms of returns and shock transmission of Chinese equities depends on the share classification. There are three major findings which differ from the findings from the univariate models in Chapter 3 which examine spillover effect: 1) the degree of correlations among Chinese markets from the multivariate tests is found to be stronger than the univariate models; 2) univariate tests found one-way spillover from AS and BS to HS in the GFC, whereas a multivariate test confirms the synchronisation between HS and all AS and BS in the GFC; 3) even though the univariate model found higher integration between China's markets and other Asian markets, that model does not find evidence that supports the contagion effect. The multivariate model found that there is evidence supporting the contagion effect and recoupling hypothesis (these concepts are defined in sections 1.4.2 and 1.4.3) between Chinese equities and other advanced and emerging markets.

Moreover, there is consistent evidence throughout the four sub-periods that Chinese equities are more related to the markets in the Asian region than other intra-regional markets such as the US, UK and Germany, suggesting the existence of regional dependence, which is similar to the results from Chapter 3. Both models in Chapter 3 and Chapter 4 also found that the degree of volatility spillover between Chinese equities and the other markets is generally stronger in the crisis periods compared to the non-crisis periods. Both models also found that there is a strong correlation among AS and BS throughout the four sub-periods.

The remainder of this study is structured as follows. Section 4.2 reviews the literature on volatility spillover across stock returns, adopting univariate and multivariate approaches. Section 4.3 describes the data and methodology. Section 4.4 presents the research questions and hypotheses. Section 4.5 discusses the empirical results. Section 4.6 concludes.

4.2. Literature review

The majority of literature regarding multivariate joint dependence using GARCH models, in both emerging and advanced markets, found significant evidence of market interdependence among different countries in both stock market returns and volatility levels. Some common conclusions include that US shocks play an important role in explaining other markets' returns variations; own-volatility spillover (or internal shocks) are more useful in explaining the variation of volatility of a stock market than cross-volatility spillover (external shocks); countries tend to have higher interactions with other countries in the same region than across regions; and there is a recoupling hypothesis or contagion effect during the GFC.

Syriopoulos et al. (2015) found that shocks in the US industrial and financial sectors have a significant impact on the returns of BRICS markets, where Brazil and India are mostly impacted using a multivariate VAR-GARCH model on daily industry returns from January 2005 to December 2013. Dungey and Gajurel (2015) employed a latent factor model on daily stock returns of major advanced markets, namely the US, France, Germany, Japan, and the UK and emerging BRIC markets from January 2004 to December 2010. They found that contagion from the US plays a significant role in explaining a large portion of the variations in stock returns in both advanced and emerging markets. Xu and Hamori (2012) found that before the GFC, the causal relationship of stock prices in mean and variance is significant between the US and Russia, India and China (two-way) from August 2004 to September 2008, while the relationship remained between the US and Russia and India after the GFC from September 2008 to April 2010, suggesting a change in investors' sentiments.

In addition, the existing literature also found that the variation in the volatility level of a market is more likely to be explained by a market's internal shocks than external shocks (cross-volatility spillover). Worthington and Higgs (2004) investigated multivariate return and volatility spillover among three Asian advanced (HK, Japan and Singapore) and six emerging markets (Indonesia, Malaysia, the Philippines, Thailand, Korea and Taiwan) using a multivariate GARCH model from 1998 to 2000. They found a high level of return dependence among these Asian markets, suggesting that the volatility level of a country is more influenced by domestic factors than by cross-market volatility spillover. Boubaker, Jouini, and Lahiani (2016) also confirmed that the majority of the volatility level in many Asian markets, especially China, is explained by their own contributions rather than the external shocks.

Yarovaya, Brzeszczyński, and Lau (2016) examined the transmission channels of return and volatility spillover in stock and futures among 10 developed and 11 emerging markets in Asia, the Americas, Europe and Africa from 2005 to 2014 using a variance decomposition VAR model. In general, return spillover across stock markets was found to be significant at both the intra-regional and inter-regional level, while volatility spillover is more prominent at the intra-regional level. The authors found that developed markets in Asia are most influenced by the UK compared to the Americas and other European countries, and HK is the most influential market among other countries in the Asian region with high spillover from HK to other Asian markets. In addition, they found that most Asian markets are more influenced by their own shocks than by external shocks from other Asian countries. Nevertheless, the spillover effect is significant between Europe and the Americas, suggesting an existence of inter-regional information transmission. The authors also suggested that geographic proximity could be relevant in the intensity of volatility spillover, since they found that the highest volatility spillover happens within a region rather than across regions. Similarly, Bala and Takimoto (2017) found that emerging markets (Nigeria and Brazil) are more susceptible to their own-volatility spillover than cross-volatility spillover compared to advanced markets (Japan, US, UK and HK), suggesting that shock transmission is stronger among advanced markets than emerging markets.

The existing literature also found increased market integration during the GFC, confirming the recoupling hypothesis and contagion effect. Bala and Takimoto (2017) employed multivariate GARCH and BEKK-GARCH models on weekly stock market data in Nigeria, Japan, the US, UK, Brazil and HK from January 1994 to January 2016 and found significant evidence of increased return and volatility spillover among emerging markets and advanced markets during the GFC 2007-2009. Moreover, the developed markets had a higher correlation with each other than with emerging markets. Mensi et al. (2016) found that the return spillover among BRICS markets increased strongly during the GFC, supporting the recoupling hypothesis using a multivariate DCC-fractionally integrated asymmetric power ARCH (FIAPARCH) model. Karanasos, Yfanti, and Karoglou (2016) found that the conditional correlations in volatility increased during the GFC among many global markets including the UK, US, Germany, France, Japan, Singapore, HK and Canada using a multivariate AR-DCC-FIAPARCH model, suggesting a herding behaviour among those countries. Hemche, Jawadi, Maliki, and Cheffou (2016) found an increase in dynamic correlations in many advanced and emerging markets (France, UK, Italy and Japan) following the GFC using a DCC-GARCH model. Boubaker et al. (2016) found a contagion effect between the US equity market and other advanced and emerging markets following the GFC using long-run Granger causality, Johansen's cointegration test, impulse response function and variance decomposition tests.

Moreover, the existing literature also found asymmetric behaviour in return and volatility spillover across markets. Mensi et al. (2016) revealed that skewed Student-t FIAPARCH models outperform and provide smaller in-sample and out-sample forecasting errors compared to non-skewed Student-t FIAPARCH models for Brazil, Russia, India, China and South Africa. Bala and Takimoto (2017) detected asymmetric behaviour in developed markets (Japan, US, UK and HK) during 1994 to 2016. Karanasos et al. (2016) found that leverage effect in the stock return volatility remained evident from 1994 to 2016 for eight advanced markets (UK, US, Germany, France, Japan, Singapore, HK, Canada).

Despite substantial evidence concerning mutual return/volatility spillover between major economies due to various reasons such as globalisation, trading links and geographic proximity, the literature focusing on the global and regional dependence of China's markets remains inconclusive. (Sazali et al., 2014) examined a same-day spillover effect in price and volatility between China and four major stock markets within the Asia-Pacific basin region (Australia, Japan, HK and NZ) from May 2004 to August 2010 using AR and GARCH models. They confirm the open/close effect in both price information and volatility among these Asian markets. A one-way volatility spillover from the US to HK, Shanghai and Shenzhen markets is evident from 2001 to 2013 but not vice versa (Mohammadi & Tan, 2015). Li and Giles (2015) examined the asymmetric multivariate volatility spillover between global stock markets including the US, Japan and six Asian emerging markets (China, India, Indonesia, Malaysia, the Philippines and Thailand) from 1993 to 2012 using a Vector autoregressive (VAR) model. They found evidence of a unidirectional transmission of shocks from the US to other emerging markets, and that the spillover is stronger during the AFC. Dungey and Gajurel (2015) confirmed that the variance in stock returns of the Shanghai market during the GFC was predominantly impacted by the US. Nishimura et al. (2016) explored the return and volatility spillover effect on five-minute returns data from January 2013 to March 2014 during the periods of overlapping trading hours in the Shanghai Composite Index and Japan. The authors also found one-way return spillover from the Chinese to the Japanese market and no volatility spillover between these markets, even though these countries are geographically proximal and strongly linked in trading. The authors of that study claimed that the restriction on foreign investment in the Chinese market and lack of diversified international portfolios among individual Chinese investors are two possible factors explaining the unresponsive reactions in China's stock returns to changes in Japanese markets.

On the contrary, Moon and Yu (2010) found evidence of increased shock transmission from the Shanghai market to international stock markets since 2005. Zhou, Zhang, and Zhang (2012) studied volatility spillover between China (HK, Taiwan, Shanghai) and major stock markets (US, UK, France, Germany, Japan, India, Korea, Singapore) from 1996 to 2009, based on a forecast-error variance decomposition VAR framework. They found an increased global integration of China since 2005; however, the domestic interactions among China's markets are more prominent than regional interactions with Western and Asian markets. In addition, the authors found global segmentation of the SHSE index during the GFC. Mensi et al. (2016) found evidence of increased market linkages between China, Brazil, India and Russia during the GFC. Johansson (2010) supported the evidence of increased regional and global integration of China's markets; however, the author also found that this phenomenon occurred at a very slow pace and from very low levels since the GFC. Similarly, Hussain and Li (2018) observed that the correlation between the Chinese Securities Index (CSI) 300 (which consists of the largest 300 stocks, mostly AS, on both the Shanghai and Shenzhen markets) and developed stock markets (US, Canada, UK, Germany, Japan and Australia) is very low. They found the dependence between China and the US to be the lowest, and between China and Australia to be the highest. Neither of these studies examined the contagion effect and volatility spillover for AS, BS and HS, separately. Chiang and Chen (2016) explored the dynamic correlations among China, HK, Taiwan and Korea using a DCC-GARCH model from 1998 to 2014. They found that stock returns in China are mostly related to HK, followed by Taiwan and Korea, while the correlations with the US and Europe are low, suggesting that dynamic correlations are closely tied to geographic locations.

Due to the differences in market accessibility and operational features, some studies have attempted to distinguish the dependence behaviour of AS and BS at regional and global levels using a multivariate GARCH model. However, HS are seldom explored in the existing literature. Ke et al. (2010) studied the volatility spillover between Shanghai A-share and Shanghai B-share markets with the US, Japan, UK, Germany, HK and Korean markets from 2005 to 2009 using univariate GARCH and EGARCH models and a bivariate GARCH model. Their study did not consider HS and a multivariate dependence structure. Wang and Wang (2010) used a trivariate threshold BEKK-GARCH model to evaluate the volatility spillover between Greater China (AS and BS in Shanghai and Shenzhen markets, HK and Taiwan) and the US and Japan markets from 1992 to 2004. They found that the impact of negative news from China to the US is greater than the impact from the US to China. In addition, they found that the Shanghai market is less interrelated with the world than the HK market, suggesting that the level of market interdependence is positively associated with the level of market openness. Qiao et al. (2010) examined volatility spillover between A- and B-share markets and the HK market using weekly data from January 1995 to March 2005 and a SWARCH model. In addition to the exclusion of HS and GFC analysis, the use of weekly data might have eliminated instantaneous transmission in stock return volatility, which happens at a daily frequency and which is found in many studies (Glick & Hutchison, 2013; Moon & Yu, 2010; Syriopoulos et al., 2015). Sun (2014) examined the linear long-run integration in returns of A-share, B-share and HS markets and other countries using the bivariate Johansen and Juselius (1990) cointegration and bivariate Granger causality methods without accounting for volatility dependence. This method does not capture non-linear dependence. In addition, it does not account for heteroskedasticity and serial correlation, which are prominent distributional features of the joint dependence of stock returns (Forbes & Rigobon, 2002; Pierdzioch, 2004; Zhang & Wang, 2012; Zhao, 2010). Ho, Shi, and Zhang (2016) explored volatility persistence and asymmetries in AS, BS and HS and Red Chip indexes from 1997 to 2013. They found that volatility persistence and asymmetries are significantly evident in these markets. In addition, they found that the correlations of these markets are state-dependent using a regime-switching DCC-GARCH model, suggesting that macro-economic conditions are the main factors behind the correlation behaviours in different states. Since the thesis aimed to establish a comprehensive analysis from different perspectives regarding the first and second moments of cross-market stock returns, this chapter looks at the time-varying property of interdependencies among markets in the sample. Therefore, further tests for regime-switching correlations are not the main focus and can be considered for future research to keep the scope of this thesis manageable.

Asymmetry in volatility spillover usually refers to the phenomenon where bad news and good news have unequal impact on the volatility of a stock market (Koutmos, 1996). Leverage effect is when bad news has more impact than good news of the same size, as has been documented abundantly in empirical studies for many markets such as the US, UK, Germany, Japan and China (Bekaert & Wu, 2000; Diebold & Yilmaz, 2012; Koutmos & Booth, 1995; Reyes, 2001). It is often found that a GARCH model that accounts for asymmetry in the impact of news on volatility outperforms a standard symmetric GARCH model (Alberg et al., 2008; Peters, 2001; Shamiri & Hassan, 2005). The Nelson (1991) EGARCH model is selected for this study for the following main reasons. First, it models log conditional variance so that it can explicitly capture asymmetries in the volatility of stock returns without having positiveness restriction of the coefficients' parameters. Other comparable models such as QGARCH, APARCH and GJR-GARCH are restricted to the positiveness of the variances (Hentschel, 1995; Sentana, 1995). In addition, the condition for stationary variance for an EGARCH model is a GARCH coefficient of lower than one, which is easy to interpret and monitor. On the other hand, for comparable models such as QGARCH, TGARCH and GJR-GARCH, the stationary condition is more complicated and difficult to interpret. An EGARCH model has been found to be robust for equity markets (Huo & Ahmed, 2017). Therefore, the combination of DCC and EGARCH models allows for the capture of the effect of asymmetry and dynamic correlations in volatility spillover among China's markets and the studied major markets. Multivariate EGARCH, which was introduced by Koutmos and Booth (1995), has been employed in empirical studies of interdependence among financial markets under the multivariate joint dependence process – such as examining return and volatility dynamics among four African equity markets (Kuttu, 2014) – to explain time-varying volatility of credit spreads on European bonds (Batten & In, 2006), volatility spillover between stock prices, and exchange rates among G-7 countries (Yang & Doong, 2004) and among Asian stock markets during the AFC 1997 (In, Kim, Yoon, & Viney, 2001).

Finally, apart from a vast literature using GARCH and copula models to examine the dependence at the second-order moment, there is an intense interest on the heavy-tailed properties examined using recently developed models such as the asymptotically chi-squared test statistic (Hill & Aguilar, 2013) or Generalised Likelihood Estimator for the GARCH(1,1) model derived from tail-trimming samples under the stationarity assumption (Hill & Prokhorov, 2016). Chen and Ibragimov (2019) examined the relationship between A and H-shares using Gabaix and Ibragimov (2011) and Ibragimov and Müller (2016) inference methods and found that while all A-shares and H-shares had finite first and third moments, the second and fourth moments may be infinite for some A-shares and for all H-shares with small truncation levels. Those findings are worth noting for further research, especially for those financial markets that exhibit very heavy tails with stationary data and which can also be extended to non-stationary cases.

4.3. Data and Methodology

4.3.1. Data

The data used in this chapter is the same data used across the whole thesis (as described in section 2.1), in order to ensure consistency and to allow comparisons across the models used in this thesis. Similar to the previous chapters, the data is divided into four sub-periods as follows:

1. Pre-GFC period: from 1 May 2002 to 26 February 2007 (871 observations).
2. GFC period: from 27 February 2007 to 29 May 2009 (410 observations).
3. Extended-crisis period: from 30 May 2009 to 6 June 2012 (539 observations).
4. Post-crisis period: from 7 June 2012 to 31 July 2017 (912 observations).

The daily closing prices are downloaded from Bloomberg for each market as shown in **Figure 2-1**, and then converted to a first difference natural logarithm to make each time series stationary. More information about these sub-periods and the data can be found in sections 2.1 and 2.2. The standardised residuals for each time series are obtained from the best-fitted GARCH model from Chapter 3 and are converted to uniform marginals using the Rank method. This process assigns a ranking unit for each observation within a time series.

4.3.2. Model description

An EGARCH model is adopted in this study to capture the prominent distribution properties of stock returns and their conditional volatility that was established in the literature and empirical studies; that is, serial correlation, heteroskedasticity and asymmetry in marginal distributions as discussed in Chapter 3.

To allow for dynamic correlations, a multivariate DCC-EGARCH model is used to model the time-varying behaviour of correlations of Chinese equities in this chapter. Multivariate dependence analysis using a GARCH framework is common in the modelling of stock market dependencies and dynamic correlation analysis can be enabled by the use of a BEKK model or DCC model (Engle &

Sheppard, 2001; Hassan & Malik, 2007). The DCC model is not restricted to the number of series and thus has a computational advantage compared to the BEKK models (Tsay 2013). This allows the estimation of large covariance matrices, enabling a feasible test for the studied sample in this chapter. The multivariate EGARCH model with k dimension introduced by Koutmos (1996) can be expressed as follows:

Conditional mean:

$$R_{i,t} = \mu_{i,t} + \beta_{i,0}R_{i,t-1} + \sum_{j=1}^{k}\beta_{i,j}R_{j,t-1} + \varepsilon_{i,t} \text{ for } i, j = 1, 2, \ldots, k \tag{4.1}$$

Conditional variance:

$$h_{i,t} = \ln(\sigma_{i,t}^2) = \omega_{i,t} + \sum_{j=1}^{k}\alpha_{i,j}f_j(z_{j,t-1}) + \gamma_i ln(\sigma_{i,t-1}^2) \tag{4.2}$$

$$f_j(z_{j,t-1}) = [|z_{j,t-1}| - E(|z_{j,t-1}|)] + \delta_j z_{j,t-1} \tag{4.3}$$

$$\sigma_{i,j,t} = \rho_{i,j}\sigma_{i,t}\sigma_{j,t} \text{ for } i, j = 1, 2, \ldots, k \text{ and } i \neq j \tag{4.4}$$

Equation (4.1) describes the returns of k markets as a VAR, where the conditional mean in each market, $R_{i,t}$ (with a mean $\mu_{i,t}$ and variance $\sigma_{i,t}^2$), is a function of past own returns, measured by the parameter $\beta_{i,0}$ as well as the cross-market past returns effect, which is measured by $\beta_{i,j}$. A significant $\beta_{i,j}$ for $i \neq j$ indicates price spillover across markets; that is, the past return of market j can explain the current return of market i.

The conditional variance of the returns in each market, $\sigma_{i,t}^2$, given by equation (4.2), is an exponential function of its past own GARCH effect γ_i which measures the persistence of volatility, and the cross-market standardised innovations $\alpha_{i,j}$ which measures the volatility spillover effect. The asymmetric function $f_j(z_{j,t-1})$ is determined by past standardised innovations: $z_{j,t} = \varepsilon_{i,t}/\sigma_{i,t}$. The term $[|z_{j,t-1}| - E(|z_{j,t-1}|)]$ measures the magnitude effect. The term $\delta_j z_{j,t-1}$ measures the sign effect. A significant positive $\alpha_{i,j}$ and negative δ_j imply that negative innovations in market j have a higher impact on the volatility of market i than positive innovations; that is, a shock transmission exhibits a leverage effect. The unconditional variance is finite if $\gamma_i < 1$. If $\gamma_i = 1$, the unconditional variance does not exist and the conditional variance follows an integrated process of order one, which is less likely due to the exponential specifications (Hsieh 1989). Equation (4.4) is just the conditional covariance. This equation is not used for any test, but it is there for the purpose of completeness.

The Engle (2002) DCC model is a generalisation Bollerslev (1990) CCC model. Time-varying conditional covariance matrix H_t can be given as follows:

$$\mathrm{H}_t = D_t R_t D_t \text{ where } D_t = diag(h_{1,t}^{\frac{1}{2}}, h_{2,t}^{\frac{1}{2}}, \ldots, h_{k,t}^{\frac{1}{2}}) \tag{4.5}$$

H_t is a $k \times k$ matrix of conditional covariances of the residual term ε_t. D_t is a $k \times k$ matrix of conditional standard deviation (or volatilities) of each return. The conditional variances $h_{i,t}$ follow an EGARCH(1,1) process as described in Chapter 3. R_t is a $k \times k$ conditional correlation matrix which is positive definite. The estimation of R is achieved by the modelling of a proxy process Q_t as follows:

$$\mathrm{Q}_t = \bar{Q} + a(z_{t-1}z'_{t-1} - \bar{Q}) + b(\mathrm{Q}_{t-1} - \bar{Q}) = (1 - a - b)\bar{Q} + az_{t-1}z'_{t-1} + b\mathrm{Q}_{t-1} \qquad (4.6)$$

where a and b are non-negative scalars, with a restriction of $a + b < 1$ to ensure stationarity and positive definiteness of Q_t. $\bar{Q}$ is the unconditional matrix of the standardised errors z_t. When estimating the DCC model for a multivariate non-normal distribution, there is a shape parameter. The correlation matrix R_t is then obtained by rescaling Q_t such that:

$$R_t = diag(\mathrm{Q}_t)^{-1/2}\mathrm{Q}_t diag(\mathrm{Q}_t)^{-1/2} \qquad (4.7)$$

The estimation of the DCC parameters is conducted using a two-stage approach. First, the standardised residuals of each time series are estimated from an EGARCH(1,1) model. Second, the standardised residuals of each of China's markets and other markets in the sample (12 explanatory variables in one equation) are fitted to a DCC model to test for the dynamics of correlations of these markets in a multivariate context.

4.3.3. Model specification

The multivariate DCC-EGARCH model of Koutmos and Booth (1995) and Engle (2002) is used to model time-varying conditional correlation of asymmetric volatility spillover between the aforementioned markets. The model is expressed as:

Conditional covariance model – volatility spillover to each of China's markets:

$$h_{CH,t} = \ln\left(\sigma^2_{CH,t}\right) = \omega_{CH,t} + \textstyle\sum_{j=1}^{k} \alpha_{CH,j} f_j\left(z_{j,t-1}\right) + \gamma_{CH} ln(\sigma^2_{CH,t-1}) \qquad (4.8)$$

$$f_j\left(z_{j,t-1}\right) = \left[\left|z_{j,t-1}\right| - E(\left|z_{j,t-1}\right|)\right] + \delta_j z_{j,t-1} \qquad (4.9)$$

If $\alpha_{CH,j}$ is significant and positive, volatility spillover from China to market *i* is evident. The DCC estimation is modelled by equation (4.5). If the joint significance of parameters *a* and *b* are different from zero, this validates the appropriateness of the DCC model. The Ljung-Box test and the robust version of the rank-based test introduced by Dufour and Roy (1986) is used to test for conditional heteroskedasticity in the standardised residuals of the multivariate DCC model. The results from these models and the robustness tests are presented in the next section.

4.4. Hypotheses

Research question 1: Is volatility spillover under the multivariate context evident between China's markets and other studied markets, especially for the A-share market since it is a 'closed' market?

H_0: There is no evidence of multivariate volatility spillover between China's markets and other markets in the sample.

H_1: There is evidence of multivariate volatility spillover between China's markets and other markets in the sample.

If α in equation (4.8) is significant at 5%, it rejects the null hypothesis of no spillover effect, suggesting an existence of volatility spillover from one market to another.

Research question 2: Is there evidence of time-varying correlation between China and other markets in the sample?

H_0: There is no evidence of time-varying correlation between China's markets and other markets in the sample.

H_1: There is evidence of time-varying correlation between China's markets and other markets in the sample.

If the DCC coefficients a_t and b_t from equation (4.6) are jointly significant, this suggests that time-varying correlation is an appropriate assumption to the studied data.

Research question 3: Are the joint dependence structures in terms of return correlation and volatility spillover of AS, BS and HS homogenous or heterogeneous?

Research question 4: Did China's equities experience market segmentation during the GFC and extended-crisis periods (decoupling effect) as found in the existing literature, or contagion effect?

Research questions 3 and 4 are for comparison purposes. Therefore, there is no hypothesis for these questions. Instead, they will be addressed in the discussion of the empirical analysis.

4.5. Empirical results

A multivariate DCC-EGARCH(1,1) is conducted on standardised residuals estimated from an EGARCH(1,1) of the marginals to examine the asymmetric volatility spillover in a multivariate context that allows time-varying correlations. The estimation of the DCC model is implemented with a Student-t error distribution and a Gaussian error distribution. The Student-t model has a much lower AIC (-142.8) compared to the normality assumption (70.7). Therefore, the Student-t error distribution is selected for the multivariate DCC model. Finally, standardised residuals of fitted EGARCH and DCC models are tested with serial correlations and heteroskedasticity to check the multivariate fit and the univariate EGARCH fit (Minović, 2008).

The DCC model is fitted on the standardised residuals of GARCH(1,1) and EGARCH(1,1) with normal and Student-t error distributions. Based on the AIC, DCC-EGARCH(1,1) with Student-t distributed errors is the most suited model, which confirms the appropriateness of the EGARCH model and the Student-t distribution compared to symmetric GARCH and a normality assumption. This section presents the results of the DCC-EGARCH(1,1) model with Student-t error distribution.

Table 4-1 presents the DCC estimate. If the DCC coefficients a_t and b_t from equation (4.6) where k = 1, 2,…,12 are jointly significant (p-values are less than 1%), this confirms the validation of the DCC model. For all of the four sub-periods, p-values of the joint significance of these coefficients range from 0.000 to 0.0012, which rejects the null hypothesis that either of the two coefficients equal zero, hence indicating that these coefficients are jointly significant. Thus, the DCC model provides a good fit to the sample data, suggesting that the correlation of China's markets is time-varying. The DCC coefficient a_t is approximately zero (but significantly different from zero), while the coefficient b_t is approximately one, implying the conditional correlation is declining over time ($0 < b_t < 1$) towards $(1 - b_t)/b_t$.

Table 4-1 also provides model diagnostics including Ljung-Box Q(m) and the robust version of the rank-based test $Q_k^r(m)$ at 10 and 15 lags, which are standard lags for this test for conditional heteroskedasticity in the fitted model standardised residuals. These tests are commonly used in the existing literature (Allen et al., 2013; Mohammadi & Tan, 2015). The former test is suitable for a normality distribution, while the latter test performs better for heavy tail distribution (Tsay, 2013). In the pre-GFC period, the Q(m) test at 15 lags of the standardised residuals fails to reject the null hypothesis of no conditional heteroskedasticity for HS at the 5% significance level. The Q(m) test at 20 lags fails to reject the null hypothesis of no conditional heteroskedasticity for HS, SHB, and SZA at the 5% significance level. Both Q(m) and $Q_k^r(m)$ tests fail to reject the null hypothesis of no conditional heteroskedasticity in the residuals at the 5% level for the GFC period, extended period and post-crisis period. This indicates that conditional heteroskedasticity cannot be detected in the standardised residuals of the multivariate DCC model, suggesting the fitted model seems adequate for the data.

Table 4-1. Estimated DCC parameters, a_t and b_t and the robustness test $Q_R(15)$ for a multivariate model of each of China's markets with all other markets in the sample (13 variables) – full sample

	HS	SHA	SHB	SZA	SZB
Pre-GFC period					
[Joint]a_t	0.0061***	0.0040***	0.0045***	0.0037***	0.0041***
[Joint]b_t	0.9655***	0.9690***	0.9688***	0.9693***	0.9697***
Q(15) of std res.	24.12	30.76**	26.53***	27.80**	30.58**
$Q_k^r(15)$ of std res.	2769.03***	2764.12***	2855.33***	2726.44***	2787.74***

Q(20) of std res.	26.87	33.84**	28.92	30.71	32.91**
$Q_k^r(20)$ of std res.	3583.71***	3593.32***	37414.36***	3537.98**	3615.11***
GFC period					
[Joint]a_t	0.0127***	0.0106***	0.0084***	0.0097***	0.0087***
[Joint]b_t	0.8977***	0.9084***	0.9104***	0.8981***	0.9043***
Q(15) of std res.	23.43	22.09	20.84	20.50	20.74
$Q_k^r(15)$ of std res.	2456.69	2509.88	2431.84	2528.13	2462.86
Q(20) of std res.	25.93	25.98	23.99	24.06	23.91
$Q_k^r(20)$ of std res.	3356.56	3440.57	3361.12	3495.73	3354.94
Extended-crisis period					
[Joint]a_t	0.0093***	0.0066***	0.0072***	0.0077***	0.0069***
[Joint]b_t	0.8932***	0.9281***	0.9170***	0.9204***	0.9155***
Q(15) of std res.	18.90	20.88	13.83	18.01	16.80
$Q_k^r(15)$ of std res.	2601.78	2545.75	2524.14	2525.40	2600.33
Q(20) of std res.	22.61	26.29	22.82	23.06	24.52
$Q_k^r(20)$ of std res.	349.02	3448.88	3406.67	3438.53	3478.45
Post-crisis period					
[Joint]a_t	0.0067***	0.0068***	0.0061***	0.0059***	0.0062***
[Joint]b_t	0.9447***	0.9359***	0.9421***	0.9421***	0.9381***
Q(15) of std res.	19.10	14.33	20.55	13.12	20.71
$Q_k^r(15)$ of std res.	2608.37	2523.37	2587.98	2532.41	2628.64
Q(20) of std res.	27.22	23.80	27.61	20.74	28.50
$Q_k^r(20)$ of std res.	3403.10	3287.95	3362.93	3294.19	3450.37

Note: *** and ** indicate significance at the 1% and 5% levels respectively. All DCC parameters are significant at the 1% level, which rejects the null hypothesis that either of the two coefficients equals zero, indicating the coefficients a_t and b_t are jointly significant in all four sub-periods. The multivariate model includes 13 variables consisting of each of China's markets and all the other emerging markets (Indonesia, Malaysia, the Philippines, Thailand) and advanced markets (HK, Singapore, Japan, Australia, NZ, UK, Germany and US) in the sample. The null hypothesis of the portmanteau test for Q(n lags) of the standardised residuals and the robust version of the rank-based test Q_k^r(n lags) of the standardised residuals show no conditional heteroskedasticity in the standardised residuals of the multivariate DCC model.

Table 4-2 presents the DCC-EGARCH parameters of the covariance equations (4.8) and (4.9), $\alpha_{i,j}$, γ and δ. Significance $\alpha_{i,j}$ indicates the existence of a volatility spillover effect from other markets to China's markets. The findings show that shock transmission from other markets to HS is evident at the 1% significant level, which rejects the null hypothesis of no spillover and implies the existence of volatility spillover from other markets to HS. However, the p-values of the volatility spillover from other markets to AS and BS is higher than 5%, which fails to reject the null hypothesis of no spillover and indicates the spillover from other markets to AS and BS is not evident in the pre-GFC period. In the GFC period, volatility spillover from other markets to HS, SHA and SZB is evident at the 5% significance level or lower. In the extended-crisis period, all of China's markets received shock transmission from all other markets in the sample. In the post-crisis period, volatility spillover from other markets is evident for HS only, which is similar to the pre-GFC period. This shows that the volatility of the A- and B-share markets were impacted by the volatility from other markets in the sample during the crisis periods only (GFC and extended-crisis periods). In addition, δ is significant at 1% for all cases, which confirms that the volatility spillover is asymmetric. All γ parameters are significant, which indicates the existence of a GARCH effect in the volatility of China's markets, meaning that the volatility of these markets is fairly persistent.

Table 4-2. Estimates of DCC EGARCH parameters

	HS	**SHA**	**SHB**	**SZA**	**SZB**
Panel A: Pre-GFC period					
$\alpha_{i,j}$	-0.0653***	-0.0139	-0.0318	-0.0261	-0.0014
γ	0.9625***	0.9620***	0.9492***	0.9595***	0.9189***
δ	0.0733***	0.1929***	0.3796***	0.2046***	0.2727***
Panel B: GFC period					
$\alpha_{i,j}$	-0.0729**	-0.0731***	-0.0919	-0.1204	-0.2185***
γ	0.9731***	0.9499***	0.8799***	0.7833***	0.8669***
δ	0.2679***	-0.0702***	0.395***	0.1848	0.2370***
Panel C: Extended-crisis period					
$\alpha_{i,j}$	-0.0620***	-0.1199***	-0.3445***	-0.2732***	-0.1725***
γ	0.9681***	0.9195***	0.7165***	0.8945***	0.9120***
δ	0.0961***	0.0860***	0.1584***	0.0067***	0.0921***
Panel D: Post-crisis period					
$\alpha_{i,j}$	-0.0953***	0.0113	-0.0225	-0.0093	-0.0356
γ	0.9723***	0.9941***	0.9881***	0.9915***	0.9792***
δ	0.0764***	0.1420***	0.2665***	0.1513***	0.2548***

Note: *** and ** indicate significance at 1% and 5% respectively.

Finally, we evaluate the pattern of pairwise dynamic correlations over each sub-period between each of China's markets and other markets in the sample, as summarised in **Table 4-3**. To group the studied countries by the level of correlations, the dynamic correlations are categorised into four quantiles: (lowest) 25% quantile, 50% quantile, 75% quantile and 100% quantile. Classification using quantiles also gives an indication about the distribution of pair-wise correlations based on the correlation level which allows the interpration of highest and lowest correlations. The use of quantiles in analysing and interpreting data is also popular among academics and industry experts (Ando & Bai, 2020; Baur, Dimpfl, & Jung, 2012). In the pre-GFC period, 25% of the variables (correlations) of HS pairs fall within 0.12 to 0.35. HS–US, HS–Malaysia, HS–NZ and HS–Philippines are those pairs that have correlations which fall in this range. There are four main findings: (1) HK, Singapore and Japan are most correlated to China's markets, and correlation between China's markets and NZ, Germany, the UK and US is generally lower than the correlation between China's markets and other Asian markets such as Indonesia, Philippines, Malaysia, Thailand and Australia; (2) the US has the lowest correlation with China's markets throughout the four sub-periods, which is consistent with the finding of Mohammadi and Tan (2015); (3) there is clear evidence of increased correlation between each of China's markets with other markets during the GFC period and the extended crisis period, confirming the existence of contagion effect; and (4) the correlation of A-share pairs and B-share pairs in the post-crisis period is higher than the pre-GFC period's level, whereas the correlation of H-share pairs in the post-crisis period is quite similar to the pre-GFC period, indicating that the regional and global integration of A-share and B-share markets has increased over time, but not the H-share market.

Table 4-3. Multivariate DCC correlation between each of China's markets and other markets in the sample

	0-0.25 quantile	> 0.25-0.5 quantile	> 0.5-0.75 quantile	> 0.75-1 quantile
Panel A: Pre-GFC period				
HS	0.12 – 0.35	> 0.35 – 0.42	> 0.42 – 0.54	> 0.54 – 0.73
	US, Malay, NZ, Phil	Indo, UK, Ger, Thai	Aus, Japan	HK, Sing
SHA	-0.03 – 0.08	> 0.08 – 0.11	> 0.11 – 0.14	> 0.14 – 0.31
	Phil, NZ	Indo, UK, US, Ger	Malay, Thai, Aus	HK, Sing, JP
SHB	-0.02 – 0.07	> 0.07 – 0.10	> 0.10 – 0.14	> 0.14 – 0.32
	Phil, US	NZ, Ger	Indo, Thai, UK	Malay, HK, Sing, JP, Aus
SZA	-0.04 – 0.06	> 0.06 – 0.09	> 0.09 – 0.13	> 0.13 – 0.28
	Phil, US	UK, Ger	Indo, Thai, Aus, NZ	HK, Sing, JP
SZB	0.02 – 0.13	> 0.13 – 0.16	> 0.16 – 0.21	> 0.21 – 0.39
	Phil, NZ, Ger, US	Indo, Thai, Aus, UK	Malay, Sing, JP	HK
Panel B: GFC period				
HS	0.28 – 0.57	> 0.57 – 0.64	> 0.64 – 0.74	> 0.74 – 0.96
	US	UK, Ger, NZ, Phil, JP	Indo, Malay, Thai	HK, Sing, Aus
SHA	-0.04 – 0.21	> 0.21 – 0.27	> 0.27 – 0.34	> 0.34 – 0.58
	NZ, UK, Ger, US	Thai		HK, Sing

			Indo, Malay, Phil, JP, Aus	
SHB	0.04 – 0.24	> 0.24 – 0.30	> 0.30 – 0.36	> 0.36 – 0.58
	US	Phil, Thai, NZ, UK, Ger	Japan	Aus, Malay, HK Sing
SZA	-0.02 – 0.18	> 0.18 – 0.24	> 0.24 – 0.31	> 0.31 – 0.51
	UK, US	Thai, NZ, Ger	Indo, Phil, JP, Aus	Malay, HK, Sing
SZB	0.06 – 0.29	> 0.29 – 0.35	> 0.35 – 0.42	> 0.42 – 0.61
	UK, Ger, US	Phil, Thai, JP, NZ	Indo, Sing, Aus	Malay, HK
Panel C: Extended-crisis period				
HS	0.26 – 0.49	> 0.49 – 0.57	> 0.57 – 0.67	> 0.67 – 0.96
	US	Malay, Thai, JP, Ger, UK, Phil, NZ	Sing, Indo, Aus	HK
SHA	014 – 0.25	> 0.25 – 0.29	> 0.29 – 0.36	> 0.36 – 0.59
	Ger, US	Phil, Thai, JP, UK	Indo, Malay, Aus, NZ	HK, Sing
SHB	0.03 – 0.18	> 0.18 – 0.23	> 0.23 – 0.29	> 0.29 – 0.46
	UK, Ger, US	Phil, JP	Indo, Malay, Thai, Aus, NZ	Indo, HK, Sing
SZA	0.06 – 0.18	> 0.18 – 0.23	> 0.23 – 0.27	> 0.27 – 0.49
	Ger, US	Phil, JP, UK	Malay, Thai, NZ	Indo, HK, Sing, Aus
SZB	0.13 – 0.26	> 0.26 – 0.32	> 0.32 – 0.38	> 0.38 – 0.57
	UK, Ger, US	Thai, NZ, JP	Malay, Phi, Aus	Indo, HK, Sing
Panel D: Post-crisis period				
HS	0.20 – 0.39	> 0.39 – 0.45	> 0.45 – 0.55	> 0.55 – 0.94
	US	Thai, NZ, Ger	Indo, Malay, Phil, JP, UK	HK, Sing, Aus
SHA	-0.03 – 0.15	> 0.15 – 0.19	> 0.19 – 0.26	> 0.26 – 0.67
	NZ, Ger, US	UK	Indo, Malay, Phil, Thai, JP	HK, Sing, Aus
SHB	-0.04 – 0.11	> 0.11 – 0.14	> 0.14 – 0.17	> 0.17 – 0.54
	NZ, Ger, US	UK	Indo, Malay, Phil, Thai, JP, Aus	HK, Sing
SZA	0.01 – 0.12	> 0.12 – 0.16	> 0.16 – 0.20	> 0.20 – 0.51
	Ger, US	Indo, NZ	Malay, Phil, Thai, JP, UK	HK, Sing, Aus

SZB	0.01 – 0.18	> 0.18 – 0.21	> 0.21 – 0.25	> 0.25 – 0.58
	Ger, US	Malay, NZ, UK	Indo, Phil, Thai, JP	HK, Sing, Aus

Note: The dynamic correlations are categorised into four quantiles: (lowest) 25% quantile, 50% quantile, 75% quantile and 100% quantile. For example, in the pre-GFC period, 25% of the variables (correlations) of HS pairs fall within 0.12 to 0.35. HS–US, HS–Malaysia, HS–NZ and HS–Philippines are those pairs that have correlation fall in this range. Indo = Indonesia, Malay = Malaysia, Phil = Philippines, Thai = Thailand, HK = Hong Kong, Sing = Singapore, JP = Japan, Aus = Australia, NZ= New Zealand, Ger=Germany.

4.6. Conclusion and recommendations

For research question 1, examinations of dynamic correlation using the multivariate DCC-EGARCH model show that there is abundant evidence of multivariate volatility spillover, especially in the crisis periods (GFC and extended-crisis periods). The correlation of A-share pairs and B-share pairs in the post-crisis period is higher than the pre-GFC period's level, whereas the correlation of H-share pairs in the post-crisis period is quite similar to the pre-GFC period, indicating that the regional and global integration of A-share and B-share markets has increased over time. This finding is similar to the univariate EGARCH models, as discussed in Chapter 3. Interestingly, some markets have high correlation with HS and have low correlation with A-share and B-share markets; for example, Indonesia, Malaysia and NZ.

Both univariate EGARCH and multivariate DCC models find a strong link between all Chinese equities (AS, BS and HS) and HK. The integration between HS and HK is understandable because they have similar market accessibility. The correlation between AS and BS and HK could be the result of a combination of factors; for example, the economic link between China and Hong Kong, the open access to the Hong Kong market for Mainland China's investors through the Stock Connect programs (SH-HK and Shenzhen-Hong Kong introduced in 2014 and 2016) (Huo & Ahmed, 2017; Yao et al., 2018), as mentioned in several previous sections such as 3.9.3 and 4.1. Even though AS seem like a 'closed' market due to the restriction on foreign access to invest in AS, there is also strong evidence that AS and BS experienced a herding effect. This finding has addressed the first research question. The results from the univariate models indicate that AS and BS are correlated with HS, and HS have a strong link with the HK market. Thus, spillover from and to AS can be spread through BS and HS as a bridging channel. While foreign investors might have limited access to AS, and invest in BS and HS only, due to the hidden dynamics of transmission channels among AS, BS and HS, their portfolio can be exposed to the volatility in AS markets.

Moreover, similar to the univariate models, the multivariate models found evidence that inter-regional integration for Chinese equities is generally stronger than intra-regional integration. These models found that Chinese equities in general are more related to Hong Kong, Singapore, Japan and Australia than with the US, UK and Germany, which is possibly due to the geographical proximity and strong trading links, suggesting that geographic locations could play an important role in determining the intensity of market correlations. This is also consistent with the findings documented in the study of Yu, Fang, et al. (2018) and the existing literature, as mentioned in section 4.2.

The finding also found that correlations in these studied markets are time-varying and a model that accounts for this property is more appropriate than the model that assumes constant correlations. This has addressed the second research question.

For research question 3, the findings suggest that there are both similarities and differences in the joint behaviour of volatility spillover and dynamic correlations among AS, BS and HS, indicating that the degree and extent of regional and global integration in terms of returns and shock transmission of Chinese equities depends on the share classification. The multivariate DCC model found differences in regional and global correlations of AS, BS and HS and the spillover effect varies with the state of the market, which indicates a difference in the joint behaviour of Chinese equities in the crisis and non-crisis periods. In the non-crisis periods (pre-GFC period and post-crisis period), volatility spillover from other markets is only evident in HS. In contrast, the volatility spillover from other markets to HS, SHA, SZA and SZB is evident in the GFC and to all Chinese equities (HS, SHA, SHB, SZA, SZB) in the extended-crisis period. For this reason, AS, BS and HS can perform differently in different market states. The findings suggest that investors should be aware of these differences when forming investment strategies for AS, BS and HS. The existing literature based on the Shanghai Composite Index regarding this phenomenon without accounting for the heterogeneity in the market integration behaviour of AS, BS and HS might be misleading. Therefore, from both empirical and theoretical perspectives, the findings from this study suggest that accounting for heterogeneity in the joint dependence structure of AS, BS and HS is necessary to examine their regional and global linkages in different economic states. Thus, these markets should be studied separately.

The findings confirm the recoupling hypothesis in the GFC and extended-crisis periods for AS and BS, which addresses research question 4, indicating that these Chinese equities were exposed to external risks in a heightened volatility condition. This is in contrast to the findings from the univariate EGARCH models. The univariate model in Chapter 3 found regional linkages in terms of volatility spillover for AS and BS in the non-crisis periods and found regional and global segmentation for A- and B-share markets during the GFC and extended-crisis periods, whereas the multivariate DCC model indicated the existence of market segmentation in terms of volatility spillover in AS and BS in the non-crisis period and recoupling in the crisis periods.

Further, evidence of volatility spillover from other markets to HS was found in all four sub-periods and the degree of spillover effect did not increase considerably in the GFC period, hence a contagion effect in volatility spillover was not supported in HS. However, the volatility spillover to HS from other markets increased by almost 40% in the post-crisis period compared to the pre-GFC period, and by 54% compared to the extended-crisis period. This finding implied that HS appeared to be more susceptible to the volatility from other markets, and the degree of impact from other markets to HS was on an upward trend over the last 10 years. Moreover, leverage effect was evident for all pairs with significant spillover, which is consistent with the findings from the univariate models.

Chapter 5 Dependence analysis using bivariate copulas

This chapter evaluates the joint dependence between each of China's markets and other studied markets particular to the tail dependence to address the following research question for each sub-period:

1) What is the structure of the joint dependence between each of China's markets and other markets in the sample?

2) Is there a change in the dependence structure of these markets in the crisis periods?

3) Is there heterogeneity in the regional and global joint dependence structure among AS, BS and HS?

The design of this chapter is as follows. Section 5.1 provides an introduction to the chapter, followed by a discussion of the existing literature in this field, in section 5.2, including the copula theory and the theory related to the main copula functions used in this chapter. Section 5.3 describes the data and methodology. Section 5.4 presents the research hypotheses. Section 5.5 reports the results. Section 5.6 concludes and recommends.

5.1. Introduction

The association between two stock markets can be modelled at two levels: 1) first moment (for example, price and returns); and 2) second moment (for example, volatility of returns). Chapter 3 and Chapter 4 have highlighted the importance of volatility spillover modelling and applied univariate GARCH and EGARCH models and multivariate DCC-EGARCH models to capture the asymmetry in the distributional volatility of stock returns for each market, and the dynamics in volatility spillover between China's markets and other markets under a multivariate context. The findings of these chapters provide evidence that volatility spillover among studied countries can be applied to asset allocation and portfolio construction in quantifying volatility spillover across stock markets, which is consistent with Billio and Caporin (2009). While GARCH models are useful in capturing instantaneous volatility transmission, they cannot capture the overall dependence of returns, specifically the tail dependence. This chapter examines tail dependence in financial returns between each of China's stock markets – that is, AS, BS and HS – and other global markets in the sample using copulas.

Moreover, the decoupling-recoupling hypothesis and contagion effect are crucial concepts in financial modelling, as defined and discussed in section 1.4.2 and 1.4.3, which are supported by the findings in Chapter 4. These phenomena were documented in both the GFC and the Greek sovereign debt crisis (Floros et al., 2013; Wyrobek & Stańczyk, 2013; Yeyati & Williams, 2012). The decoupling between the emerging markets such as BRICS and the US during the GFC was also documented in the literature (Dooley & Hutchison, 2009; Willett et al., 2011).

Tail dependence is particularly important in the context of globalisation and relaxed market regulation (Mensi, Hammoudeh, Shahzad, & Shahbaz, 2017; Yao et al., 2018). As shown in Chapter 2, the daily returns of the markets in this thesis are non-normally distributed with excess kurtosis and fat tails, which is consistent with existing literature on the distributional properties of financial return time series (Fang et al., 2015; Mohammadi & Tan, 2015; Wang et al., 2013). Conventional measures of dependence, such as Pearson's correlation coefficient, which measure the dependence around the mean of the distribution, can be inadequate in capturing the actual joint behaviour of stock returns, as stock returns are usually found to be non-normally distributed with heavy tails, as discussed in Chapter 2. Tail dependence plays a vital role during high volatility periods such as recession, crisis and bear markets (Mensi et al., 2017) where the financial data does not conform to the normal distribution. Chapter 3 shows that the standardised residuals of the stock return given by a GARCH process exhibit serial correlation, implying volatility clustering. The Quantile-Quantile (Q-Q) plot shown in **Figure 5-1** indicates that each of the return time series does not have a normal distribution, further supporting the argument that the normality assumption is not practical for these studied markets. A fat tail distribution indicates that extremal events are observed more frequently than expected under the assumption of normality. Therefore, it is necessary to understand the dependence structure of the tail distributions of these markets.

As mentioned in Chapter 3, there is a strong motivation to investigate market integration between China and major advanced and emerging markets. In addition, the findings from Chapter 3 and Chapter 4 highlight the differences in the transmission of shocks and information behaviour of AS, BS and HS, which necessitates the need to study these shares separately and is consistent with the existing literature, as discussed in sections 3.2 and 4.2.

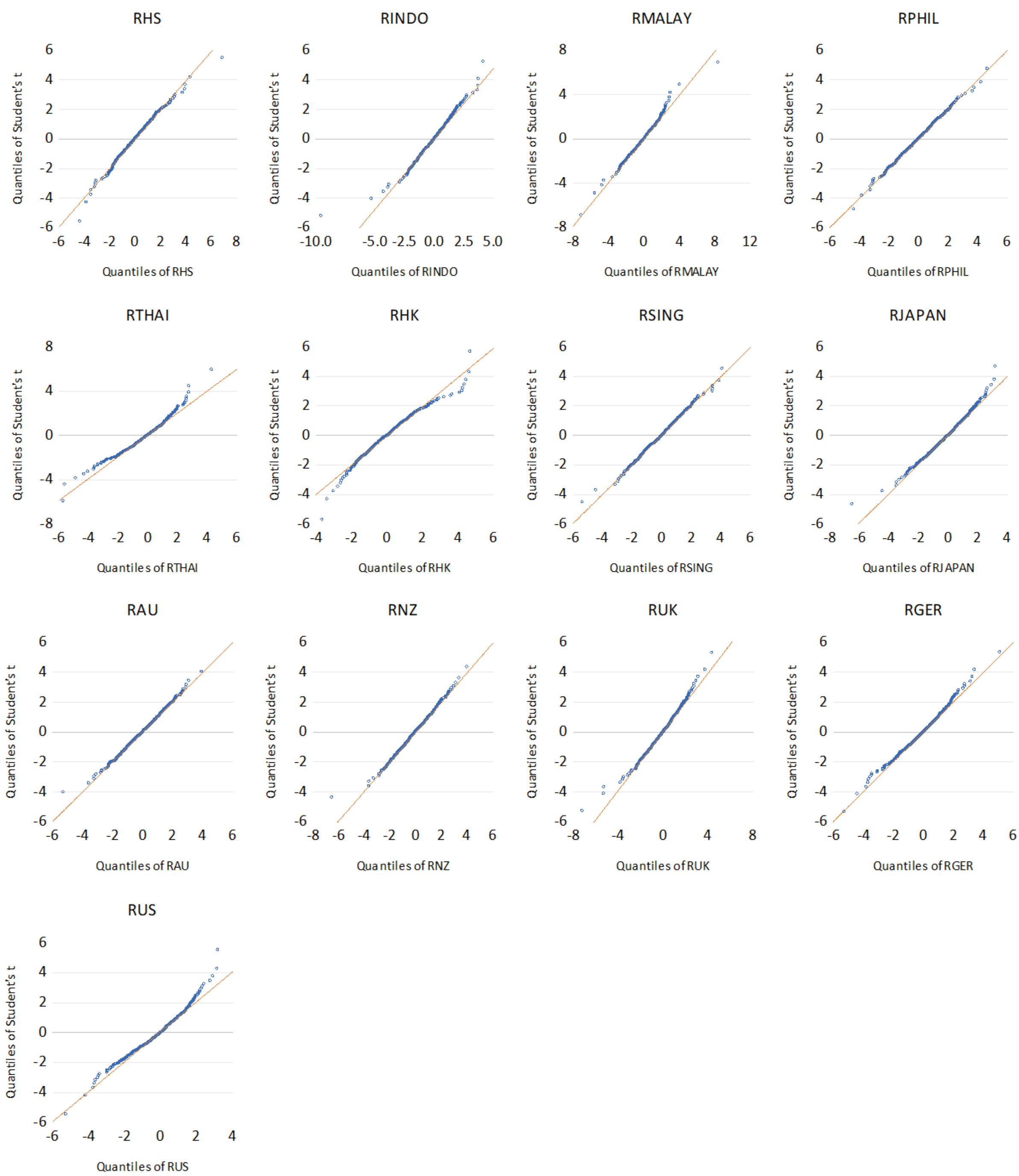
Many studies have investigated the bivariate and multivariate dependence structure of Chinese stock markets with major international markets (Glick & Hutchison, 2013; Johansson, 2010; Wang, Chen, & Huang, 2011); however, only few papers examined AS, BS and HS separately and simultaneously (Ho & Zhang, 2012; Luo, Brooks, & Silvapulle, 2011). In addition, these studies used old data up to 2009, which cannot capture the effect of the GFC, the European debt crisis in 2012, and the openness policies of China's stock markets which contributed to the changing regional and global market interactions of China's equities (Wang et al., 2017). The differences between this chapter and the study of Guo and Wang (2016) lie in the data frequency and method. That study used time-varying copula to describe the dependence structure in the volatility of five minutes and 15 minutes price data between Shanghai and Shenzhen stock markets from 2004 to 2014. While the contribution of that study is significant, high frequency data might be biased due to various issues such as the intra-day seasonal effect in volatility arising from the time-of-day phenomena; for example, market opening and closing in equity markets and the concentration of volume and high degree of noise in the volatility that is present in intra-day data (Allez & Bouchaud, 2011; Goodhart & O'Hara, 1997). This chapter provides a useful comparison for that study using daily data and bivariate copulas. In addition, this chapter is an expansion in studied markets which includes 17 markets and three major share types in China, while that study focused on Shanghai and Shenzhen only. Hence, none of those papers cited above provided a comprehensive study of the modelling of regional and global market dependence of AS, BS and HS simultaneously.

Furthermore, while Chapter 4 found evidence of the time-varying property in the return correlations, the aim of this thesis is to provide a comparison on the volatility of stock returns and tail dependence from different methods, and therefore, to keep the scope manageable, correlations are assumed to be constant for all other models including the EGARCH model in Chapter 3, bivariate copulas in this chatper and multivariate copulas in Chapter 6. Examining cross-market relationships between different markets using time-varying copulas as mentioned in section 5.2.1 provides potential for future research.

This chapter examines whether market dependence is evident in these studied markets. If there is evidence of dependence, there are three pertaining research questions: 1) What is the structure of the joint dependence between each of China's markets and other markets in the sample?; 2) Is there a change in the dependence structure of these markets in the crisis periods?; and 3) Is there heterogeneity in the regional and global joint dependence structure among AS, BS and HS? This chapter uses seven different copula functions to capture the dependence structure of these pairs to address research question 1. Research question 2 will be answered by observing the best-fitting copulas and the degree of Kendall's tau parameters for these pairs in the non-crisis and crisis periods. Research question 3 will be addressed by comparing the best-fitting copulas for A-share pairs, B-share pairs and H-share pairs.

This chapter is significant for many reasons. First, tail dependence is fundamental to evaluate many important concepts in financial modelling associated with crises such as contagion effect and recoupling hypothesis. The study of tail dependence among stock markets, therefore, provides crucial implications for estimating an optimal portfolio, hedging and options pricing. In addition, evaluating tail dependence using the copula approach is a recently developed method in modelling joint dependence of stock returns. Hence, this chapter creates an empirical context for applying copulas in evaluating the joint dependencies between global stock markets and major Chinese share types. Given the size of China's economy and the rapid expansion of China's stock markets, evaluating the global and regional dependence of three major share types in China is of interest to global investors, fund managers and policymakers. This chapter expands the limited literature on the joint dependence of China's AS, BS and HS with various advanced and emerging markets over the last 15 years. Finally, this chapter provides useful findings which confirm the differences in the joint dependence structures and behaviours of these Chinese share types in both non-crisis (pre-GFC and post-crisis periods) and crisis periods (GFC and extended-crisis periods). Thus, investors and fund managers should take these differences into account when forming investment and hedging strategies for these stocks.

The copula approach is selected because it provides flexibility in capturing the joint distribution from a combination of different types of marginal distributions. This method also provides a practical approach to examine asymmetries in the tail dependence of the joint distributions effectively. In order to capture negative dependence and positive dependence, a wide range of copulas is applied including elliptical copulas (no tail dependence Gaussian copula and symmetric tail dependence Student-t copula), Archimedean copulas (Clayton, Gumbel and Rotated-Gumbel) and non-symmetric tail dependence copulas (rotated Joe-Gumbel BB7 and BB1 copulas). Gaussian and Student-t copulas are most commonly used in the existing literature as a benchmark because Gaussian copulas have no tail dependence and Student-t copulas have symmetrical tail dependence (Beckmann, Berger, Czudaj, & Thi-Hong-Van, 2019; Fortin & Kuzmics, 2002; Turgutlu & Ucer, 2010). However, as documented in Chapter 3, the stock returns of these markets are found to exhibit asymmetries, which is consistent with the vast majority of empirical studies. Therefore, it is necessary to include asymmetric tail dependence in the analysis of the joint distribution of stock returns. Hence, this chapter includes the rotated Joe-Gumbel and BB7 copulas which have different upper and lower tail dependencies, and the upper tail dependence Gumbel copula and the lower tail dependence Clayton and Rotated-Gumbel copulas. The selection of these copulas enables a comprehensive analysis of the joint distributions between the studied markets.



Note: The straight line is the theoretical normal distribution. The curve is the empirical distribution of each stock return. The graph shows that for each market there are some points that fall on the line, but the majority of the curve falls off the line and especially curves off in the tails. This implies a non-normal distribution. The left (or lower) and right (or upper) tails of the empirical distribution of each market also fall outside of the straight line, which indicates a fat tail distribution. Some of the markets where tails are strongly dispersed from the straight line include Australia, Germany, Japan, HS, SHA, SHB, SZA, SZB, the UK and US.

Figure 5-1. Quantile-Quantile (Q-Q) plot for the return series of each stock market – full sample

5.2. Literature review

5.2.1. Cross-market linkages and tail dependence

This chapter expands the analysis undertaken in Chapter 4 by focusing on the tail dependence of bivariate distributions and multivariate distributions between China's markets and other markets in the sample. In modelling market interdependence of stock returns, intuitively, joint dependence estimates such as bivariate and multivariate dependence are essential in providing information on the co-movement process of stock returns or volatilities, which separate univariate models fail to do. Bivariate dependence, on the other hand, provides a direct and straightforward interpretation of the results for the direction and the causality between two markets and is a common approach in empirical studies. Multivariate dependence estimates the regional or global dependence of a group of markets with a global market; for example, between BRICS markets and the US (Mensi et al., 2016). Pearson's correlation as a dependence measure relies on the assumption that two series must be Gaussian. This assumption is commonly violated when modelling financial time series such as stock returns and volatilities, since those time series are commonly non-normally distributed, and exhibit kurtosis, skewness and fat tails which are documented abundantly in the aforementioned empirical literature. In addition, Pearson's correlation assigns equal weights to all observations in the body and in the tails, hence the dependence measure, as an average, will provide an underestimation of the probability of co-crashes if the dependence in the joint loss tail is higher than the dependence in the body. To overcome these shortcomings in modelling a bivariate or multivariate dependence structure, one can employ the family of copula functions because this method allows modelling the marginal and the joint distribution separately. For example, a valid bivariate distribution can be constructed from a normal marginal distribution and exponential marginal distribution via copulas. As such, this method has become increasingly appealing over the last two decades in the modelling of financial time series.

Significant increase in tail dependence is found during a financial crisis, suggesting tail dependence should be the measure of financial contagion during a financial crisis (Rodriguez, 2007; Wen, Wei, & Huang, 2012; Ye, Liu, & Miao, 2012). Hence, it is necessary to study the dependence across markets at the tails of the distributions. Several studies have been conducted to examine the bivariate and multivariate dependence of global equity markets using copula functions for the joint distributions and the GARCH models for the marginal distributions. Fortin and Kuzmics (2002) found that there is evidence of high dependence in lower tails and low dependence in upper tails between European stock indices, and that the tail dependence of a bivariate distribution is asymmetric using a bivariate GARCH model for the marginals and the copula for the joint distribution. Dajcman (2013) found asymmetric lower tail dependence between the three largest Central and Eastern European stock markets (Hungary, Czech Republic and Poland) and two major Eurozone stock markets (Germany and France) using the Joe-Clayton copula. Jiang, Nie, and Monginsidi (2017) found a high level of tail dependence between the ASEAN-5 stock markets in the short run (one or two years after the ASEAN trading links launched in 2012) and during the GFC (both upper and lower tail dependence) using the Student-*t* copula for symmetric tail dependence and Gumbel and Clayton for positive and negative tail dependence respectively. This finding implies that those countries are prone to move together during an economic shock period (in both signs) such as the ASEAN trading links or the GFC, suggesting that the likelihood for the whole region to boom or crash together is considerably high. Rémillard, Papageorgiou, and Soustra (2012) used a time-varying Markovian copula to model the multivariate dependence between the Canadian and US exchange rate and oil prices. Reboredo et al. (2016) used symmetric copula functions (Gaussian and Student-t) and asymmetric copula functions (Gumbel, Clayton, rotated Gumbel and rotated Joe) to examine the dependence structure between the stock returns of a set of emerging economies (Brazil, Chile, Colombia, India, Mexico, Russia, South Africa and Turkey) and exchange rates (USD and EUR). Their study suggested that lower tail dependence is stronger than upper tail dependence.

Many papers have studied the dependence structure of Chinese stock markets using bivariate copula functions. Kenourgios et al. (2011) investigated financial contagion (increased correlation during a crisis period) between the emerging BRIC markets and the US and UK using a multivariate regime-switching Gaussian copula model to capture non-linear correlation dynamics during five financial crises from 1995 to 2006. Their results suggested that the emerging markets are more prone to financial contagion because the increase in the correlation between the BRIC markets is larger than those between them and the developed markets. Fang et al. (2015) used the double-dynamic asymmetric copula model to capture the multivariate dynamics and the asymmetries in the joint dependence structure between the Shanghai and New York stock markets from 1991 to 2013. They found that the copula parameters are not time-varying and a constant correlation model might be a better fit – and there exists strong tail dependence between these markets. Hussain and Li (2018) analysed the tail dependence distribution using daily, weekly and monthly data between the CSI 300 and other major markets including the US, UK, Canada, Germany, Japan and Australia from 2005 to 2015. They found that the dependence between those developed markets is low, with the highest market correlation between China and Australia and the lowest correlation between China and the US. Zhang, Paya, and Peel (2009) examined the dynamic linkages between daily returns of Shanghai and HK stock markets from 1996 to 2008 using a copula approach. They found strong evidence of time-varying dependence with different degrees at both tails of these two markets. Wen et al. (2012) used time-varying copula models, and the CCC and DCC-GARCH models on the daily MSCI index returns to capture the non-linear and time-dependent relationship between the markets in China and other global markets from 2000 to 2009. They found that the Chinese market is most related with the markets in Japan and the Pacific and that the variability of their dependencies with those markets is also highest. None of these studies have examined the regional and global linkages of A-, B- and H-share markets simultaneously.

Few studies have examined the cross-market dependence structure of AS, BS and HS. Luo et al. (2011) described the regional and global dependence structure of A-share markets using the copula approach and found weak dependence and no tail dependence between Chinese markets and Hong Kong, Singapore, Thailand, Korea, Taiwan and Australia before the introduction of the QFII 2002 which enables some foreign institutional investors to invest in AS with restrictions. After the placement of this policy, symmetric and asymmetric tail dependencies are evident for these Chinese markets from 2002 to 2009. Lu, Lai, and Liang (2012) used a time-varying copula-GARCH model with Hansen's skewed Student-t innovations to investigate the dynamic dependence between investor sentiment and stock returns in AS and BS in the Shanghai market from 2005 to 2009. It was found that the stock returns of A- and B-share markets tend to increase more when investors become bullish and that this correlation was time-varying. It was also found that the variations in the covariances of the B-share market were higher than in the A-share market, indicating that the dependence structure between investor sentiment and stock returns was more volatile in B-share markets than in A-share markets. Guo and Wang (2016) used time-varying copulas to describe the dependence structure in the volatility of five minutes and 15 minutes price data between Shanghai and Shenzhen stock markets from 2004 to 2014. They found asymmetric dependence distribution with upper tail dependence was evident during the volatile period, indicating a strong tendency of the volatilities of AS and BS to move together during heightened volatility periods. None of these papers examined the regional linkages of AS, BS and HS simultaneously. Hence, this chapter aims to close this gap by focusing on distinguishing the differences in regional and global market dependencies of A-, B- and H-share markets.

The aforementioned studies show that the application of copulas in empirical studies was frequent because this approach allows the modelling of joint dependence structures separately from the marginal distributions. In addition, the copula functions can accommodate the modelling of different dependence structures – including average dependence such as the Gaussian copula, symmetric tail dependence such as the Student-t copula, asymmetric positive lower and upper tail dependencies such as the Clayton (1978) copula and the Gumbel (1960) copula respectively, negative average dependence such as the Frank (1979) copula, and negative upper tail dependence such as the Joe (1997) copula – so they can be used to construct both bivariate and multivariate distributions effectively (Chandra, 2015; Rémillard et al., 2012).

Patton (2012) conducted a survey that reviews multivariate modelling using different estimation and inference methods for copulas including full parametric, semi-parametric and non-parametric methods. Under the parametric approach, both marginal and copulas parameters are estimated parametrically, such as marginal densities being modelled by a GARCH or ARMA process, while dependence parameters are measured by the maximum estimation likelihood approach. This is one of the most common approaches in finance. Under the semi-parametric approach, a marginal distribution can be estimated non-parametrically (for example, empirical distribution functions), while copulas are estimated parametrically (for example, pseudo maximum likelihood). Under the non-parametric approach, both marginal and copula parameters are estimated by a non-parametric model. This chapter follows the common practice in the existing literature, which employs the semi-parametric approach. The benefit of this approach is the estimation of marginal distributions using a GARCH model, which accounts for prominent distributional properties of time series of stock returns, as fully discussed in chapters 2 and 3, while the copula parameters are estimated by a pseudo maximum likelihood (that is, Kendall's tau). This method is tempting because the variances of the copula parameters estimated from the maximum likelihood estimation are independent of the parameter estimation errors of the marginal distributions and have thus been increasingly used (Chen & Fan, 2006; Ning et al., 2015). The next section provides further details on the selected copulas and the related concepts to copulas, including Kendall's tau, Sklar's theorem and the Fréchet–Hoeffding bounds for the joint distributions. Sklar's theorem explains the concept of copula. The copula parameters are estimated based on Kendall's tau, which is restricted by the Fréchet–Hoeffding bounds.

5.2.2. Kendall's tau and Spearman's rho

In this section, two non-parametric alternatives of rank correlation coefficients – Kendall's tau and Spearman's rho – are discussed. Rank correlation measures the ordinal association between two variables based on their rank. For example, the Spearman's rho will be high if the two variables have a similar rank between the two variables. These are crucial measures of dependence of an elliptical distribution between two variables (rank correlation) (Coffman, Maydeu-Olivares, & Arnau, 2008; Nguyen, Bhatti, Komorníková, & Komorník, 2016) – such as heavy-tailed distributions which are often observed in daily financial time series as shown in the Q-Q plots in **Figure 5-1** and section 2.3, for which linear correlations are often inappropriate and misleading. Two important definitions of Kendall's tau and Spearman's rho for the case of bivariate dependence are presented below.

Assume $(x_1, y_1)^T$ and $(x_2, y_2)^T$ are two observations from a vector $(X, Y)^T$ of continuous random variables. According to Nelson (1991), $(x_1, y_1)^T$ and $(x_2, y_2)^T$ are concordant if $(x_1 - y_1)(x_2 - y_2) > 0$ and, discordant if $(x_1 - y_1)(x_2 - y_2) < 0$. So, concordance measures the tendency of two or more variables to be all large or to be all small simultaneously (Taylor, 2007). Discordance is the reverse state of concordance.

Kendall's tau for a random vector $(X, Y)^T$ is defined as

$$\tau(X,Y) = P\{(X-\tilde{X})(Y-\tilde{Y}) > 0\} - P\{(X-\tilde{X})(Y-\tilde{Y}) < 0\}, \tag{5.1}$$

where $(\tilde{X}, \tilde{Y})^T$ is independent of $(X, Y)^T$. Kendall's tau measures this difference of probabilities. The Kendall's tau is expressed in terms of a bivariate copula of X_1 and X_2 as follows:

$$\tau(X,Y) = 4\iint_{[0,1]^2} C(u_1,u_2)d\,C(u_1,u_2) - 1 \tag{5.2}$$

Hence, Kendall's tau for *(X, Y)*^{T} is simply the probability (P) of concordance minus the probability of discordance. Kendall's tau correlation measures the strength of the dependence between two variables ranging from -1 to 1.

Spearman's rho for the random vector *(X, Y)*^{T} is given by $\rho(X, Y) = 3\{P[(X - X')(Y - Y') > 0] - P[(X - X')(Y - Y') < 0$, where *(X,Y)*^{T} and $(\tilde{X}, \tilde{Y})^T$ $(X', Y')^T$ are independent. Similar to Kendall's tau, Spearman's rho is used to measure the degree of association between two variables without relying on the assumption of data distribution. Spearman's rho also ranges from -1 to 1. For more information about the mathematical proofs for these definitions, please see Kendall and Stuart (1979) and Embrechts, Lindskog, and McNeil (2001).

5.2.3. Copula – the Sklar's theorem

The Sklar (1959) theorem states that there exists a copula *C* that links multivariate distribution function F to its uniformly distributed marginal distribution functions ($F_1,\ldots, F_n$). In other words, the dependence structure can be modelled separately from the marginal distributions by copula functions. If the marginal distributions are used to construct the multivariate distribution, they are required to be uniformly distributed. Copulas are defined as follows.

Definition 1: A *d*-dimensional copula, $C: [0,1]^d: \rightarrow [0,1]$ is a cumulative distribution function (CDF) with uniform marginals. Let *F* be the *d*-dimensional CDF *F* with marginals $F_1,\ldots, F_d$. There exists a copula $C(u) = C(u_1, \ldots, u_d)$ with the following properties:

1. $C(u) = C(u_1, \ldots, u_d)$ is non-decreasing in each component, u_i.
2. The i^{th} marginal distribution is obtained by setting $u_j = 1$ for $j \neq i$ and since it is a uniform distribution, $C(1, \ldots, 1, u_i, 1, \ldots, 1) = u_i$.
3. For $a_i \leq b_i, P(U_1 \in [a_d, b_d])$ must be non-negative.

If *X* has continuous CDF, F_X, then $F_X(X) \sim U[0,1]$. Now let $X = (X_1, \ldots, X_d)$ be a multivariate random rector with CDF F_X with continuous and increasing marginals. Then by Definition 1, it follows that the joint distribution of $F_{X_1}(X_1), \ldots, F_d(X_d)$ is a copula, C_X.

Theorem 1 (Sklar 1959's theorem)

The Sklar's theorem states that for a *d*-dimensional CDF, *F*, with marginals $F_1,\ldots, F_d$, then there exists a copula, *C*, such that $F(x_1, \ldots, x_d) = C\big(F_1(x_1), \ldots, F_d(x_d)\big)$. For all $x_i \in [-\infty, \infty]$ and $i = 1,\ldots, d$. If F_i is continuous for all $i = 1,\ldots, d$, then C *is unique.*

For a bivariate distribution, let $x = (x_1, x_2)$ be a two-dimensional random vector with joint distribution $F(x_1, x_2)$ and marginal distributions $F_i(x_i), i = 1, 2$. Similar to the above, there exists a copula $C(x_1, x_2)$ such that $F(x_1, x_2) = \mathrm{P}(X_1 < x_1, X_2 < x_2) = C\big(F_1(\mathrm{x}_1), F_2(x_2)\big)$ (Nelson, 1991). Again,the bivariate copula $C(u_1, u_2)$ is unique if F_i are continuous. There exists upper (lower) tail dependence λ_U (λ_L) when there is a positive joint probability of positive (negative) outliers. The upper tail dependence is defined as $\lambda_U = \lim_{u \to 1^-} P(U_1 > u | U_2 > u) = \lim_{u \to 1^-} \frac{C^*(u,u)}{1-u}$. The lower tail dependence is given by $\lambda_L = \lim_{u \to 0^+} P(U_1 < u | U_2 < u) = \lim_{u \to 0^+} \frac{C(u,u)}{u}$.

5.2.4. The Fréchet–Hoeffding bounds for joint distribution functions

The upper and lower bounds for a joint distribution function measured by a copula function are subject to the Fréchet-Hoeffding bounds (Nelson, 1991). M^n, Π^n and W^n are defined on $[0, 1]^n$. $M^n(\mathrm{u}) = \min(u_1, \dots, u_n)$; $\Pi^n(\mathrm{u}) = u_1, \dots, u_n$; and $W^n(\mathrm{u}) = \max(u_1, \dots, u_n)$. For every *n*-copula C, the Fréchet-Hoeffding inequality theory defines:

$$M^n(u_1, \dots, u_n) \leq C\,(u_1, \dots, u_n) \leq W^n(u_1, \dots, u_n) \tag{5.3}$$

For n = 2, the upper and lower bounds are themselves copulas, and we have seen that M^n and W^n are the bivariate distributions functions of the random vectors $(F, 1 - F)^T$ and $(F, F)^T$ respectively, where $F \sim F(0,1)$ (that is, F is uniformly distributed on [0,1] as defined in section 4.3.2). In this case, M^n describes perfect negative and W^n describes perfect positive dependence.

5.2.5. Elliptical copulas

Elliptical copulas and Archimedean copulas are two major classes of copulas that are well known in risk management applications (Berger, 2013; Kole, Koedijk, & Verbeek, 2007) and multivariate time series (Rémillard et al., 2012).

5.2.5.1. Gaussian copula

The multivariate *d*-dimensional Gaussian copula, with v degrees of freedom (d.o.f) which is part of the elliptical distribution family, is a natural benchmark with tail independence. This function is given by:

$$C_P^{Gaus}(u) = \Phi_P\big(\Phi^{-1}(u_1), \dots, \Phi^{-1}(u_d)\big) \tag{5.4}$$

The bivariate Gaussian copula is formed when d = 2. In this case, Φ_P denotes the joint cumulative distribution function of a bivariate Gaussian distribution with mean vector zero and 2x2 correlation matrix, P. Φ^{-1} refers to the inverse cumulative distribution function of a standard univariate normal distribution. The parameter ranges from -1 to 1.

The relationship between Kendall's tau and the Gaussian copula parameter is $\tau = \frac{2}{\pi}\arcsin(\rho)$. ρ is a parameter which indicates the dependence level. The Gaussian copula does not specify the upper or lower tail dependence and does not imply volatility clustering. Hence, this copula is designed to model average dependence with Gaussian distribution.

The Gaussian and Student-t copulas belong to the elliptical copula family. These copulas display the average dependence of a joint density function. The Gaussian copula does not have tail dependence, so it serves as a benchmark for comparison purposes (Li & Kang, 2018; Wang et al., 2011).

The Student-t copula assumes the dependence structure has a Student-t distribution. This copula has symmetric tail dependence. Both Gaussian and Student-t copulas can only capture positive dependence, and therefore if a joint distribution displays negative dependence during bull or bear markets, this cannot be captured by Gaussian and Student-t copulas. Therefore, Gaussian and Student-t copulas are commonly used together with other classes of copulas such as the Archimedean copula family – Gumbel and Clayton copulas – to model the asymmetric tail dependence and other asymmetric or symmetric tail dependence copulas that can capture negative dependence such as Frank and Joe copulas.

A Gaussian copula can be suitable to describe the symmetric dependence structure with tail independence. (Turgutlu & Ucer, 2010) examined the dependence structure of monthly stock returns between various emerging markets in Europe and Asia and developed markets using Gaussian, Gumbel and Gumbel survival copulas. The results suggest that Gaussian and Gumbel survival copulas are the best fit for most markets, indicating that most markets are likely to crash together and display a considerable level of dependence in general.

5.2.5.2. Student-t-copula

The multivariate Student-t-copula (*t*-copula) with v d.o.f., zero mean and correlation ρ, which also corresponds to an elliptical distribution, is defined by Rayens and Nelsen (2000) as:

$$C_{v,P}^{ST}(u) := t_{v,P}(t_v^{-1}(u_1), \dots, t_v^{-1}(u_d)) \tag{5.5}$$

A d-dimensional copula C is a d-dimensional distribution function on $[0,1]^d$ with standard uniform marginal distributions. When $d = 2$, the function is a bivariate copula function. The relationship between Kendall's tau and the Student-t copula parameter is given: $\tau = \frac{2}{\pi}\arcsin(\rho)$. The lower and upper tail dependence coefficients are $\lambda_U = \lambda_L = 2\bar{t}_{v+1}\left(\sqrt{\frac{(v+1)(1-\rho)}{1+\rho}}\right)$, where $\bar{t}_{v+1}(u) = 1 - t_{v+1}(u)$ and t_{v+1} is the Student-t distribution function with $v + 1$ degrees of freedom. If v approaches infinity, λ_U approaches zero. Unlike the Gaussian copula, the Student-t copula does not only capture the dependence around the mean, but also in the tails. Student *t*-copula allows volatility clustering with equal probability. This copula assumes that the dependence structure follows the Student-t distribution.

Gaussian and Student-t copulas are less common for the dependence structure between markets with geographic proximity or which have strong links to fundamental factors such as trading. Mensi et al. (2017) used symmetric copulas (Gaussian, Frank, Placket copulas), Student-t copula and asymmetric copulas (Gumbel and rotated Gumbel, Clayton and SJC copulas) to investigate the tail dependence between world crude oil prices and four major regional developed stock markets (US, Canada, Europe, and the Pacific without Japan). In their study, the autoregressive fractionally integrated moving average-fractionally integrated generalised autoregressive conditional heteroskedastic (ARFIMA-FIGARCH) process was used to construct skewed Student-t marginal distributions that incorporated long-range memory. The results suggested that the dependence structure of oil price returns and four regional stock markets exhibited rotated Gumbel with significant lower tail dependence in bear markets. The dependence is positive and short-lived. In long-run horizons, symmetric Joe-Clayton with various tail dependence structures were found for these markets. For the Pacific, Europe and the US, the joint density function with oil had asymmetric and positive tail dependence, indicating that the association between oil and stock markets varies during bull and bear markets.

5.2.6. Archimedean copulas

Archimedean copulas include Clayton, Gumbel and rotated Gumbel, which are asymmetric tail dependence copulas that can capture one side of the tail dependence. These copulas are useful in evaluating dependence at extreme values because they can capture upper tail dependence (Gumbel copula) and lower tail dependence (rotated Gumbel and Clayton copulas).

The Archimedean copula family parameters are measured by Kendall's τ. Genest and MacKay (1986) define a general bivariate Archimedean with v d.o.f as:

$$C^{Arc}(u_1, u_2) = \varphi^{-1}(\varphi(u_1) + \varphi(u_2)), \tag{5.6}$$

where C is the function from $[0,1]^2$ to $[0,1]$. C is a copula if and only if φ is convex.

$$\varphi^{[-1]}(t) = \begin{cases} \varphi^{-1}(t), & 0 \leq t \leq \varphi(0) \\ 0, & \varphi(0) \leq t \leq \infty \end{cases} \tag{5.7}$$

$$\varphi(\varphi^{[-1]}(t)) = \begin{cases} t, & 0 \leq t \leq \varphi(0) \\ \varphi(0), & \varphi(0) \leq t \leq \infty \end{cases} \tag{5.8}$$

5.2.6.1. Clayton copula

The bivariate Clayton (1978) copula is an Archimedean copula that models greater dependence in the left tail than in the right tail and is given by:

$$\mathrm{C}_{\theta}^{Clay}(u_1, u_2) := \left(u_1{}^{-\theta} + u_2{}^{-\theta} - 1\right)^{-\frac{1}{\theta}} \tag{5.9}$$

The generator is: $\phi(t) = \theta^{-1}\left(t^{-\theta} - 1\right)$, where $\theta \in [-1, +\infty)\backslash\{0\}$. The parameter θ indicates the dependence level of two variables. If $\theta = -1$, it implies independence. When θ approaches infinity, the Clayton copula approaches the Fréchet-Hoeffding lower bound, which implies perfect dependence. The relationship between Kendall's tau and the Clayton copula parameter is given: $\tau = \frac{\theta}{\theta+2}$. The upper tail dependence is $\lambda_U^{Clay} = 0$ and the lower tail dependence is $\lambda_L^{Clay} = 2^{-1/\theta}$.

The Clayton copula can only capture lower tail dependence. This copula is also designed to capture clusters of low volatilities, but not high volatilities.

5.2.6.2. Gumbel copula

The bivariate Gumbel (1960) copula is another Archimedean copula, but in contrast to the Clayton copula, the Gumbel copula exhibits greater dependence in the right tail than in the left tail. This copula is given by:

$$C_{\theta}^{Gu}(u_1, u_2) := exp(-[(-\ln u_1)^{\theta} + (-\ln u_2)^{\theta}]^{\frac{1}{\theta}}) \tag{5.10}$$

Its generator is: $\phi(t) = (-\log(t))^{\theta}$, where $\theta \geq 1$. $\theta = 1$ implies independence. When θ approaches infinity, the Gumbel copula approximates the Fréchet-Hoeffding upper bound, which means perfect dependence. Like the Clayton copula, the Gumbel copula cannot capture negative dependence.

The relationship between Kendall's tau and the Gumbel copula parameter is given: $\tau = 1 - \theta^{-1}$. The upper tail dependence is $\lambda_U^{Gu} = 2 - 2^{-\theta}$ and the lower tail dependence is $\lambda_L^{Gu} = 0$. The Gumbel copula is also an extreme value copula that can be created by multiple distributions of extreme values over stable distributions. In the Gumbel copula function, φ is a continuous, strictly decreasing function from [0,1] to [0,∞] such that $\varphi(1) = 0$. $\varphi^{[-1]}: [0, \infty] \to [0,1]$ is the pseudo-inverse function. $\varphi^{[-1]}$ is continuous and decreasing on [0, ∞] and strictly decreasing on [0, $\varphi(0)$]. If $\varphi(0) = \infty$, then $\varphi^{[-1]} = \varphi^{-1}$. In the *t*-copula, t_v^{-1} is the inverse of the *t*-distribution, $t_{p,v}$ is the multivariate joint distribution and v is the degrees of freedom.

Asymmetric and positive tail dependence copulas such as Gumbel and Joe copulas are more common for market volatility dependence structures. Peng and Ng (2012) used the mixed Gumbel-Clayton (MGC) copula to model both sides of tails of the dependence structure, which overcomes the limitation that both Gumbel and Clayton copulas can only capture one side of a joint distribution. The results suggest that cross-market contagion is more probable for the lower tail dependence of stock returns and the higher tail dependence of volatility. This finding indicates that volatility dependence is higher during high turbulence markets such as bull markets or recessions. Fortin and Kuzmics (2002) used symmetric Gaussian, and Student-t-copulas, Archimedean copulas (Clayton, Gumbel), Joe copulas and the rotated Gumbel and Joe copulas to test normality or *t*-dependence versus asymmetric tail dependence of daily volatility between three European markets including the UK, Germany and France from 1990 to 2001. The results indicated that the bivariate distribution between these three markets was always characterised by an asymmetric lower tail dependence structure; that is, Clayton or rotated Gumbel copula or the rotated Joe copula.

5.2.6.3. Rotated Gumbel (RG) copula

Since the Gumbel copula can only capture the upper tail dependence, rotating this copula 180 degrees is used to capture the other side of the tail dependence, while the estimation procedure remains the same (Li & Kang, 2018). The rotated bivariate Gumbel copula BB1 (rotated 180 degrees) is to capture lower tail dependence only, which is given by:

$$C_\theta^{RG}(u_1,u_2) = -\frac{1}{\theta}\log(1+\frac{(e^{-\theta u_1}-1)(e^{-\theta u_2}-1)}{e^{-\theta}-1}), \tag{5.11}$$

The relationship between Kendall's tau and the Frank copula parameter is given by $\tau = 1 - \theta^{-1}$. The upper tail dependence is $\lambda_U^{RG} = 0$ and the lower tail dependence is $\lambda_L^{RG} = 2 - 2^{1/\theta}$.

5.2.7. Clayton-Gumbel (CG) or BB1 copula

CG or BB1 copula can capture the dependence at both tails with different parameters; that is, non-symmetrical tail dependence (Czado, Schepsmeier, & Min, 2012). Including the BB1 copula is to ensure both tails of the dependence structure are examined. A bivariate BB1 copula is given as:

$$\begin{aligned} C_\theta^{BB1}(u_1,u_2) &= u_1 + u_2 - 1 + C_G(1-u_1, 1-u_2;\theta) \\ &= 1-\left(1-\left[(1-(1-u_1)^{\delta^{-\theta}} + (1-(1-u_2)^{\delta^{-\theta}}) - 1\right]^{-\frac{1}{\theta}}\right)^{\frac{1}{\delta}}, \end{aligned} \tag{5.12}$$

with $0 < \theta < \infty$. Like the Gumbel copula, the BB1 copula parameter is positive. The generator function of this copula is $\phi(t) = (t^{-\theta} - 1)^{\delta}$. The relationship between Kendall's tau and the BB1 copula parameter is given as $1 - 2/\delta(\theta+2)$. The upper tail and lower tail parameters are $2^{-1/(\theta\delta)}, 2 - 2^{1/\delta}$ respectively.

5.2.8. Joe-Clayton (JC) or BB7 copula

The JC copula is also known as the BB7 copula introduced by Joe (1997), and it is an asymmetrical tail dependence copula with different dependencies. A bivariate JC copula is given as:

$$\begin{aligned} C_\theta^{JC}(u_1,u_2) &= \eta(\eta^{-1}(u_1) + \eta^{-1}(u_2)) \\ &= 1-\left(1-\left\{\left[1-\left(1-u_1{}^{-\delta}\right)^{-\theta}\right]^{-\theta} + \left[(1-\left(1-u_2{}^{-\delta}\right)^{-\theta}\right]^{-\theta} - 1\right\}^{-\frac{1}{\theta}}\right)^{\frac{1}{\delta}}, \end{aligned} \tag{5.13}$$

where $\eta(s) = 1 - \left[1-(1+s)^{-\frac{1}{\theta}}\right]^{\frac{1}{\delta}}$. The upper tail dependence is $\lambda_U^{JC} = 2 - 2^{1/\delta}$ with $\lambda_U^{JC} \in (0,1)$ and the lower tail dependence is $\lambda_L^{JC} = 2 - 2^{1/\delta}$ with $\lambda_L^{JC} \in (0,1)$. The JC parameters are calculated as $\theta_t = \omega + \beta\theta_{t-1} + \alpha\frac{1}{q}\sum_{j=1}^{q} u_{t-j} - v_{t-j}$. The Kendall's tau of the JC copula with full expression is:

$$\tau(\delta,\theta) = \begin{cases} 1-2/[\theta(2-\delta)] + 1\beta(\theta+2, 2/\delta-1)/(\delta^2\theta) & 1 \le \delta < 2 \\ 1- \ [\Phi(2+\theta) - \Phi(1) - 1]/\theta & \delta = 2 \\ 1-2/[\theta(2-\delta)] - 4\pi/[\delta^2\theta(2+\theta)\sin 2\pi/\delta) B(1+\theta+2/\delta, 2-2/\delta] & \delta > 2 \end{cases}$$

where $B(\cdot)$ is the beta function and $\Phi(\cdot)$ is the gamma function. By the convergence theorem, Kendall's tau is continuous for all $\delta \ge 1$. This copula can capture the dependence at both tails of a joint distribution with different tail dependencies. Therefore, it can capture the distribution form that has both tails' dependence but does not fit symmetric tail dependence. Therefore, a combination of symmetric Student-t copula and non-symmetric BB7 copula can provide a comprehensive approach to measure the bivariate tail dependence structure. **Table 5-1** summarises the copula functions used in this chapter.

Table 5-1. Summary of the main features of the copula functions used in Chapter 5

No	Copula	Generator function	Parameter range	Kendall's t	Tail dependence	Notes
1	Gaussian	-	$\rho \in (-1,1)$	$\frac{2}{\pi}\arcsin(\rho)$	0, 0	No tail dependence
2	Student-t	-	$\rho \in (-1,1), \nu > 2$	$\frac{2}{\pi}\arcsin(\rho)$	$2\bar{t}_{\upsilon+1}\left(\sqrt{\frac{(\upsilon+1)(1-p)}{1+p}}\right)$	Symmetric tail dependence
3	Clayton	$\theta^{-1}(t^{-\theta}-1)$	$\theta \geq 0$	$\frac{\theta}{\theta+2}$	$2^{-1/\theta}, 0$	Lower tail dependence
4	Gumbel	$exp(-[(-\ln \mathrm{u})^{\theta}+(-\ln v)^{\theta}]^{\theta^{-1}})$	$\theta \geq 1$	$1-\theta^{-1}$	$0, 2-2^{1/\theta}$	Upper tail dependence
5	Rotated-Gumbel	$-\frac{1}{\theta}\log(1+\frac{(e^{-\theta u_1}-1)(e^{-\theta u_2}-1)}{e^{-\theta}-1})$	$\theta \geq 0$	$1-\theta^{-1}$	$2-2^{1/\theta}, 0$	Lower tail dependence
6	BB1	$u + \mathrm{v} - 1 + C_G(1-u, 1-\mathrm{v}; \theta)$	$0 < \theta < \infty$	$1-2/\delta(\theta+2)$	$2^{-1/(\theta\delta)}, 2-2^{1/\delta}$	Different tail dependencies
7	Joe-Clayton	$1-[1-\{(1-u_1{}^{-\theta})^{-\delta}+(1-u_2{}^{-\theta})^{-\delta}-1\}]^{1/\theta}$	$\theta \geq 1, \delta > 0$	See Section 5.2.8 for full expression	$(2^{-1/\delta}, 2-2^{1/\theta})$	Different tail dependencies

5.2.9. Estimating copula-based bivariate and multivariate time series models

To measure the parameters for the selected copulas in this chapter, one can use Naïve estimators or the maximum likelihood estimation (MLE), also called pseudo log-likelihood method (PLM) (Caillault & Guegan, 2005; Patton, 2012).

The Naïve estimators are the priori estimations of the upper tail and lower tail parameters which are obtained by a bootstrap method and simulations. The validity of this method relies heavily on the assumptions of the joint distribution. In addition, this method is computationally intensive and subject to mathematical biases when the value of the upper tail dependence is below a threshold. The PLM selects the best copula based on the information criteria without specifying the copula's distributions. Compared to the Naïve estimators, this approach is much easier to execute and does not require prior knowledge of the tail dependence. Since the Naïve estimator approach does not necessarily outperform PLM (Caillault & Guegan, 2005), PLM is favoured in the existing literature, thanks to its simple operation and interpretation without specifying tail dependence structure (Breymann, Dias, & Embrechts, 2003). Also, PLM can accommodate the estimation of Kendall's tau and Spearman's rho for the selected copulas (Tófoli, Ziegelmann, & Silva Filho, 2012).

Therefore, PLM is selected in this chapter and the estimation procedure will involve two steps. The first one is to estimate the marginal distribution using a GARCH process, and the second is to estimate the copula parameters based on the maximum likelihood.

In brief, copulas are selected for two main reasons. First, this approach allows the separate modelling of the marginals and the dependence structure. Using the PLM estimation method allows the modelling of tail dependence without prior knowledge or assumption. Second, various copulas' functions can capture the general dependence such as Gaussian, the symmetric tail dependence such as Student-t, the non-symmetric tail dependence such as BB1 and BB7, and the asymmetric tail dependence such as Archimedean copulas. The combination of these functions can provide a comprehensive approach to describe the dependence structure between the Chinese markets and the emerging and advanced markets in the sample.

5.3. Data and methodology

5.3.1. Data

The analysis examines the same data that was used for the GARCH modelling in Chapter 3 and Chapter 4 and is described in section 2.1. The daily closing prices are downloaded from Bloomberg for each market, as shown in **Figure 2-1**, and then converted to a first difference natural logarithm to make each time series stationary.

The data is subdivided into four sub-periods as follows:

1. Pre-GFC period: from 1 May 2002 to 26 February 2007 (871 observations).
2. GFC period: from 27 February 2007 to 29 May 2009 (410 observations).

3. Extended-crisis period: from 30 May 2009 to 6 June 2012 (539 observations).
4. Post-crisis period: from 7 June 2012 to 31 July 2017 (912 observations).

More detail on these sub-periods is provided in sections 2.1 and 2.2.

5.3.2. Methodology

The dependence structure captured by a copula approach is estimated based on marginal distributions. A common approach in empirical studies of stock returns for estimating the marginal distributions is the GARCH model, as shown in section 4.2, since a GARCH model can capture significant distributional properties of stock returns effectively; that is, heteroskedasticity and volatility clustering, as discussed in sections 2.3.4, 2.3.5, 3.7 and 3.8. This methodology has three steps.

Firstly, each time series is estimated by a GARCH process. Daily stock returns (first difference log returns) are fitted to different GARCH models with GED distribution including ARMA(0,1)-GARCH(1,1), ARMA(1,0)-GARCH(1,1), and EGARCH (1,1) because those models are the best-fitting models to the data, as discussed in sections 3.4.2 and 3.5.3. Then, the standardised residuals are extracted from the best-fit GARCH model based on the AIC for each time series. The residuals of each time series extracted from a conditional return equation from a GARCH process are transformed into uniform variates using the Rank method. This process assigns a ranking unit for each observation within a time series. The transformation does not impact the value of Kendall's tau.

Secondly, the bivariate distribution is fitted to a range of copulas, and the best-fitting copula is selected based on the AIC. These transformed marginals in step one are fitted to eight different copula functions, following the approach of Boubaker and Sghaier (2013) and Allen, McAleer, and Singh (2017). These copula functions include Gaussian copula with tail independence, Student-t copula with symmetric tail dependence, Clayton copula with lower tail dependence, Gumbel copula with upper tail dependence, rotated Gumbel with lower tail dependence and BB1 copula and JC (BB7) copula which are the two tail dependence copulas with asymmetric upper and lower tail dependencies. The best-fitting copula is selected based on the AIC. The main specifications of these copula functions used in this chapter are presented in **Table 5-1**.

Finally, the joint dependence structure is analysed based on the best-fitting copula and the estimated coefficients from the copula tests. The right tail dependence Gumbel copula can capture the upper tail dependence of the volatility of these markets, especially during the crisis periods (GFC period and extended-crisis period). The Gaussian copula can be found during non-crisis periods (pre-GFC period and post-crisis period). Since these studied markets exhibit volatility clustering, as shown in section 2.3.4, the analysis might also find left tail dependence characterised by the Clayton copula for these stock markets during non-crisis periods. It will not be unusual to find a Student-t copula and BB1 or BB7 copulas in both good and bad market conditions.

5.4. Hypotheses

The research objective is to evaluate the bivariate dependence structure for each of China's markets and other studied markets using seven different copula functions, as outlined in the three research questions at the start of this chapter.

In line with these research questions, this chapter aims to address the following hypotheses:

H_0: There is no evidence of dependence between each of China's markets and the other markets in the sample.

H_1: There is evidence of dependence between each of China's markets and the other markets in the sample.

An independence test is used to assess the market dependence for each pair, followed by the measure of tail dependence and copula parameters to quantify the tail dependence. If the p-value of the independence test is less than 0.05, it rejects the null hypothesis of no evidence of dependence at the 95% confidence level, implying evidence of general or tail dependence. The dependence is quantified with the best-fitting copulas, and the copula parameter will describe the degree of the tail or general dependence. Alternatively, p-values higher than 0.05 fail to reject the null hypothesis of no evidence of dependence, implying there is not enough evidence to suggest the existence of dependence between each of China's markets and other markets in the sample.

For research question 1, the dependence of each pair is captured by the copulas mentioned in sections 5.2.5 to 5.2.9. For example, the Student-t copula captures symmetric tail dependence at both sides, while an Archimedean copula can only capture tail dependence at one side. For research question 2, changes in the best-fitting copula and the values of Kendall's tau parameters indicate changes in the dependence structure in the non-crisis and crisis periods. Research question 3 will focus on the differences and similarities in the best-fitting copulas for each of China's share markets when pairing with other studied markets.

5.5. Empirical results

The estimates of tail dependence parameters and the results of the copula fitting process for each pair of markets between each of China's markets and other markets including the best-fitting copula, copula parameters, Kendall's tau parameters, p-values of the independence test and AIC are summarised in Appendix B (HS versus other markets), Appendix C (SHA versus other markets), Appendix D (SHB versus other markets), Appendix E (SZA versus other markets) and Appendix F (SZB versus other markets). The best-fitting copula for each pair of markets is selected based on the AIC.

The results show that the p-value of the independence test is zero or less than zero in most cases, which rejects the null hypothesis of independence, indicating the existence of dependence for most of China's pairs throughout the four sub-periods.

5.5.1. Tail dependence of H-shares (HS)

Appendix B reports the copula results between HS and other markets from every sub-period.

In the pre-GFC period, all HS pairs reject the null hypothesis of independence at the 5% significant level or lower, providing strong evidence of dependence between HS and all other markets in the sample. The markets that had the highest dependence level (as measured by Kendall's tau) with HS in this period are HK (0.48), Singapore (0.42), Japan (0.34), Australia (0.3) and Indonesia (0.29). The markets that had the lowest dependence level with HS include SZA and SHA (both at 0.1), SHB (0.11), NZ (0.13) and SZB (0.15). The dependence structure for 12 out of 16 HS pairs are described by the symmetric tail dependence Student-t-copula including Chinese markets (AS and BS), the ASEAN-5 except for Singapore, and the advanced markets (HK, Japan, NZ and Germany), evidencing market dependencies in both tails. The joint dependence between HS and some advanced markets – Singapore, Australia, the UK and US – are captured by an asymmetric tail dependence BB7 copula with higher left tail dependence. These results show that symmetric tail dependence which is described by a Student-t copula was dominant for HS pairs in the pre-GFC period. A similar finding was documented by Zhang et al. (2009). In addition, for some cases that experienced asymmetric tail dependencies; that is, HS–Singapore, HS–Australia, HS–UK, and HS–US, the dependence in the right tail was higher than the left tail in this period. These results demonstrate that HS had higher dependence with the advanced markets of Australia, the UK, US and Singapore during the time of market rise than market fall in the pre-GFC period.

In the GFC period, no evidence of independence was found for any HS pair, as indicated by the p-value of the independence test being lower than 0.05, which fails to reject the null hypothesis of independence at the 5% significance level. In contrast to the pre-GFC period, HS was most related to A- and B-share markets in the GFC period and least related to major advanced markets. SHA (0.8), SHB (0.64), SZA (0.51), SZB (0.48) and Indonesia (0.47) had the highest dependence with HS in this period, whereas the US (0.18), Germany (0.27), UK (0.29), NZ (0.31) and Australia (0.33) experienced the lowest dependence with HS. This finding suggests a clear shift in the joint behaviour of HS with other markets during the GFC, particularly a recoupling with the Mainland Chinese shares and decoupling from the advanced markets.

Compared to the pre-GFC period, tail dependencies increased significantly in many HS pairs such as SHA (8 times higher from 0.1 to 0.8), SHB (5.8 times higher from 0.11 to 0.64), SZA (5.1 times higher from 0.1 to 0.51), SZB (3.2 times higher from 0.15 to 0.48), NZ (2.4 times higher from 0.13 to 0.31), the Philippines (2.3 times higher from 0.17 to 0.40), Malaysia (65% increase from 0.26 to 0.43), Indonesia (62% increase from 0.29 to 0.47), Thailand (48% increase from 0.27 to 0.40) and the UK (38% increase from 0.21 to 0.29). These findings support the contagion effect in these HS pairs in the GFC period, according to the definition of Forbes and Rigobon (2002), which is consistent with the literature outlined in section 5.2. More importantly, there was a shift in the joint distribution structure of HS pairs in this period compared to the pre-GFC period: 1) from symmetric tail dependence to asymmetric tail dependence; and 2) from stronger upper tail dependence to stronger lower tail dependence. This result infers higher systematic risk among these markets in the crisis period, which could be due to contagion and spillover effect.

Moreover, six out of 16 HS pairs were captured by the symmetric tail dependence Student-t copula, namely SHB, SZB, Indonesia, Thailand, NZ and Germany. Eight HS pairs were best-fitting with asymmetric tail dependence BB1 and BB7 copulas. Among them, five pairs had stronger left tail dependence (SZA, Malaysia, the Philippines, Japan and Australia), and three pairs had stronger right tail dependence (HK, Singapore and US). In addition, two pairs (SHA and UK) were described by the left tail dependence Survival Gumbel copula. The reliance on left tail dependence copulas increased, which enforces the popular view of higher market interdependence – higher systematic risk during the crisis. These findings support the recoupling theory and the contagion effect during the GFC, especially at the left tail dependence, as mentioned in section 5.2.

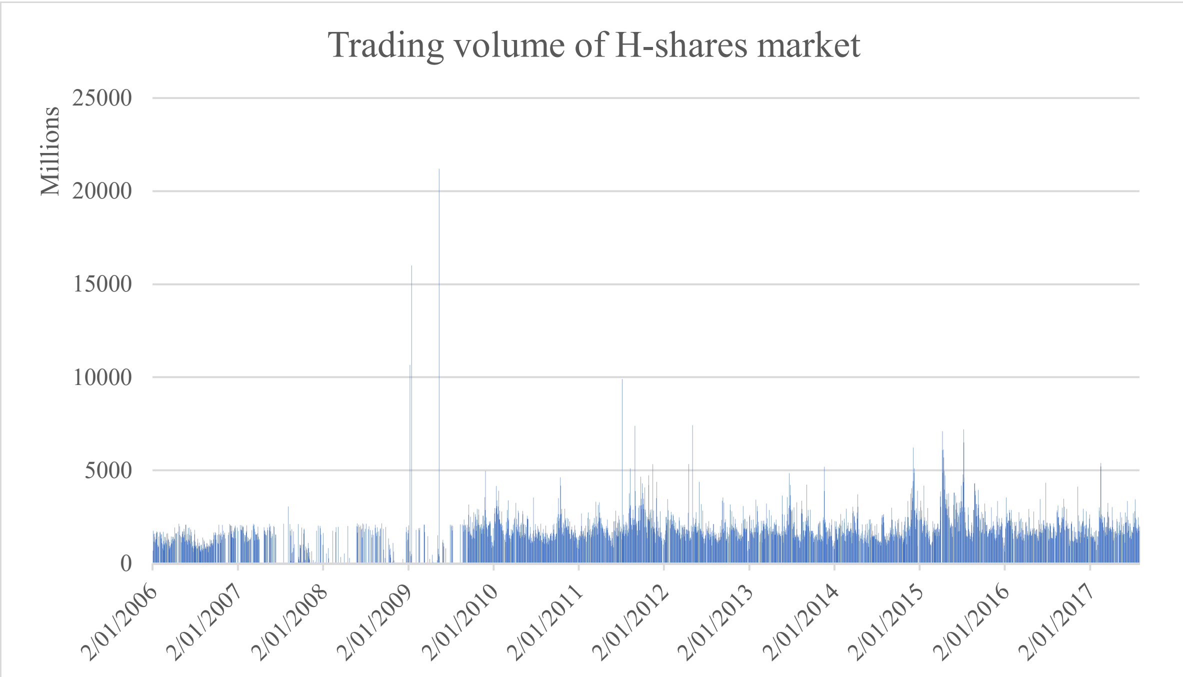
In the extended-crisis period, all HS pairs pass the independence test and reject the null hypothesis of independence at the 5% significance level or lower. Similar to the GFC period, among all other markets, HS was most related to AS and BS in the extended-crisis period: SHA (0.82), SHB (0.56), and SZA and SZB (both at 0.48). HS was least related to the advanced markets such as the US (0.21), Germany (0.26), the UK and NZ (both at 0.28) and Australia (0.3). The Student-t copula was dominant for 12 out of 16 pairs: SHB, SZA, ASEAN-5 markets and the advanced markets – HK, Japan, Australia, the UK and Germany. The joint distribution between HS and NZ/US was captured by an asymmetric tail dependence BB7 copula with stronger left tail dependence. Interestingly, the tail independent Gaussian copula was best fitted for HS and HK/Singapore. This phenomenon implied the deviation of the HS market from the regional trend, especially during extreme movements; that is, HK and Singapore. This observation could reflect the possibility that overseas investors might distinguish between HS and other HK stocks and have different investment sentiments for HS and other HK stocks during this period. This finding is understandable due to the fact that HS are issued by Mainland Chinese companies. Since mid-2014, the Mainland Chinese share markets have outgrown the two primary financial hubs in Asia – Singapore and HK – in terms of size. This finding supports the view that global investors' sentiment has shifted from Singapore and HK to Mainland China's equities, facilitated by the liberalised capital policies in China.

In the post-crisis period, the independence hypothesis is rejected for all HS pairs at the 5% significance level or lower. HS was most related to HK (0.74), followed by Singapore (0.41), Australia (0.34), SHA (0.33) and SZB (0.31). HS had the lowest dependence with some advanced markets such as the US (0.14), NZ (0.17), Germany (0.24) and some Mainland Chinese equities including SZA (0.25) and SHB (0.26). Both asymmetric and symmetric tail dependencies were found in abundance, while asymmetric tail dependencies outweighed symmetric tail dependencies. The dependence structures between HS and five emerging markets including SZA, Indonesia, Malaysia, Thailand and the Philippines were captured by a Student-t copula with symmetric tail dependence. The dependence structure between HS and Singapore/Germany was described by a lower tail dependence Survival Gumbel copula. Asymmetric tail dependencies were found for nine out of 16 pairs which were captured by a BB1 copula (SHA, SHB, HK, Japan, and UK) and BB7 copula (SZB, Australia, NZ and US). Moreover, there were more pairs with stronger right tail dependencies than the ones with stronger left tail dependencies, suggesting higher dependence between HS and many advanced and emerging markets in extreme positive movements. It is also worth noting that the dependence level between HS and many markets changed considerably in the post-crisis period compared to the pre-crisis period such as HK (increased by 1.54 times), SHA (3.3 times higher), SZB (2 times higher), the Philippines (1.6 times higher), the UK (1.3 times higher), Japan (1.25 times lower), SHB (2.4 times higher), SZA (2.5 times higher) and NZ (1.3 times higher). The dependence level of some HS pairs increased slightly or remained stable, such as Singapore, Australia, Malaysia, Indonesia, Thailand, Germany and the US.

In brief, all HS pairs reject the independence test hypothesis at the 5% significance level or lower in any given period, showing strong evidence of dependence between HS and other markets in the sample. The three main findings for the HS market are: 1) symmetric tail dependence was dominant in the pre-GFC period and the extended-crisis periods, whereas lower tail dependence and asymmetric tail dependence with stronger left tail dependencies were recorded for many HS pairs during the GFC and the post-crisis periods; 2) recoupling hypothesis and the contagion effect was found for many HS pairs in the GFC period, with significant increase in the dependence level, especially with AS and BS; and 3) there was an apparent change of market interdependence of HS from the non-crisis periods to crisis periods and vice versa. HS were more related to HK and other global financial centres such as Japan, Singapore and Australia, and least related to AS and BS in the non-crisis periods (pre-GFC and post-crisis periods). HS and other global markets showed strong co-momentum during non-crisis periods, whereas during the heightened volatility periods, HS was more associated with AS and BS. The strong linkages with global markets during the pre-GFC period and post-crisis period are consistent with the empirical literature on market integration of advanced stock markets (Diebold & Yilmaz, 2012; Fry-McKibbin et al., 2014). The increased correlation between HS and AS and BS during the crisis periods indicated the decoupling in HS from the global markets and recoupling to the Mainland Chinese equities. This could be because these shares are issued by the same Chinese companies; changes in investors' sentiments for Chinese equities; and the herding behaviour in A- and B-share markets, as mentioned in sections 3.2 and 4.2.

Wang and Jiang (2004) found that the movement of AS is subject to investor sentiments and market-specific risk that is specific to Shanghai and Shenzhen, while the returns of HS are susceptible to the investor sentiment and market-specific risk in both Shanghai, Shenzhen and HK. Their study found that HS behave more like HK stocks than Mainland China stocks from 1995 to 2001. Market illiquidity especially heightened illiquidity during the GFC, and can be a contributing factor escalating the segmentation of HS and the world markets. Due to the impact of the crisis, Chinese equities appeared less appealing, and investors pulled out from Chinese shares. Given herding behaviour in Mainland Chinese share markets, as mentioned in sections 3.2 and 4.2, sell-off in HS could escalate investors panic in A- and B-share markets. Thin trading on HS during the GFC period, as shown in **Figure 5-2** supported this explanation. This fact might also explain why market independence between HK and HS was weaker during the crisis periods (from 0.48 in the pre-GFC period to 0.37 in GFC and extended-crisis periods).

Even though HS and other advanced markets such as HK and Singapore had strong correlation during the non-crisis periods, segmentation between these markets appeared, and recoupling between HS and Chinese AS and BS was evident during the crisis period. Hence, investors should be cautious when investing in HS during a crisis period, since the association between HS and other markets varied with the state of market conditions.



Source: Thomson Reuters

Figure 5-2. Trading volume of HS in the GFC and extended-crisis period, in millions

5.5.2. Tail dependence of Shanghai A-shares (SHA)

Appendix C reports the copula results between SHA and other markets for four sub-periods.

In the pre-GFC period, some SHA pairs fail to reject the null hypothesis of independence at the 5% significance level, including the Philippines, the UK and US, suggesting market segmentation between SHA and these markets. Aside from this, all other SHA pairs pass the independence test at the 5% significance level. The highest dependence level was recorded between SHA and other Chinese equities comprising SZA (0.81), SHB (0.61), SZB (0.57), HK (0.15) and HS (0.1). The lowest dependence level was documented between SHA and advanced markets including Germany, Thailand, Australia, Malaysia and Japan (ranges from 0.05 to 0.07). The results also show that the dependence level between SHA and other AS and BS was much more potent than between SHA and other cross-border markets, which is consistent with the GARCH results from Chapter 3. The symmetric tail dependence Student-t copula was the most common structure, which was found for SHB, SZA, Indonesia, Malaysia, Thailand, NZ and Germany. The joint distributions of SHA with SZB, HK and Singapore were captured by a BB1 copula (SZB, HK) and a BB7 copula (Singapore), with significantly stronger right tail dependence. Right tail dependence was captured by the Gumbel copula between SHA and Japan/Australia.

In the GFC period, except for the US, all other SHA pairs reject the null hypothesis of independence at the 5% significance level. In this period, SHA was most correlated with HS (0.8), SHB (0.75), SZA (0.65), SZB (0.62) and Indonesia (0.35), and least correlated with Germany, the UK, NZ, Thailand and Australia (ranges from 0.1 to 0.16). This phenomenon continued from the pre-GFC period. However, market integration in many SHA pairs increased significantly in this period, such as HS (8 times higher), Indonesia (4.4 times higher), Thailand (3.8 times higher), Malaysia (3 times higher), Australia (2.7 times higher), Japan (2.3 times higher), NZ and Germany (2 times higher), Singapore (88% higher), and the Philippines and UK (from no dependence to dependence), supporting the contagion effect. In addition, most of the joint distributions of SHA pairs were captured by the symmetric tail dependence Student-t copula (12 out of 14 or 85.71%). Asymmetric tail dependence was found for Japan with lower tail dependence, and the UK with upper tail dependence. Increased numbers of dependent pairs in both tails in the GFC period supported the recoupling hypothesis for SHA.

In the extended-crisis period, all SHA pairs reject the independence test at the 1% significance level, evidenced by p-values lower than 0.01. SHA continued to show robust integration with other Chinese equities in this period, such as HS (0.82), SZA (0.71), SHB (0.65), SZB (0.62) and HK (0.4). This period continues to observe the lowest correlation with the West and advanced markets, including the US, Germany, UK, NZ and Japan (ranges from 0.09 to 0.2). The symmetric tail dependence captured by a Student-t copula was only found in seven out of 15 SHA pairs including some emerging markets – SHB, Indonesia, Malaysia, the Philippines, Thailand and advanced markets, namely Japan and Australia, but most of them are in Asia. Asymmetric tail dependence was found for SHA and Singapore which was modelled by a BB1 copula with stronger right tail dependence, suggesting that investor sentiment was restored for SHA in this period. A left tail dependence Survival Gumbel copula was found between SZA and other advanced markets, namely NZ, UK, Germany and the US. This finding suggests that SHA and these markets were more dependent on the extreme adverse movements than positive ones. This finding suggests that while investors might enjoy the co-gains between SHA and Singapore, they were mindful of a co-crash and adverse shocks transmitted among SHA and other major advanced markets in the West.

In the post-crisis period, a rejection of independence is significant at the 5% level or lower for all SHA pairs apart for the US, which fails to reject the null hypothesis of independence at the 5% significant level. High market integration between SHA and other Chinese equities remained during this period, such as SZA (0.65), SHB (0.59), SZB (0.55), HK (0.41) and HS (0.33). In this period, SHA was least correlated with advanced markets including Germany, NZ and the UK, and emerging markets in the region, namely the Philippines and Malaysia (ranging from 0.06 to 0.12). The segmentation between SHA and these two emerging markets could be due to the strong recovery and growth in the Chinese equities, while the economic growth rate in these emerging markets was impacted by regional and local political strains in the region during this period. Tail dependencies were evident in many pairs, where symmetric tail dependence captured by a Student-t copula was dominant (SHB, SZA, SZB, Malaysia, the Philippines and Thailand, NZ, UK and Germany). A BB1 copula was captured for the joint dependence of SHA and HK and Japan with stronger right tail dependence, indicating a continuing strong momentum in investors' sentiment for SHA in this period. Left tail dependence also existed in between SHA and some neighbouring markets – Indonesia, Singapore and Australia – indicating the existence of co-crash probability between these countries in poor market conditions.

In brief, there are a few key findings. Firstly, evidence of tail dependencies between SHA and other emerging and advanced markets was abundant in all four sub-periods, in which symmetric dependence was dominant in the pre-GFC, extended crisis and post-crisis periods. Secondly, the recoupling hypothesis and contagion theory were found in many SHA pairs (both emerging and advanced markets) in the GFC period. Thirdly, SHA was mostly related to AS and BS in pre-GFC and post-crisis periods while it was mostly related to HS in the GFC and extended-crisis periods, which could be due to herding behaviour in A-share markets influenced by HS. The dependence between SHA and the Asian markets (both emerging and advanced markets) was generally stronger than with other global markets from the West, including the US, UK and Germany. This finding is consistent with the literature that inter-regional integration is generally higher than the intra-regional integration is tied to geographic proximity (Chiang & Chen, 2016; Wang et al., 2011). Other driven factors of market integration could be the established trading position between China and other economies in the region and China's liberalised capital policies. Further, China has implemented various market openness initiatives such as the China Belt and Road Initiative in 2013, and the establishment of the New Development Bank and Asian Infrastructure Development Bank to fund infrastructure projects in Asia, as mentioned in section 3.9.

Market interdependence of SHA with advanced and emerging markets appeared to increase over the time, indicating that the capital deregulation policies in China had some effect on the regional interaction between China and the Asian markets, which is consistent with the existing literature (Li, 2012; Yao et al., 2018).

Market segmentation between SHA and the US was consistently evident throughout the four sample periods. This finding is interesting and could be explained by a strong trading position between two countries, big forex and gold reserves (China is the top country worldwide that has the highest forex and gold reserves), which create a buffer in an economic emergency and cushions against the adverse shocks from other global markets such as the US (Dooley & Hutchison, 2009). It could also be the investment barriers imposed by the Chinese government in managing the risk exposure arising from the flow of foreign funds to China's stock markets (Nishiotis, 2004).

5.5.3. Tail dependence of Shanghai B-shares (SHB)

Appendix D presents the results of the bivariate copula tests for SHB and each other market in the sample over the four sub-periods.

In the pre-GFC period, independence was evident in some SHB pairs at the 5% significance level including the Philippines, UK, Germany and the US. For other markets, independence was rejected at the 5% significance level or lower including SZA, SZB, SHA, HS, HK, Singapore, Malaysia, Australia, Thailand, Japan, NZ and Indonesia. Similar to SHA, SHB had a robust integration with other Chinese equities including SZA (0.63), SZB (0.61), SHA (0.61), HK (0.15) and HS (0.11). The interdependence degree between SHB and the Mainland Chinese equities was at least five times higher than with other cross-border markets (including HS), which is a clear indication that SHB was more integrated with other Chinese markets than with cross-border markets in the pre-GFC period. The lowest dependence was recorded between SHB and some Asian markets including NZ, Japan, Thailand, Australia and Malaysia (range from 0.06 to 0.07). In this period, SHB was a small market but attracted global investment, which might explain why SHB did not follow other established markets in the region. Tail dependencies were captured by various structures including the symmetric tail dependence Student-t copula (SZA, SHA, HK, HS, Malaysia, Thailand and Indonesia), upper tail dependence Gumbel copula (Singapore, Japan, Australia and NZ), and asymmetric tail dependence BB1 with stronger right tail dependence (SZB).

In the GFC period, only SHB–US failed to reject the independence hypothesis at the 5% significance level, indicating market segmentation between SHB and the US, which is similar to the case of SHA. SHB continued to have the highest dependence with SHA (0.75), SZB (0.69), SZA (0.68), HS (0.64) and HK (0.32). In this period, SHB was least correlated with Germany, UK, NZ, Thailand and Japan (ranging from 0.11 to 0.14). Various tail dependence structures were documented including the symmetric tail dependence Student-t copula (SHA, SZA, HS, Indonesia, Thailand and Germany), asymmetric tail dependence BB1/BB7 copulas (SZB/Malaysia – stronger right tail dependence, HK – stronger left tail dependence), lower tail dependence Survival Gumbel copula (Singapore, the Philippines, Australia and NZ), Clayton copula (Japan) and upper tail dependence Gumbel copula (UK). Left tail dependencies were recorded in this period much more than the pre-GFC period, suggesting a contagion effect in the lower tail. Contagion effect was supported during the GFC for many cross-border

SHB pairs, evidenced by a strong increase in market dependencies including HS (5.8 times higher from 0.11 to 0.58), HK (2.1 times higher from 0.15 to 0.32), Malaysia (3.1 times higher from 0.07 to 0.22), Singapore (2.8 times higher from 0.08 to 0.22), Indonesia (3.2 times higher from 0.06 to 0.19), Australia (2.6 times higher from 0.07 to 0.18), Japan (2.3 times higher from 0.06 to 0.14), Thailand (1.9 times higher from 0.07 to 0.13) and NZ (2.2 times higher from 0.06 to 0.13), with recoupling specially recorded between SHB and UK/Germany/Philippines (independence to dependence). This finding is consistent with the existing literature which documented higher dependence and higher probabilities of a co-crash than co-gain during the GFC period (Białkowski & Serwa, 2005; Dungey & Gajurel, 2014; Glick & Hutchison, 2013).

In the extended-crisis period, SHB–US remained independent, as the p-value for this pair fails to reject the null hypothesis of independence at the 5% significance level. Again, highest dependence was observed between SHB and Chinese equities including SZA (0.67), SHA (0.65), SZB (0.63), HS (0.56) and HK (0.31), and the lowest dependence was captured for Germany, the UK, NZ, Thailand and Japan (ranges from 0.07 to 0.17). The symmetric Student-t copula was the most common dependence structure for SHB pairs during this period (SZA, SHA, SZB, HS, HK, Australia, the Philippines, Malaysia, Japan, Thailand and UK). Other dependence structures were also evident, including the tail independence Gaussian copula (Indonesia), and lower tail dependence Survival Gumbel copula (Singapore, NZ and Germany).

In the post-crisis period, similar to the GFC and extended-crisis period, the US and SHB remained segmented. All other SHB pairs reject the independence tests at the 5% significance level, indicating market dependence. SZA (0.61), SHA (0.59), SZB (0.57), HK (0.32) and HS (0.26) had the highest correlation with SHB. Germany, NZ, the UK, Malaysia and the Philippines (range from 0.05 to 0.11) had the lowest correlation with SHB. These findings are consistent with the previous periods. The symmetric Student-t copula was most commonly found (SZA, SHA, HK, Japan, Australia, Thailand, the Philippines, Malaysia, the UK and NZ). An asymmetric tail dependence BB7 copula (SZB – higher left tail dependence, HS – higher right tail dependence) and lower tail dependence Survival Gumbel copula (Singapore, Indonesia) were also recorded.

In general, the findings for SHB are similar to SHA. Firstly, SHB had stronger dependence with Chinese AS and BS than with cross-border markets, which remained consistent throughout the four sub-periods. Similar to SHA, regional integration in SHB was higher than inter-regional integration, which was discussed in section 5.5.2. Secondly, the contagion effect was found for many SHB pairs including HS, HK, Malaysia, Singapore, the Philippines, Indonesia, Australia, Japan, Thailand, NZ, the UK and Germany. Thirdly, the dependence between SHB and HK increased significantly by two times from the pre-GFC period to the post-crisis period, which could be due to the introduction of the SH-HK Stock Connect program launched in 2014 (Huo & Ahmed, 2017). Fourthly, similar to SHA, market segmentation between SHB and US is evident in four sub-periods even though SHB is accessible to overseas investors. This finding shows an investment preference because SHB was still correlated with European markets. This could also be because of the policies implemented in China that have protected China from taking too much exposure from the risks transmitted by the US market, as discussed in section 5.5.2. Another reason could be that SHB is a small market compared to A-share markets and the US, so SHB did not fully reflect the global trend. By 31 July 2017, SHB's trading volume reached 32 million shares, which is approximately 4% of the US market (691 million shares). Finally, apart from symmetric tail dependence, left tail dependence or stronger left tail dependence was more common than upper tail dependence during the GFC period, which indicates higher systematic risk, as discussed in sections 5.5.1 and 5.5.2.

5.5.4. Tail dependence of SZA

The empirical findings from the bivariate copula testing between SZA and other markets in the sample in four sub-periods are presented in **Appendix E**.

In the pre-GFC period, some SZA pairs including Germany, the US, UK and the Philippines failed to reject the independence hypothesis at the 5% significance level, implying market segmentation. The top five highest dependence SZA pairs are SHA (0.81), SHB (0.63) and SZB (0.59), followed by HK (0.15) and HS (0.1). Similar to SHA and SHB, the dependencies between SZA and other Mainland Chinese equities were much more robust than the cross-border SZA pairs (at least 3.9 times higher). Various tail dependence structures were found for SHB pairs such as the symmetric Student-t copula (SHA, SHB, HS, NZ, Indonesia and Thailand), asymmetric tail dependence BB1 copula (SZB) and BB7 copula (Singapore) with stronger upper tail, Gaussian copula (HK), and upper tail dependence Gumbel copula (Malaysia, Japan and Australia). Thus, many markets exhibited right tail dependence.

In the GFC period, apart from the US, all other SZA pairs reject the independence hypothesis at the 5% significance level, showing market segmentation between the US and SZA. Similar to the pre-GFC period, the highest dependence SZA pairs were SHB (0.68), SHA (0.65), SZB (0.63) and HS (0.51). The lowest dependence was recorded between SZA and Germany, UK, NZ, Thailand and Japan (ranges from 0.09 to 0.14). There was considerable increase in the dependence level in the GFC period: HS (5.1 times higher), Australia (3.4 times higher), Thailand (3 times higher), Malaysia (2.9 times higher), Indonesia (2.7 times higher), Singapore (2.5 times higher), HK, Japan and NZ (2 times higher), the Philippines and Germany (from no dependence to symmetric tail dependence) and the UK (from no dependence to upper tail dependence), supporting the contagion effect. The symmetric Student-t copula was the most common dependence structure for many SZA pairs in this period (SHB, SHA, SZB, HK, Malaysia, Singapore, Australia, Indonesia, the Philippines, Thailand and Germany). Other dependence structures were also found, including tail dependence BB1 copula (HS) with higher lower tail dependence, left tail dependence Clayton copula (Japan) and right tail dependence Gumbel copula (NZ and the UK). There was a shift from the dependence structure of SZA pairs from upper tail dependence to lower tail dependence in the GFC period.

In this extended-crisis period, the US remained segmented from SZA. All other SZA pairs reject the independence hypothesis at the 5% significance level or lower. The SZA pairs that had the highest dependence were SHA (0.71), SHB (0.67), SZB (0.61), HS (0.48) and Australia (0.31). SZA had the lowest dependence with Germany, the UK, NZ, Japan and the Philippines (ranging from 0.08 to 0.17). The dependence level of SZA pairs, in general, remained similar to the level in the GFC period. The symmetric tail dependence Student-t copula was found for all pairs, except for SHA, NZ and Germany, which were captured by a lower tail dependence Survival Gumbel copula.

In this post-crisis period, segmentation between the US and SZA continued. SHA (0.65), SZA (0.61), SZB (0.55), HK (0.29) and HS (0.25) had the highest dependence with SZA. NZ, Germany, the UK, Malaysia and Indonesia (ranging from 0.05 to 0.1) had the lowest dependence with SZA. Only two types of dependence structures were found in this period, namely the symmetric tail dependence Student-t copula (SHA, SZA, SZB, HK, HS, Thailand, Japan, the Philippines, Indonesia, Malaysia, UK and Germany) and a lower tail dependence Survival Gumbel copula (Australia and Singapore). This finding could be due to a shift in investors' preferences in Mainland China from Singapore, which was discussed in section 5.5.3, and due to differences in the economic growth between Australia and China. While Australia experienced a sluggish economy, the strong recovery continued in China. Since Australia was reliant on China for exporting resources, it was exposed to a great deal of risk from fluctuations from China's economy.

In brief, the findings for SZA are similar to SHA and SHB, which are briefly summarised here: 1) there was strong integration between SZA and other Chinese equities; 2) contagion effect was supported between SZA and many advanced and emerging markets within the Asian region in the GFC; and 3) regional integration for SZA increased in the post-crisis period compared to the pre-GFC period. All these findings are well discussed and explained in sections 5.5.1 to 5.5.3.

5.5.5. Tail dependence of Shenzhen B-shares (SZB)

Appendix F reports the results of the bivariate copula tests for SZB and each other market in the four sub-periods.

In the pre-GFC period, SZ–Philippines was the only pair that failed to reject the null hypothesis of independence at the significant 5% level, indicating market segmentation. SZB had the highest dependence with other A- and B-share markets including SHB (0.61), SZA (0.59), SHA (0.57) and other advanced markets in the region such as HK (0.18), HS (0.15) and Singapore (0.12). SZB had the lowest correlation with global markets, including the UK, US, Germany, NZ and Australia (ranging from 0.05 to 0.0.9). This finding confirms that regional integration and geographic proximity could play a role in cross-market dependence. Symmetric tail dependence was detected for some SZB pairs during this period, captured by the symmetric Student-t copula, such as Malaysia, Thailand, HK, NZ, UK, Germany and the US, whereas right tail dependence described by a Gumbel copula was found between SZB and some Asian markets including Indonesia, Japan and Australia.

In the GFC period, apart from the US, all SZB pairs rejected the independence hypothesis at the 5% significance level. Again, SZB had the highest dependence with SHB (0.69), SZA (0.63), SHA (0.62), HS (0.48), Indonesia (0.36) and Malaysia (0.27). SZB had the lowest correlation with Germany, the UK, NZ, Australia and Japan (ranges from 0.14 to 0.19). The dependence between the SZB and many advanced and emerging markets increased significantly; for example, HS (3.2 times higher), Indonesia (3.6 times higher), Malaysia (2.7 times higher), the Philippines (no dependence to tail dependence), Thailand (2.8 times higher), HK (1.3 times higher), Singapore (1.8 times higher), Japan (2.1 times higher), Australia (2.1 times higher), NZ (2.3 times higher), the UK (3 times higher), and Germany (2 times higher). This finding confirmed the contagion effect for these SZB pairs. In addition, various types of dependencies were found for SZB pairs; that is, symmetric tail dependence Student-t copula (Thailand), asymmetric tail dependence BB7 copula with stronger right tail dependence (Indonesia, Malaysia and Germany), BB1 copula with stronger left tail dependence (HK, Singapore and Japan), upper tail dependence Gumbel copula (UK and US), lower tail dependence Survival Gumbel copula (the Philippines and Australia) and a Clayton copula (NZ).

In the extended-crisis period, rejection of the independence hypothesis was significant for all pairs at the 5% significance level, including the US. The dependence between SZB and other AS and BS was still highest (SHB 0.63, SHA 0.62 and SZA 0.61), HS (0.48), HK (0.38). Markets that experienced the lowest correlation with SZB were the US, Germany, UK, NZ and Thailand (ranging from 0.07 to 0.20). The symmetric tail dependence Student-t copula was recorded for both emerging and advanced markets including SHB, SZA, HS, Australia, the Philippines, Japan, Thailand, NZ and the UK. BB1 and BB7 copulas were found for SHA (stronger lower tail dependence), Singapore (stronger upper tail dependence), and the US (stronger upper tail dependence). Apart from this, tail independence captured by a Gaussian copula was documented between SZB and HK, Indonesia, Malaysia and Germany. This finding implies that SZB does not correlate with those markets during extreme movements. This result could be because SZB is a small market in terms of size, and therefore the impact from the regional trend was not clearly reflected in this market.

In the post-crisis period, all SZB pairs rejected the independence hypothesis at the 5% significance level. SHB (0.57), SHA (0.55) and SZA (0.55) were the top three pairs with the highest dependence level in this period, followed by HK (0.35), HS (0.31), Australia (0.17) and Singapore (0.16). There was a shift in the regional integration of SZB from the pre-GFC period to the post-crisis period. SZB had the lowest correlation with Germany, the UK, NZ, Malaysia and the Philippines (ranging from 0.07 to 0.14). The degree of correlation between SZB and other markets in the middle range basket does not differ considerably to the degree of correlation with those markets in the lowest correlation basket (ranges from 0.14 to 0.15), indicating that the degree of inter- and intra-regional integration of SZB is quite similar. This phenomenon is unique and is not observed for other AS and BS (SHA, SHB and SZA). This finding also showed that there was an increase in the correlation degree between SZB and other advanced global markets such as Germany, the UK, Australia and NZ. Furthermore, there were three types of dependence structures in this period, including the symmetric tail dependence Student-t copula, asymmetric tail dependence BB7 copula and lower tail dependence Survival Gumbel copula. The Student-t copula remained the most common dependence structure for the majority of pairs (9 out of 12 pairs, or three-quarters), which was found for both emerging markets (SHA, SZA, Malaysia, the Philippines and Thailand) and advanced markets (HK, Japan, Australia, NZ, UK and Germany). The dependence structure of SZB–Indonesia and SZB–Singapore was described by an asymmetric lower tail dependence Survival Gumbel copula. Further, a BB7 copula was found for SHB (stronger lower tail dependence), HS and the US (stronger upper tail dependence).

In brief, there are differences and similarities in the findings for SZB and other A- and B-share markets. The similarities are: 1) contagion effect was evident in many SZB pairs in the GFC; 2) Student-t copula was the most common dependence structure; and 3) there was a shift from upper tail dependence to lower tail dependence in the GFC. Unique behaviours that were also observed in the SZB market are: 1) the gap in the correlation degree between SZB and intra-regional countries such as the US, Germany and the UK and between SZB and Asian markets was reduced considerably in the post-crisis period; and 2) tail independence was recorded between SZB and some advanced and emerging markets in the region in the extended-crisis period. This finding shows that SZB did not experience dependence with some markets in the region during extreme fluctuations, which could be because SZB is a small market compared to other markets in the region. Therefore, the impact from regional trend was not clearly reflected. There are several findings from the bivariate copula testing, which are summarised in **Table 5-2**.

Table 5-2. Summary of the key findings for each Chinese market

	Highest dependence in the non-crisis periods	**Highest dependence in the crisis periods**	**Most common copula in non-crisis periods**	**Most common copula in crisis periods**	**Changes in the dependence level from pre-GFC to post-GFC**	**Contagion effect**
HS	Pre-GFC: HK, SING, Japan, AU, INDO Post-crisis: HK, SING, AU, SHA, SZB	AS, BS, INDO, Malay	Pre: Student-t, no lower tail dependence Post: Student-t and BB7 and more evidence of lower tail dependence (no asymmetric upper tail)	GFC: Student-t, BB1 (no asymmetric upper tail dependence) Extended: Student-t (no asymmetric tail dependence)	Increased integration with AS and BS, and with other major advanced and emerging markets (increased regional and global integration)	A and B, advanced and emerging
SHA	AS, BS, HK, HS	HS, AS, BS, HK or INDO	Pre: Student-t Post: Student-t, more asymmetric lower tail, no asymmetric upper tail	GFC: Student-t Extended: Student-t and more evidence of lower tail dependence (no asymmetric upper tail)	Decreased integration with other AS and BS Increased regional (including HK) and global integration and integration with HS	HS, advanced and emerging
SHB	AS, BS, HK, HS	AS, BS, HS, HK	Pre: Student-t and asymmetric upper tails (no asymmetric lower tail) Post: Student-t and asymmetric lower tail (no asymmetric upper tail)	GFC: asymmetric lower tail, both tails dependence Extended: Student-t (no asymmetric upper tail)	Decreased dependence with other AS and BS Increased global and regional interdependence	HS, advanced and emerging
SZA	AS, BS, HK, HS	AS, BS, HS, HK	Pre: Student-t and asymmetric upper tail (no asymmetric lower tail) Post: Student-t and lower tail (no asymmetric upper tail)	GFC: Student-t Extended: Student-t (no asymmetric upper tail)	Increased integration with other A- and B- shares Decreased global and regional interdependence	HS, advanced and emerging
SZB	AS, BS, HK, HS	AS, BS, HS, INDO or HK	Pre: Student-t and asymmetric upper tail (no asymmetric lower tail) Post: Student-t and asymmetric lower tail (no asymmetric upper tail)	GFC: BB1 and BB7, asymmetric lower tail Extended: Student-t and Gaussian (no asymmetric upper tail)	Increased integration with other AS and BS Decreased regional and global interdependence	HS, advanced and emerging

Note: The crisis periods include GFC and extended-crisis periods. The non-crisis periods include pre-GFC and post-crisis periods.

5.6. Conclusions and recommendations

This chapter used seven different copula functions to address the research questions regarding the dependence structure for each of China's markets and other studied markets, and reported the heterogeneity in the dependence structure for these pairs in the non-crisis and crisis periods and the heterogeneity in the joint dependence structure and dependence level among AS, BS and HS when pairing with other studied markets.

There are some major findings that are similar to the ones from Chapter 4 including: 1) the integration among Chinese equities was generally higher than the regional integration; 2) US is one of the countries that had the lowest correlation with Chinese equities; 3) there was an increased regional correlation of Chinese equities during the GFC period. Details of these findings are presented below.

The results show abundant evidence of dependence between these pairs and the key conclusions are summarised below. Firstly, market integration remained strong among Mainland Chinese equities (AS and BS) over the four sub-periods overall. The integration among AS and BS was also generally much higher than their regional and global integration, supporting the view that Chinese AS and BS, in general, are still segmented from the rest of the world, regardless of the capital liberalisation policies. While the Chinese government, on the one hand, is supporting market openness through various liberalised capital policies, as mentioned in section 1.3.1, to boost the regional integration, on the other hand, their share markets, especially in Mainland China, are under a 'close watch' from the government. Government intervention has also been implemented in the Mainland share markets during major adverse catastrophic events such as the GFC, in order to stabilise the market. While foreign investors can invest directly in China's companies, their available markets; that is, BS, are very trivial, as mentioned in section 5.5.4 and section 1.3, compared to the A-share markets.

In addition, the Chinese government has maintained a strong reserves position over many years, which has created good insulation for their markets and economy from outsiders' risks. Over the four sub-periods, in general, market segmentation between the US and Chinese equities (AS, BS and HS) is evident, which is consistent with the literature (Hussain & Li, 2018). Even though China is the biggest export destination of the US, the US has a bilateral trade deficit with China, whereby the US is also the biggest consumer of Chinese goods and services and which created a cushion against the impact from China. This trade position eased the dependence of the US on China's economy. According to figures published by The Office of the United States Trade Representative (2018), the US goods and services trade deficit with China was US$378.6 billion in 2018 and the imports from China were three times more than the exports to China. According to the World Bank, China and the US are among the top countries which hold the highest forex and gold reserves in the world over many years, and this has helped insulate them from increased volatility in global economies. While investors from these markets still experienced short-term fluctuations from adverse shocks between each other, which could be due to panic, these reactions are usually very short-lived, such as seen in the market stock crash Black Monday in August 2015 or the massive sell-off in October 2018.

However, while China might be somewhat successful in blocking the risks from other global markets, their AS and BS have a strong correlation with HS and are hence exposed directly to the risk from the HS market, given that HS are the primary channel for raising overseas funds for Mainland Chinese companies. This relationship is evident in the joint behaviour of HS and China's markets during crisis and non-crisis periods, as aforementioned.

Geographic location could be a reason for the weak integration between Chinese equities and markets in the West such as Germany and the UK. Chinese markets, including HS, were more integrated with Asian markets (regional integration) than with the US and European markets (UK, Germany) (global integration), as discussed in section 5.5.

Secondly, the Student-t copula, capturing the symmetric tail dependence, was dominant in any given period, for all Chinese markets. This finding is consistent with empirical literature which found that the Student-t copula provides a good fit to financial time series, since it can capture the dependence structure at extreme values in both tails, which is often observed in financial return data (Breymann et al., 2003; Di Clemente & Romano, 2004; Vaz de Melo Mendes & Aíube, 2011).

Moreover, there was a shift in the joint dependence structure for all Chinese markets over time. Right tail dependence was evident only in the pre-GFC period, whereas left-tail dependence appeared in the subsequent periods, indicating higher systematic risks during extreme adverse market movements. For example, the dependencies between HS–SHA and HS–UK were characterised by a Student-t copula and a BB7 copula respectively in the pre-GFC period, while they exhibited left-tail Survival Gumbel copula in the GFC period. This suggests that benefits from co-gains were wiped out, while the risk of a co-crash left. Similarly, dependence was found in both tails between HS and Germany/Singapore in the pre-GFC period, while only left-tail dependence was found between HS and these countries in the post-crisis period.

For each Chinese market (SHA, SHB, SZA, SZB and HS), some pairs shifted from weaker to stronger lower tail dependence or from asymmetric upper to lower tail dependence in the GFC, suggesting evidence of a contagion effect at the lower tail. Christensen et al. (2015) also found that the leverage effect of a stock market increases significantly during a financial crisis, which could contribute to the left-tail dependencies across markets during the GFC. This finding indicated a considerably increased likelihood of these markets crashing together in the GFC period, while the likelihood to boom together vanished in the extended-crisis period and post-crisis period, implying lower portfolio diversification benefits. This finding indicates the higher systematic risks that global investors may bear when having a stock portfolio similar to the studied sample.

Further, there were differences in the highest dependence level pairs for each Chinese share market between the non-crisis periods and crisis-periods. HS was most related to major Asian markets such as HK, Singapore, Japan, Australia, Indonesia, SHA and SZB in the pre-crisis and post-crisis periods, and findings suggest that HS was united with HK. In GFC and extended-crisis periods, HS was most related to AS, BS, Indonesia and Malaysia and decoupling appeared in HS and other advanced markets, which could be since AS, BS and HS are issued by the same Mainland Chinese companies, so they bear the same risk factors. During the GFC, many investors pulled out from China's equities due to panic from the regional and global trends, which was shown by the decrease in the trading volume for AS, BS and HS during this period. It could also be that investors in AS and BS markets herd the adverse reactions from investors in the HS market, which could escalate the sell-off in AS and BS, and which was hence reflected in strong co-movements in these markets during the extreme downturn. Nevertheless, this finding highlights a unique joint behaviour in HS, which varies with the state of the market conditions. Investors should be aware of this in order to formulate an appropriate investment strategy for non-crisis and crisis periods when investing in Chinese equities.

Evidence of a significant increase in the dependence level among AS, BS and HS and between Chinese shares and other advanced and emerging markets in the GFC was abundant, which confirmed the contagion effect among these countries. There are some markets which appeared to be connected with Chinese share markets in the GFC such as SHA and UK–Philippines, SHB–SZA and Germany–UK–Philippines, and SZB and the US, indicating the existence of recoupling. This finding is not contradictory to the finding of regional and global segmentation in Chinese AS and BS, as discussed previously. Two out of three markets that experienced recoupling were B-share markets, which are small markets compared to the A-share markets. So, even though the existence of recoupling was recorded in some cases, it cannot deny the view that Chinese equities are segmented from the world, especially those markets from the West.

Changes in the dependence level from the pre-GFC period to the post-crisis period were different for each Chinese market. Even though the integration among AS and BS was much more robust than their regional and global integration, there were signs of a downward shift in integration among AS and BS, while regional integration was boosted. More robust regional integration could be fuelled by the capital liberalisation policies initiated by the Chinese government, particularly the QFII, QDII and RQFII (Chiang & Chen, 2016; Chiang et al., 2007; Yao et al., 2018).

It is also worth noting that the dependence between HK and Mainland AS and BS increased significantly since the end of the extended-crisis period, which could be tied to more substantial trading and capital links between HK and Mainland China. According to HK's Census and Statistics Department (2018), Mainland China was the biggest export market for HK, accounting for 40.4% of HK exports of goods and services, amounted to HK$310 billion in 2018. HK was also the largest source of FDI outflow and a leading destination of FDI inflow of Mainland China in 2018, accounting for 55.5% and 60.7% respectively. Further, 46.3% of the total approved overseas projects funded by Mainland China was related to HK interests. In addition, the increased interdependence could imply that Hong Kong Stock Connect programs with Shanghai in 2014 and Shenzhen in 2016 may have had some positive effects on the integration between these markets.

Overall, these findings highlight differences and similarities in the regional and global integration of AS, BS and HS. While regional and global segmentation is typical for these Chinese stock markets (in the crisis periods only), these findings suggest that the dependence results for one of China's share types cannot be generalised for all of China's stock markets. Thus, global investors should take these differences into account when forming investment and hedging strategies for these shares.

Chapter 6 Dependence analysis using multivariate vine copulas

This chapter examines the joint dependence of the 17 markets in the sample under a multivariate process to address the following questions:

1. What is the tail dependence structure in a multivariate context of the 17 markets in the sample in crisis and non-crisis periods?
2. What are the roles of HS and HK markets in the regional and global dependence of Chinese AS and BS?
3. Is there evidence of inter-regional dependence and intra-regional dependence for these studied markets?

A paper has been written from this chapter. The paper was accepted for the Financial Markets and Corporate Governance Conference in April 2020 and has been requested to be considered for a journal link to the conference.

The design of this chapter is as follows. Section 6.1 provides an introduction to the chapter. Section 6.2 discusses the key existing literature in this field including multivariate copulas, vine copulas and applications of vine copulas. Section 6.3 presents data and Section 6.4 describes the methodology. Section 6.5 presents the research questions and hypotheses. Section 6.6 reports the empirical results. Section 6.7 discusses the key findings and concludes.

6.1. Introduction

Market interdependence is an important concept in financial modelling, especially in the context of globalisation and relaxed market regulation. Amid increased chaos and volatility in global stock markets such as during the GFC 2008 and the European debt crisis in 2012, tail dependence which quantifies cross-market dependence structures during extremal events has attracted recent attention.

As mentioned in section 5.1, common measures such as Pearson's correlation coefficient can be inadequate in capturing the actual joint behaviour of stock returns, as stock returns are usually found to be non-normally distributed with heavy tails. Tail dependence plays an important role during high volatility periods such as recession, crisis and bear markets where the financial data does not conform to the normal distribution (Mensi et al., 2017). Therefore, it is necessary to understand the tail dependence structures among global stock markets.

The bivariate copula analysis in Chapter 5 showed that: 1) even though AS are restricted to only Mainland Chinese investors, regional integration of AS is still evident. The analysis also found that there is strong market integration among AS, BS and HS and HK/HS markets, and between HK/HS and other Asian markets in the sample, suggesting that HS-HK plays a role as a bridging channel in transmission information and shock innovations between AS and BS and other markets in the region; 2) there is evidence of regional dependence among the 17 markets; and 3) there is evidence of a contagion effect between Chinese shares and other markets in the sample (no evidence of contagion effect among Chinese shares). Since the bivariate analysis focuses on each pair dependence, the link among these pairs requires further analysis to be clearly established. This chapter examines the joint dependence structure of these markets under the multivariate context, which will also reveal the role of HK/HS in the regional and global integration of Mainland Chinese equities (AS and BS). The chapter assesses the multivariate dependence structure of the 17 markets in the sample and examines if the findings from the bivariate analysis still hold in a multivariate context. Therefore, this chapter uses the same data as Chapter 5, which is the data used for the whole thesis. There are 17 markets including five of China's markets and 12 major advanced and emerging markets from 2002 to 2017, with two non-crisis periods (pre-GFC period from 1 May 2002 to 26 February 2007and post-crisis period from 7 June 2012 to 31 July 2017) and two crisis periods (GFC period from 27 February 2007 to 29 May 2009 and extended-crisis period from 30 May 2009 to 6 June 2012). This chapter is an extended study of the bivariate analysis in Chapter 5 and aims to capture the complex non-linear multivariate dependence structure of these studied markets and the complexity of the changes of their structures from non-crisis periods to crisis periods.

Copulas are becoming increasingly popular for modelling the joint tail dependence among financial markets, due to the fact that they allow the modelling of the marginal distribution and joint distribution separately. Since financial returns are found to exhibit fat tails and are leptokurtotic, copulas such as t-copulas which can capture tail dependence are found to be a good fit to the financial returns data (Allen et al., 2017; Tófoli et al., 2012). The vine copula approach, a graphical model depicting multivariate dependence constructed by pair copulas introduced by Joe (1994), Cooke (1997) and Bedford and Cooke (2002), is flexible and capable of capturing the non-linear and complicated high dimensional multivariate dependence structures for a large portfolio such as an index portfolio (Chollete et al., 2009; Dissmann, Brechmann, Czado, & Kurowicka, 2013; Fink, Klimova, Czado, & Stöber, 2017). There are three common vine copula models viz. Regular vine (R-vine), Canonical vine (C-vine) and Drawable vine (D-vine) where each tree is a path; that is, one node has two edges except for the starting and ending nodes, which only have one edge, as defined in section 6.4.2. Even though the use of vine copulas is increasing, their application in the modelling of multivariate dependencies of stock returns, especially for Chinese equities, has received little attention. Therefore, Nikoloulopoulos, Joe, and Li (2012) highlighted the need for more applications of vine copulas such as R-vine and C-vine in modelling the tail dependence of financial returns. Following this recommendation, this chapter uses R-vine and C-vine to address the research questions.

While Chapter 6 showed some results for the third and fourth moments, the main focus of this thesis is to examine the second moment, therefore page 39 only discussed the second-order stationarity. There are various findings from the multivariate analysis of vine copulas in this chapter. One of the major findings is that the results reveal the hidden role of HS and HK markets in the regional market integration of the Mainland Chinese equities (AS and BS) that cannot be detected from a bivariate analysis. In contrast to common wisdom, instead of HK, HS plays a role as the bridging channel between Chinese equities and the Asian markets, whereas HK is more related to AS and BS than commonly thought. Aside from this, the findings of this chapter are consistent with the findings from the bivariate analysis in Chapter 5 and the GARCH analysis in chapters 3 and 4. For example, the studied markets comprise three groups, according to geographic proximity, including Chinese markets (AS, BS, HS and HK), Asian markets (Singapore, Thailand, Malaysia, Indonesia, the Philippines and Japan) and the other advanced markets (US, UK, Germany, Australia and NZ), suggesting that there is evidence of regional dependence (grouping of markets in the same region). Moreover, the Student-t copula is dominant in non-crisis periods, suggesting that symmetric tail dependence is the most common dependence structure. Asymmetric left tail dependence and different tail dependencies increase in the crisis periods compared to the non-crisis periods, implying correlation at the left tails is stronger than the right tails during a crisis. In addition, the US has a direct connection with only one market (either the UK or Germany) throughout the four sub-periods, suggesting that the US financial market is quite isolated in the considered sample. A contagion effect is also evident in many pairs among Asian markets and other advanced markets, and between HS and Singapore (the central node of Chinese equities and the central node of Asian markets) during the GFC. Finally, there is a rearrangement in the connection among Chinese equities. In particular, SHA was the most isolated market among Chinese AS and BS in the pre-GFC and GFC periods. After the GFC, SHA replaced SZB and became the connection node between HK and other A- and B-share markets in the extended-crisis and post-crisis periods. This finding supports the observation of 'openness' in Chinese equities, due to the introduction of capital liberalisation. It also implies that SHA plays a leading role in the connection chain among A- and B-share markets, facilitating the innovations from HK to mainland Chinese equities.

This chapter is significant for many reasons. The modelling of co-dependencies of international financial returns around the tails is important in evaluating portfolio risk because it is found that the probability of extreme events is higher for a joint distribution with significant tail dependence than a normal distribution (Chollete et al., 2009; Longin & Solnik, 2001; Støve et al., 2014). Correct specification of the joint tail distribution structure is crucial in portfolio selection, investment hedging strategy, Sharpe ratio targeting, option pricing and credit risk analysis (Poon et al., 2004). Failing to account for tail dependence structure in a multivariate joint distribution leads to underestimation of the risk of loss. For this reason, R-vine and C-vine outperform alternative linear portfolio optimisation models in optimising an efficient portfolio (Bekiros et al., 2015), and they are effective for both passive and active portfolios (Brechmann & Czado, 2013). Hence, the findings of this chapter contribute to the limited literature of copula applications in separately modelling the co-dependencies of AS, BS and HS at regional and global levels. This has important implications for a wide range of audiences including policymakers, international institutional and retail investors, fund managers and financial risk managers in various areas such as portfolio construction, estimating hedging ratios and evaluating tail risks.

The remainder of this chapter is structured as follows. Section 6.2 discusses the key existing literature in this field including multivariate copulas, vine copulas and applications of vine copulas. Section 6.3 presents data and section 6.4 describes the methodology. Section 6.5 presents the research questions and the hypotheses. Section 6.6 reports the empirical results. Section 6.7 discusses the key findings and concludes.

6.2. Literature review

Section 5.2 presents the importance of modelling tail dependence using a copula approach, and explains how bivariate copulas have been applied in the existing literature. In traditional modelling of the multivariate distribution, it is important to appropriately specify the marginal distribution. This approach faces a major challenge when the marginal distributions are unknown. For this reason, copula functions have increasingly attracted many scholars and academics in the past two decades because the copula function allows the modelling of the multivariate distribution separately from the marginal distributions, thus it has created various appealing and flexible techniques in evaluating multivariate dependence structures. This section presents additional literature to that already discussed in the introduction and to that which is related to methodology, as discussed in section 6.4.

One of the pioneering works in assessing multivariate dependence structures using copula functions is Ané and Labidi (2006). Their study used the multivariate asymmetric Student-t Cook-Johnson copula function to investigate the spillover effect in price and volatility between the daily returns of the UK, France and Germany from January 1990 to December 2001 and between the weekly returns of the US, Japan and the UK from January 1983 to December 2001. The marginal distributions were estimated by an asymmetric TGARCH, while the multivariate distributions were described by a multivariate Cook-Johnson copula function. Their results suggested that the Cook-Johnson copula-based asymmetric-*t* GARCH model outperformed the multivariate TGARCH model. Their study also revealed that spillover effects disappeared when the marginal distributions and the dependence structure were appropriately specified and only market interactions at the conditional mean of the daily data remained. Ané and Labidi's study also suggested that when non-linear relations are accounted for in the model specification, the unexpected shocks experienced in each country and volatility spillover are captured in the parameter characterising the dependence structure estimated by the copula function.

Even though the first regular vine was introduced by Joe (1994) and Cooke (1997), the application of vine copulas in modelling the dependence structure of financial returns did not start until the introduction of the graphical models, called 'vines' by Bedford and Cooke (2002). Chollete et al.

(2009) modelled asymmetric dependence in returns between global markets in the Group of 5 and Latin American regions using a multivariate C-vine copula regime. Their study confirmed that the choice of copula is critical in risk management because it impacts the estimation of the VaR of international portfolio returns. Their study also found evidence of a significant increase in dependence between the European markets in the event of either a crash or a boom.

Kenourgios et al. (2011) used multivariate regime-switching Gaussian copulas to examine the financial contagion theory for the four emerging BRIC markets and two global markets (US and UK) in five financial crises (Asian crisis 1997, Russian crisis 1998, Technology Bubble Collapse 2000, Brazilian Stock Market Crash 1997, Brazilian Crisis 2002) from 1995 to 2006. They used a Glosten, Jagannathan and Runkle (GJR) GARCH Moving Average (MA) with student-*t* distribution for the marginal distributions and Gaussian copula for the joint distribution. They provided evidence of contagion effect in those five financial crises and found that the BRIC markets were more susceptible to financial contagion, due to shock transmission in investment behaviours than to macro-fundamental changes. Their studies, however, did not use vine copulas but provided an application of multivariate copula in the regime-switching framework.

More recently, Dissmann et al. (2013) evaluated the dependence structure of 16 markets including international equity indices, fixed income and commodity indices from 2001 to 2009 using R-vine, C-vine and D-vine. The marginals extracted from the autoregressive moving average (ARMA)-GARCH process were fitted with Gaussian, Student-t, Gumbel and Frank copulas, and their survival copulas and the best-fit model was selected based on the AIC. Their study demonstrated the usefulness of R-vine copulas, which generated economically interpretable results and the superiority of R-vine copulas compared to C- and D-vine copulas in terms of modelling capabilities in capturing complicated dependence structures.

Allen et al. (2017) used R-vine and C-vine copulas to quantify the multivariate co-dependencies of DJIA index stocks from 2005 to 2011 in the four sub-periods. They found that R-vine copulas better fitted the data and were more flexible than C-vine copulas in capturing complex changes in the dependence structure across their studied period. They also found that symmetric Student-t copula is dominant during the GFC period.

Sriboonchitta, Liu, Kreinovich, and Nguyen (2014) used C-vine and D-vine to determine the multivariate dependence structure of equity stock indices in Indonesia, the Philippines and Thailand for the period 2008 to 2013. They found that the Philippines market had a significant impact on the tail dependence between the markets in Indonesia and Thailand.

Fink et al. (2017) examined 11 global equity indices in Japan, Hong Kong, Germany, the European region (Euro Stoxx 50), US and their corresponding implied volatility indices and Bloomberg Commodity ex-Agriculture and Livestock index from 2002 to 2015 using time-varying R-vine models under a Markov-switching framework. The multivariate copulas in their study were constructed from

Elliptical (Gaussian and Student-t copulas) and Archimedean bivariate copulas (Clayton, Gumbel, Frank and Joe). Fink et al. found a strong dependence between the equity index and their corresponding volatility counterparts and between countries in the same regions.

Lu et al. (2012) used a time-varying copula-GARCH model with Hansen's skewed Student-t innovations to investigate the dynamic dependence between investor sentiment and stock returns for Shanghai AS and BS from 2005 to 2009. They found that the market integration of AS and BS was time-varying and increased in a bullish market. It was also found that the variations in the covariances of BS were higher than in AS, indicating that the dependence structure between investor sentiment and stock returns was more volatile in BS than in AS.

Guo and Wang (2016) used time-varying copulas to describe the dependence structure in the volatility of five minutes and 15 minutes price data between Shanghai and Shenzhen stock markets from 2004 to 2014. They found asymmetric dependence distribution with upper tail dependence evident during the GFC, indicating a strong tendency of co-movement in volatilities between AS and BS during the heightened volatility period.

The existing literature that modelled the co-dependencies of stock returns using vine copula models (for example, C-vine, D-vine and R-vine) concluded that these models are effective and suitable in modelling the complex and non-linear dependence structure of cross-market linkages in a practical setting and provided important applications in various financial areas. Bekiros et al. (2015) applied C-vine, D-vine and R-vine copulas to the daily returns of an Australian asset mining portfolio comprising 20 gold and 20 iron ore-nickel stocks from 2005 to 2012. Their study revealed that those vine copulas could gauge the complex and non-linear dependence structure of the financial time series. Aloui and Aïssa (2016) modelled the dynamic relationship among West Texas Intermediary Crude oil, the DJIA index and the trade-weighted US dollar index returns using 10 years of daily data. Their result found evidence of lower sample error in forecasting the VaR compared to the traditional normal and historical simulation methods, suggesting that the accuracy of VaR estimates using vine copulas is improved.

Kumar, Tiwari, Chauhan, and Ji (2019) extended the application of multivariate copula functions including Gaussian, Student-t and Clayton, survival Clayton, rotated Clayton and rotated survival Clayton copulas in a regime-switching framework to examine the dependence structure between the BRICS stock markets and foreign exchange markets from 2005 to 2017. Their study also confirmed that Student-t copulas provided the lowest Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) compared to other copula functions. They noted, however, that the symmetric tail dependence was limited to the assumption that the tail dependencies of those markets were identical in bull and bear phases. They also applied R-vine copulas to VaR analysis and confirmed that the R-vine copula was superior to the standard bivariate copula framework in constructing VaR forecasts.

The existing literature found that the choice of copulas for pair copulas in constructing multivariate copulas is important (Ané & Labidi, 2006). Hence, Student-t copulas were found to play a dominant role in the existing literature in evaluating the dependence structure of financial returns, compared to other copulas, due to the fact that financial returns are non-normally distributed with skewness and fat tails. Jondeau and Rockinger (2006) applied copulas to model the dependency structure between daily stock returns of the US, Germany, France and the UK from 1980 to 1999. Their study found that tail dependence is stronger than dependency at the middle of the distribution, suggesting that skewed Student-t copulas fitted the data better than Gaussian copulas. Fischer, Köck, Schlüter, and Weigert (2009) conducted a comprehensive survey to compare the performance of different copulas in modelling the dependence structure of the German stock market, foreign exchange market and the commodity markets. They constructed multivariate and bivariate copulas from a wide range of copulas and concluded that the constructed Student-t copulas outperformed other copulas in both cases.

Many studies confirmed the appropriateness of various types of copula functions to financial stock returns such as Student-t copula, Clayton and Gumbel copulas and their rotated families that can capture the symmetric and asymmetric tail dependence, and BB1 and BB7 copulas which can capture different tail dependencies such as stronger upper or lower tail, which validates the fit of the model. Tófoli et al. (2012) compared different copula functions in evaluating co-dependencies of index stock returns in the UK, France and Germany from 1999 to 2011 and found that elliptical (Gaussian and Student-t copulas) provided a better fit to the forecasting of extreme quantiles for a portfolio compared to the Clayton copula. Allen et al. (2017) applied a mixture of 10 different types of copulas including Gaussian, Student-t, asymmetric tail dependence (Clayton, Gumbel, Frank, Joe and rotated asymmetric copulas BB1, BB6, BB7 and BB8) to analyse selected stocks in the DJIA index in the period around the GFC. Their study found that the Student-t copula was evident in the GFC period.

Other studies also confirmed the appropriateness of tail-asymmetric copulas such as Clayton and Gumbel copulas and their rotated families, which could capture the asymmetric tail dependence or BB1 and BB7, which could capture different tail dependencies such as stronger upper or lower tail. suggested that even though Student-t was best fitted to the data on likelihood-based estimates, vine copulas with the asymmetric BB1/BB7 could be used for sensitivity analysis for forecasting extreme quantiles, which could increase the accuracy of the forecasting. Moreover, they revealed that asymmetric tail dependence might be short lived, thus it might not be detected over a long time span. In this case, a vine copula model with BB1/BB7 and time-varying dependence were helpful in testing this. Their study also pointed out a need to study non-C/non-D vines for dimensions greater than six. Dissmann et al. (2013) suggested that further studies could use not only elliptical copulas such as Gaussian and Student-t, or tail-asymmetric copulas such as Clayton and Gumbel copulas, but also BB1 and BB7 for further explorations on modelling the co-dependencies of financial returns.

There is a wide range of copula applications in financial modelling and portfolio management. Brechmann and Czado (2013) constructed a regular vine copula-based factor model, called Regular Vine Market Sector model, for the Euro Stoxx 50 index to examine the multivariate dependence structure of the index from 2006 to 2010. The vine copula model was found to handle a large dimensional dataset (52 dimensions) effectively, and to be superior to comparable models such as the DCC model and the Heinen and Valdesogo's C-vine autoregressive model. The model could also evaluate the systematic and idiosyncratic risk separately. Their study also illustrated the application of vine copulas to portfolio management and confirmed that the models were useful for both active and passive management. Loaiza Maya, Gomez-Gonzalez, and Melo Velandia (2015) used R-vine copulas to examine the contagion effect in the tail dependence structure of the exchange rates in Latin American countries. Çekin, Pradhan, Tiwari, and Gupta (2019) measured the co-dependencies of economic policy and the contagion effect in Brazil, Chile, Colombia and Mexico before, during and after the GFC using R-vine copulas. They found that tail dependence was strongest before the GFC and was less predominant in the post-crisis period.

Zhang, Yan, and Tsopanakis (2018) utilised ARMA-GARCH-based R-vine copulas to quantify the tail dependencies of financial stresses between Eurozone economies. They found that an upper tail dependence was more significant for larger economies in the Eurozone, while lower tail dependence was more predominant among smaller economies. Their findings suggest that weak economies were more prone to external shocks from other countries, especially in the financial crisis. (BenSaïda, 2018) studied the dynamics of the multivariate dependence structure of 12 government bonds (the US and 11 European bonds in the Eurozone) using more advanced C-vine and D-vine copula models under the symmetrical JC copula and Markov-switching regime. Their study confirmed the existence of contagion effect in the bond markets, which was transmitted from core to stressed countries and which has remained in a high volatility state in the Eurozone bond markets since the GFC 2008 and the European sovereign debt crisis. Other applications such as estimating default probability (Dalla Valle, De Giuli, Tarantola, & Manelli, 2016), modelling extremal dependence and VaR among commodities (Yu, Yang, Wei, & Lei, 2018), evaluating systematic risks (Chen & Khashanah, 2016) and analysing the dependence of exchange rate and international trades (Praprom & Sriboonchitta, 2014) are also explored in the existing literature.

The above shows that several studies have been conducted to examine the multivariate dependence of global equity markets using copula functions. None of these studies, however, has examined the regional and global multivariate dependence structure of AS, BS and HS simultaneously, which is a gap addressed in this chapter. Due to the differences in those share types, as discussed in sections 1.3.1, 3.9, 4.6 and 5.6, there is a need to study these markets separately. The findings from Chapter 4 and Chapter 5 also confirm this need. Hence, this chapter aims to fill this gap and to take the research opportunity pointed out by Nikoloulopoulos et al. (2012), by evaluating the multivariate co-dependencies structure of the three major Chinese share-type equities and 12 other international markets including the ASEAN-5, Australia, NZ, Hong Kong, Japan, Germany, the UK and US over three sub-periods from 2012 to 2017 using R-vine and C-vine. The existing literature on regional and global co-dependencies of these Chinese markets using bivariate GARCH, multivariate GARCH and bivariate copulas can be found in sections 3.2, 4.2 and 5.2.

6.3. Data

The data used in this chapter is the same data used across the whole thesis (described in section 2.1), in order to ensure consistency and to allow comparisons across the models used in the thesis. Similar to the previous chapters, the data is divided into four sub-periods, as follows:

1. Pre-GFC period: from 1 May 2002 to 26 February 2007 (871 observations).
2. GFC period: from 27 February 2007 to 29 May 2009 (410 observations).
3. Extended-crisis period: from 30 May 2009 to 6 June 2012 (539 observations).
4. Post-crisis period: from 7 June 2012 to 31 July 2017 (912 observations).

The daily closing prices are downloaded from Bloomberg for each market, as shown in **Figure 2-1**, and then converted to a first difference natural logarithm to make each time series stationary. More information about these sub-periods and the data can be found in sections 2.1 and 2.2. The standardised residuals for each time series are obtained from the best-fitted GARCH model from Chapter 3 and are converted to uniform marginals using the rank method (for explanation, see section 5.3.2).

6.4. Methodology

6.4.1. Multivariate copulas

Bivariate copulas and the related Sklar (1959) theorem are presented in section 5.2.3. For a random vector $\boldsymbol{X} = (X_1, \dots, X_d)' \sim F$ with marginal distributions $F_i, i = 1, \dots, d$, according to Sklar's theorem, we have: $F(x_1, \dots, x_d) = C(F(x_1), \dots, (F(x_d))$. This means that there is a C-copula with d-dimension that links the marginal distributions $F(x)$ together. Moreover, if F is absolutely continuous and $F_1, \dots, F_d$ are strictly increasing continuous, then:

$$f(x_1, \dots, x_d) = \left[\prod_{k=1}^{d} f_k(x_k)\right] \times c(F(x_1), \dots, F(x_d)), \tag{6.1}$$

where small letters denote corresponding density expressions. The specification of a copula model allows the modelling of multivariate distribution separate from the marginal distributions.

6.4.2. Vine copulas

Vine copulas, or so called pair copula constructions, were first introduced by Joe (1994) as an extension of a bivariate copula, and were later introduced as a graphical representation under the name of 'vine' by Bedford and Cooke (2002). Please refer to Dissmann et al. (2013) for a comprehensive statistical reference of regular vines. By name, vine copulas specify the multivariate distribution of marginal distributions by specifying how these marginals are connected in a pair.

For three-dimensional vine copulas, as an example, let $\boldsymbol{X} = (X_1, X_2, X_3)' \sim F$ assuming all necessary densities exist, then:

$$f(x_1, x_2, x_3) = f_1(x_1) f(x_2|x_1) f(x_3|x_1, x_2) \tag{6.2}$$

Using Sklar's theorem, it holds that:

$$f(x_2|x_1) = \frac{f(x_1,x_2)}{f(x_1)} = \frac{c_{1,2}(F_1(x_1),F_2(x_2))f_1(x_1)f_2(x_2)}{f_1(x_1)} = c_{1,2}\big(F_1(x_1), F_2(x_2)\big)f_2(x_2), \tag{6.3}$$

and

$$f(x_3|x_1, x_2) = \frac{f(x_2,x_3|x_1)}{f(x_2|x_1)} = \frac{c_{2,3|1}(F(x_2|x_1),F(x_3|x_1))f(x_2|x_1)f(x_3|x_1)}{f(x_2|x_1)} =$$
$$c_{2,3|1}\big(F(x_2|x_1), F(x_3|x_1)\big)f(x_3|x_1) = c_{2,3|1}\big(F(x_2|x_1), F(x_3|x_1)\big)c_{1,3}\big(F_1(x_1), F_3(x_3)\big)f_3(x_3) \tag{6.4}$$

Combining (3), (4) and (5), the three-dimensional joint density constructed from bivariate copulas is given as:

$$f(x_1, x_2, x_3) = f_1(x_1)f_2(x_2)f_3(x_3)c_{1,2}\big(F_1(x_1), F_2(x_2)\big)$$
$$c_{1,3}(F_1(x_1), F_3(x_3))c_{2,3|1}(F(x_2|x_1), F(x_3|x_1)) \tag{6.5}$$

The selection of bivariate copulas $C_{1,2}, C_{1,3}$ and $C_{2,3|1}$ is independent of each other, thus vine copulas give a great deal of flexibility in modelling multivariate dependence separately from the univariate distributions and the bivariate joint distributions.

Regular vines (R-vines)

A Regular vine (R-vine) consists of edges and nodes, and the structure of the tree is specified by the maximum number of edges in the tree. Vine and regular vines are defined by Bedford and Cooke (2002) as follows:

Definition 6.1 Regular vine, vine: $\mathcal{V}$ is a vine on *n* elements if:

1. $\mathcal{V} = (T_1, \dots, T_m)$, T is the tree formed by bivariate marginals.
2. T_1 is a tree with nodes $N_1 = \{1, \dots, n\}$ and a set of edges denoted E_1.
3. For $i = 2, \dots, m$, T_1 is a tree with nodes $N_i \subset N_1 \cup E_1 \cup E_2 \cup \dots \cup E_{i-1}$ and edge set E_1.

   A $\mathcal{V}$ is a regular vine on *n* elements if:

   a) $m = n$
   b) T_1 is a connect tree with edge set E_1 and node set $N_1 = E_{i-1}$, with $\#N_1 = n - (i - 1)$ for $i = 1, \dots, n$, where $\#N_1$ is the cardinality of the set N_1.
   c) The proximity condition holds: for i = 2, …, n – 1, if $a = \{a_1, a_2\}$ and $b = \{b_1, b_2\}$ are two nodes in N_i connected by an edge then $\#a \cap b = 1$.

According to Bedford and Cooke (2002) and Kurowicka and Cooke (2010), a R-vine tree can be uniquely identified by two nodes – the conditioned nodes and a set of conditioning nodes; that is, edges are denoted by $e = j(e), k(e)|D(e)$ where $D(e)$ is the conditioning set. Each node in the tree represents each variable in the sample. For trees with n nodes, there are $n - 1$ edges, which means there are $n - 1$ bivariate marginals and there are $n(n - 1)/2$ off-diagonal terms in a (rank) correlation matrix. The regular vine specifies the marginal distribution, the rank correlations $r(X_1, X_2)$, $r(X_2, X_3)$ and also conditional rank correlation of X_1 and X_3 given X_2 i.e. $r(X_1, X_3|X_2 = x_2)$.

Figure 6-1 shows an illustration of a five-dimensional R-vine tree. The R-vine copula density is uniquely determined and given by:

$$c(F_1(x_1), \dots, F_d(x_d)) = \prod_{i=1}^{d-1} \prod_{e \in E_i} c_{j(e),k(e)|D(e)}(F(x_{j(e)}|x_{D(e)}), F(x_{k(e)}|x_{D(e)}) \tag{6.6}$$

where $x_{D(e)}$=$(x_1, \dots, x_d)'$indicated by the indices contained in $D(e)$.

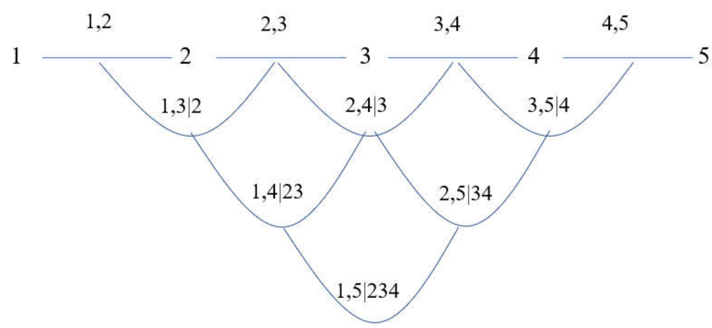


Figure 6-1. A five-dimensional R-vine.

With j=1,…,n – 1, and $i = j + 1, \dots, n$ let $T = (t_{i,j})_{i,j = 1,\dots,n}$ be the matrix for the type of bivariate copula and $P = (p_{i,j})_{i,j = 1,\dots,n}$ be the matrix of the parameters of the bivariate copulas in an R-vine structure. **Figure 6-2** is an illustration of the matrix M of a R-vine specification with five dimensions.

$M =$				$T =$				$P =$			
1											
5	3			$t_{2,1}$				$p_{2,1}$			
2	2	3		$t_{3,1}$	$t_{3,2}$			$p_{3,1}$	$p_{3,2}$		
3	5	4		$t_{4,1}$	$t_{4,2}$	$t_{4,3}$		$p_{4,1}$	$p_{4,2}$	$p_{4,3}$	
4	1	2	4	$t_{5,1}$	$t_{5,2}$	$t_{5,3}$	$t_{5,4}$	$p_{5,1}$	$p_{5,2}$	$p_{5,3}$	$p_{5,4}$

Note: The copula with conditioned variable indexed by (1,5) and conditioning variable indexed by (234), i.e. $c_{1,5|234}$ has the family copula type $t_{2,1}$ with parameter $p_{2,1}$. The copula $c_{3,2}$ is of the type $t_{5,3}$ with the parameter $p_{5,3}$.

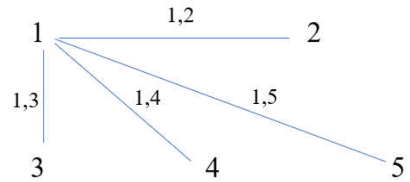
Figure 6-2. Example of the specification matrix of a five-dimensional R-vine

Canonical vines (C-vines)

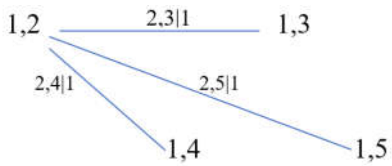
C-vines are a special case of R-vines when there is a unique single central node; that is, the root node with degree $d-i$ that connects to all other nodes. According to Aas, Czado, Frigessi, and Bakken (2009), the density of a C-vine copula is given as:

$$c\big(F_1(x_1), \dots, F_d(x_d)\big) = \prod_{i=1}^{d-1} \prod_{j=i}^{d-i} c_{i,i+j|1,\dots,i-1} F(x_i|x_1, \dots, x_{i-1}\big), F(x_{i+j}|x_1, \dots, x_{i-1})) \quad (8)$$

For this reason, C-vines are quite restrictive compared to R-vines, especially in higher dimensions**.** **Figure 6-3** illustrates a five-dimensional C-vine tree.



(a) C-vine tree 1 (unconditional)



(b) C-vine tree 2 (conditional)

Note: Each tree T has a unique node with $d-i$ edges, with i being the number conditioning variables. C-vine tree 1 has 4 edges and C-vine tree 2 has 3 edges. The node with 4 edges in tree 1 i.e. node 1 is called the root.

Figure 6-3. A five-dimensional C-vine

Drawable vines (D-vines)

A D-vine tree is a path in which each node has two edges except for the starting and ending nodes, which have only one edge. Similar to C-vines, D-vines are therefore restrictive in describing complex dependence structures. A R-vine tree can consist of both C-vine and D-vine dependence structures, hence R-vines are capable of capturing complicated multivariate dependence structures, especially for high-dimensional data. Unconditional and conditional five-dimensional D-vine trees are illustrated in **Figure 6-4**.

(a) D-vine tree 1 (unconditional)

(b) D-vine tree 2 (conditional)

Figure 6-4. A five-dimensional D-vine

The methodology used in this chapter is as follows. Firstly, each time series is estimated by a GARCH process to capture major distributional properties of stock returns; that is, heteroskedasticity and volatility clustering. Daily stock returns – first difference log returns – are fitted with the following GARCH models (assuming GED distribution): ARMA(0,1)-GARCH(1,1), ARMA(1,0)-GARCH(1,1), and EGARCH (1,1). Secondly, the standardised residuals are extracted from the best-fit GARCH model based on the AIC for each time series. Thirdly, these residuals are transformed into uniform variates using the rank method. This process assigns a ranking unit for each observation within a time series. The transformation does not impact the value of Kendall's tau. Fourthly, the rank residuals obtained from step three are fitted with R-vine and C-vine copula models which are constructed from the best-fitted bivariate copulas for each pair based on AIC. These bivariate copula functions include 1 = Gaussian copula, 2 = symmetric tail dependence t-copula, 3 = lower tail dependence Clayton copula, 4 = upper tail dependence Gumbel copula, 14 = lower tail dependence rotated Gumbel copula, 7 = BB1 copula and 9 = Joe-Clayton (BB7) copula with asymmetric upper and lower tail dependencies following the approach of Boubaker and Sghaier (2013) and Allen et al. (2017). The number assigned for each copula family function is based on the coding in R. The best bivariate copula for each pair is presented in the R-vine and C-vine trees for each edge, where pair-copula parameters are estimated by maximum likelihood. This list of copula family functions is similar to the list of copulas used in Chapter 5 for bivariate analysis. For the main features of these copula functions, please refer to sections 5.2.5, 5.2.6, 5.2.7 and 5.2.8 and **Table 5-1**. The copula theory and related theories are presented in sections 5.2.2, 5.2.3 and 5.2.4.

6.5. Hypotheses

The research objective is to study the multivariate joint tail dependence structure of all studied markets using vine copulas, as outlined in the three research questions at the start of this chapter.

There is no hypothesis for this chapter. The research questions are addressed in the findings of the multivariate vine-copula functions. The first research question will be addressed by the unconditional tree, the vine copula specification matrix and the types of copula fitted of the vine structure. The second research question will be discussed based on the vine structure captured for all Chinese markets, for example, D-vine or C-vine. The third research question will be addressed based on the vine structure captured for all studied markets.

6.6. Empirical results

The results are presented in two parts. The first section describes the dependence structure using the C-vine copula and the second section presents the results of the R-vine copula in the four sub-periods. C-vine tree 1 as shown in **Figure 6-5** gives a good picture of the strongest individual correlations, while C-vine tree 2 depicted in **Figure 6-6,** draws the conditional dependence structure. However, apart from having one single central node, C-vine is not as flexible as R-vine and is quite limited in capturing different multivariate dependence structures. For this reason, the following discussion briefly reports the results of the C-vine tree 1 and tree 2 in the pre-GFC period, but it concentrates primarily on the results of the R-vine analysis in the four sub-periods.

6.6.1. Dependence modelling using C-vines

Figure 6-5 presents the pre-GFC C-vine tree 1. The root node of the C-vine tree is the market that has the highest pair-wise dependence with other markets in the sample. Interestingly, HS are the central node for all four sub-periods, implying that HS has the strongest individual correlations with other markets in the sample.

Figure 6-6 shows the C-vine tree 2, conditional on the relationship with HS, wherein SZA becomes the central node in the pre-GFC, Australia is the centre during the GFC and extended-crisis periods, and the UK is the central node in the post-crisis period**. Figure 6-5** shows the matrix specification for C-vine in the pre-GFC period. It shows that the strongest individual correlations in the pre-GFC period are with the HS market (no. 1 in the final row) and the individual diagonal entries starting with market number 12 representing Japan, which define the edges. Japan (no. 12) is correlated with SZA (no. 4). Japan is correlated with Australia (no. 13), conditional on the relationship of SZA-HS, and so on. **Figure 6-6** also shows the same numbers appear across the rows, meaning that it is always appearing in the nodes at that level in the tree. Hence, there is only one central node in a 17-dimensional C-vine structure and 16 edges. An R-vine does not have this limitation, hence it is more capable of capturing more complex multivariate structures. Thus, our subsequent discussion focuses on the results of R-vines.

Even though there are changes in the dependence structures (copula family) and strength of the dependence for each pair from one period to another, the multivariate C-vine dependence structure with HS being the centre remains unchanged throughout the four sub-periods, even during the two crisis periods, suggesting HS has a strongest relationship with other countries in the sample. This result is consistent with the bivariate analysis in Chapter 5, which documented a strong dependence between HS and Chinese equities throughout four sub-periods. The consistency in the findings of the bivariate and multivariate analyses enforces the validation and suitability of the copula models to the studied data.

Table 6-1. Pre-GFC C-vine copula specification matrix

	HS	SHA	SHB	SZA	SZB	INDO	Malay	PHIL	THAI	HK	SING	Japan	AU	NZ	UK	GER	US
HS	12																
SHA	17	15															
SHB	15	17	3														
SZA	3	3	17	7													
SZB	7	7	7	17	14												
INDO	14	14	14	14	17	2											
Malay	2	2	2	2	2	17	10										
PHIL	10	10	10	10	10	10	17	8									
THAI	8	8	8	8	8	8	8	17	9								

HK	9	9	9	9	9	9	9	9	17	6							
SING	6	6	6	6	6	6	6	6	6	17	5						
Japan	5	5	5	5	5	5	5	5	5	5	17	11					
AU	11	11	11	11	11	11	11	11	11	11	11	17	16				
NZ	16	16	16	16	16	16	16	16	16	16	16	16	17	13			
UK	13	13	13	13	13	13	13	13	13	13	13	13	13	17	4		
GER	4	4	4	4	4	4	4	4	4	4	4	4	4	4	17	1	
US	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	17	17

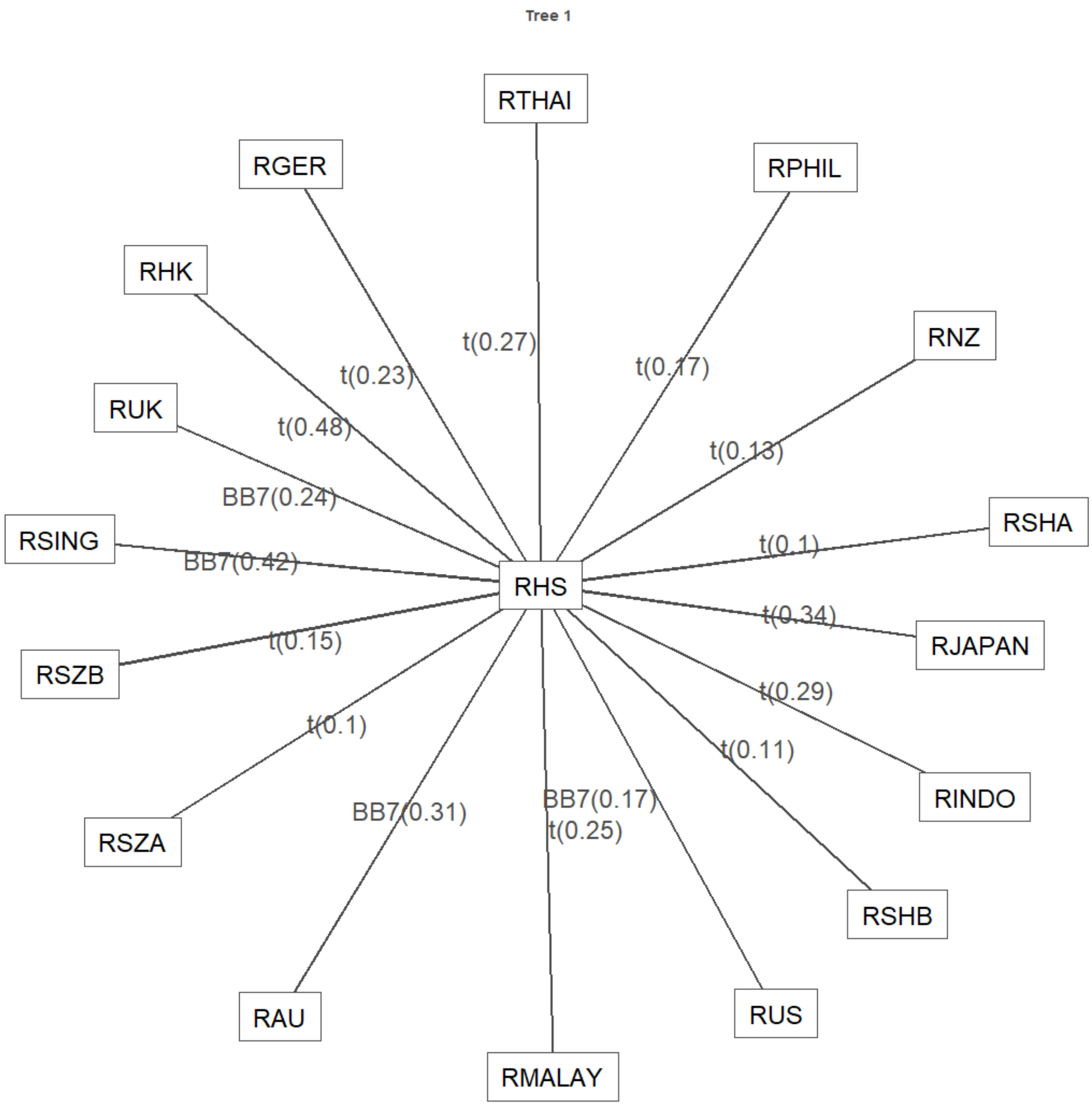


Figure 6-5. Pre-GFC C-vine tree 1

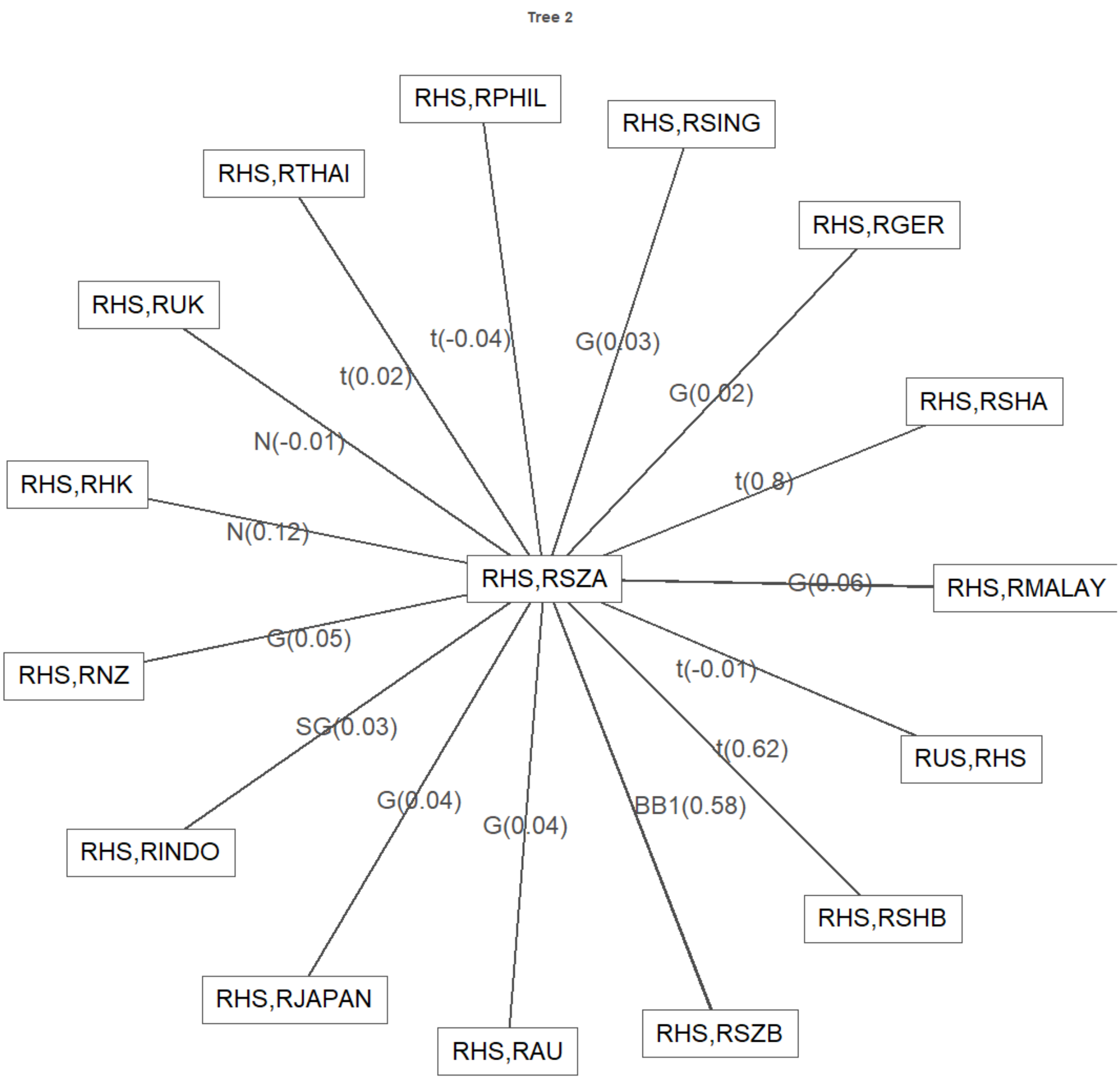


Figure 6-6. Pre-GFC C-vine tree 2, conditional on the relationship with HS

6.6.2. Dependence modelling using R-vines

Table 6-2 shows the specification matrix of the R-vine copulas over four sub-periods. The results of the R-vine tree 1 are depicted in **Figure 6-7**. **Table 6-3** presents the estimated Kendall's tau parameters for each pair in the R-vine structure in the four sub-periods. By the size of Kendall's tau parameter, the greatest dependencies belong to three groups: 1) among Chinese markets; for example, SHA and SZA (no. 2 and 4 in the first column), SZA and SHB (no. 4 and 3 in the second column), SHB and SZB (no. 3 and 5 in the third column), SZB and HK (no. 5 and 10 in the fourth column), and HK and HS (no. 10 and 1 in the fifth column); 2) between Singapore and Asian markets; that is, Malaysia–Thailand – Indonesia–HS–Japan and Singapore (no. 7, 9, 6 and 1 in the first row of 7th, 8th, 9th and 11th columns and no. 11 in the last row of these columns; no. 11 in the first row and number 12 in the last row of the 12th column); and 3) among other developed markets which are evident in the 14th to 16th columns, (Australia–NZ) (no. 13 and 15), UK–Germany (no. 15 and 16) and Germany–US (no. 16 and 17). **Figure 6-7** and **Table 6-2** show that R-vines are more flexible than C-vines and are capable of capturing complex patterns of dependence for each sub-period. In addition, different copulas are used for different dependencies conditioned across the same node as shown in **Table 6-4**. For example, in the pre-GFC period, Singapore is the central node of the Asian markets. There are five nodes that connected with Singapore, in which there are three different copulas for these dependencies (BB7 for HS–Singapore, Student-t for Thailand–Singapore, Indonesia–Singapore and Japan–Singapore, and BB1 for Malaysia–Singapore). There are various findings from the R-vine analysis, of which four findings are major.

Table 6-2. R-vine specification matrix

	HS	SHA	SHB	SZA	SZB	INDO	Malay	PHIL	THAI	HK	SING	Japan	AU	NZ	UK	GER	US
Panel A: Pre-GFC period																	
HS	2																
SHA	17	4															
SHB	16	17	3														
SZA	15	16	17	5													
SZB	14	15	16	17	10												
INDO	13	14	15	16	17	8											
Malay	12	13	14	15	16	17	7										
PHIL	8	12	13	14	15	16	17	9									
THAI	9	8	12	13	14	15	16	17	6								
HK	7	9	8	12	13	14	15	16	17	14							
SING	6	7	9	8	12	13	14	15	16	17	1						
Japan	11	6	7	9	8	12	13	14	15	16	17	11					
AU	1	11	6	7	9	9	12	13	14	15	16	17	12				
NZ	10	1	11	6	7	1	9	12	13	1	15	16	17	13			
UK	5	10	1	11	6	7	1	1	12	11	13	15	16	17	15		
GER	3	5	10	1	11	11	6	6	1	12	12	13	15	16	17	16	
US	4	3	5	10	1	6	11	11	11	13	11	12	13	15	16	17	17
Panel B: GFC period																	
HS	2																
SHA	17	4															
SHB	14	17	3														
SZA	16	14	17	5													
SZB	12	16	14	17	10												
INDO	15	12	16	14	17	6											
Malay	9	15	12	16	14	17	8										
PHIL	6	9	15	12	16	14	17	7									
THAI	8	6	9	15	12	16	14	17	9								
HK	7	8	6	9	15	12	16	14	17	1							
SING	13	7	8	6	9	15	12	16	14	17	12						
Japan	11	13	7	8	6	9	15	12	16	14	17	11					
AU	1	11	13	7	8	1	9	15	12	16	14	17	14				
NZ	10	1	11	13	7	13	1	9	15	12	16	14	17	13			
UK	5	10	1	11	13	8	13	1	13	15	11	16	16	17	16		
GER	3	5	10	1	11	7	11	13	1	13	15	15	15	16	17	15	
US	4	3	5	10	1	11	7	11	11	11	13	13	13	15	15	17	17
Panel C: Extended-crisis period																	
HS	5																
SHA	17	3															
SHB	16	17	4														
SZA	15	16	17	2													
SZB	14	15	16	17	10												
INDO	12	14	15	16	17	9											
Malay	13	12	14	15	16	17	1										
PHIL	8	13	12	14	15	16	17	6									

THAI	7	8	13	12	14	15	16	17	8								
HK	6	7	8	13	12	14	15	16	17	7							
SING	9	6	7	8	13	12	14	15	16	17	12						
Japan	11	9	6	7	8	13	12	14	15	16	17	11					
AU	1	11	9	6	7	8	13	12	14	15	16	17	13				
NZ	10	1	11	9	6	7	8	13	12	14	15	16	17	14			
UK	2	10	1	11	9	6	7	8	13	12	14	15	16	17	15		
GER	4	2	10	1	11	1	6	7	11	13	11	14	15	16	17	16	
US	3	4	2	10	1	11	11	11	7	11	13	13	14	15	16	17	17
Panel D: Post-crisis period																	
HS	5																
SHA	17	3															
SHB	9	17	4														
SZA	8	9	17	2													
SZB	16	8	9	17	9												
INDO	6	16	8	9	17	8											
Malay	12	6	16	8	16	17	10										
PHIL	7	12	6	16	10	16	17	12									
THAI	15	7	12	6	12	10	16	17	14								
HK	14	15	7	12	14	12	6	16	17	1							
SING	13	14	15	7	1	14	12	6	16	17	6						
Japan	11	13	14	15	15	1	7	7	6	16	17	7					
AU	1	11	13	14	13	15	15	15	7	6	16	17	11				
NZ	10	1	11	13	8	13	14	14	15	7	15	16	17	13			
UK	2	10	1	11	7	7	13	1	1	15	13	15	16	17	16		
GER	4	2	10	1	6	11	11	11	11	13	7	13	15	16	17	15	
US	3	4	2	10	11	6	1	13	13	11	11	11	13	15	15	17	17

(A) Pre-GFC period

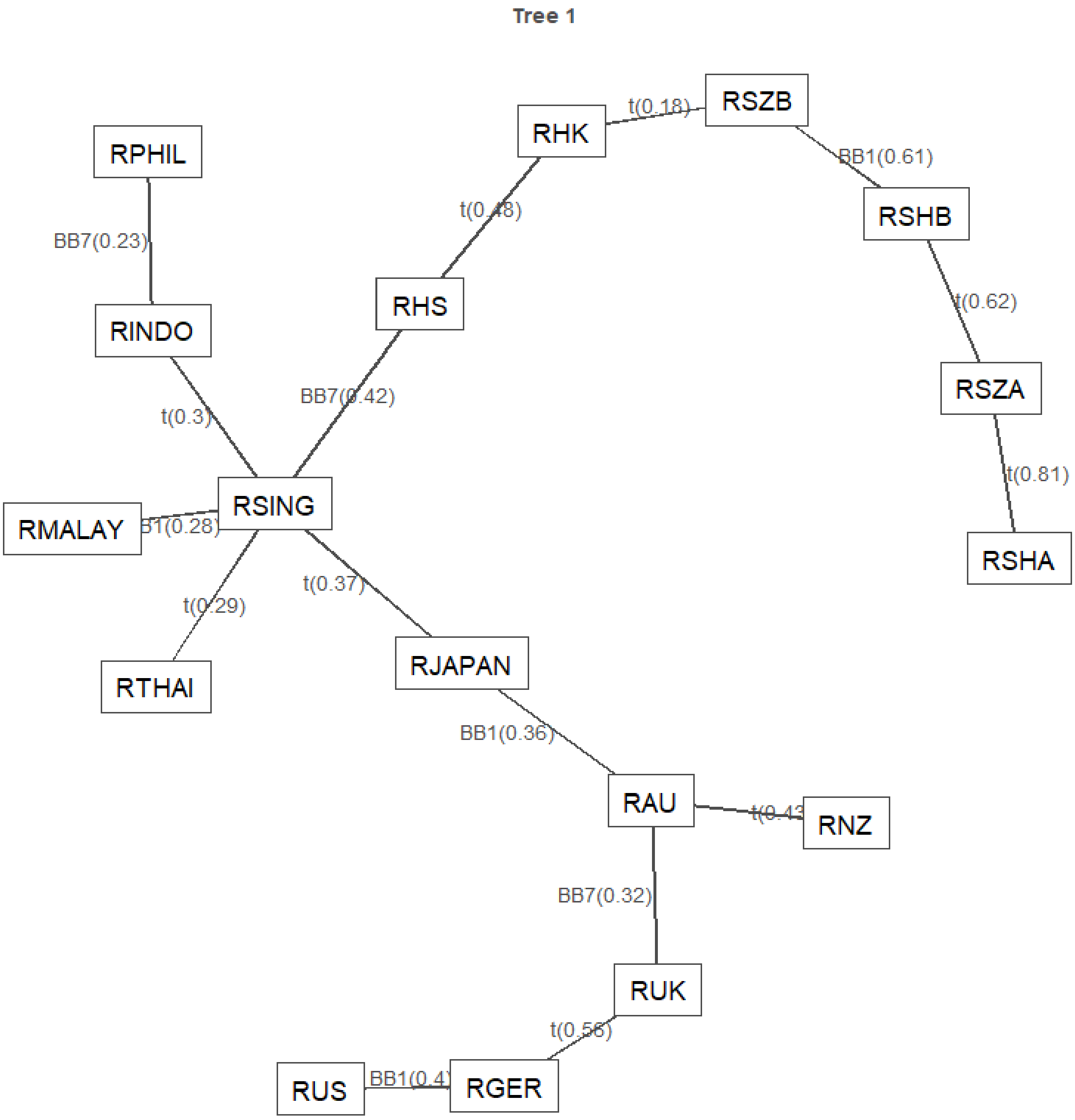


Figure 6-7. Results of R-vine tree 1

(B) GFC period

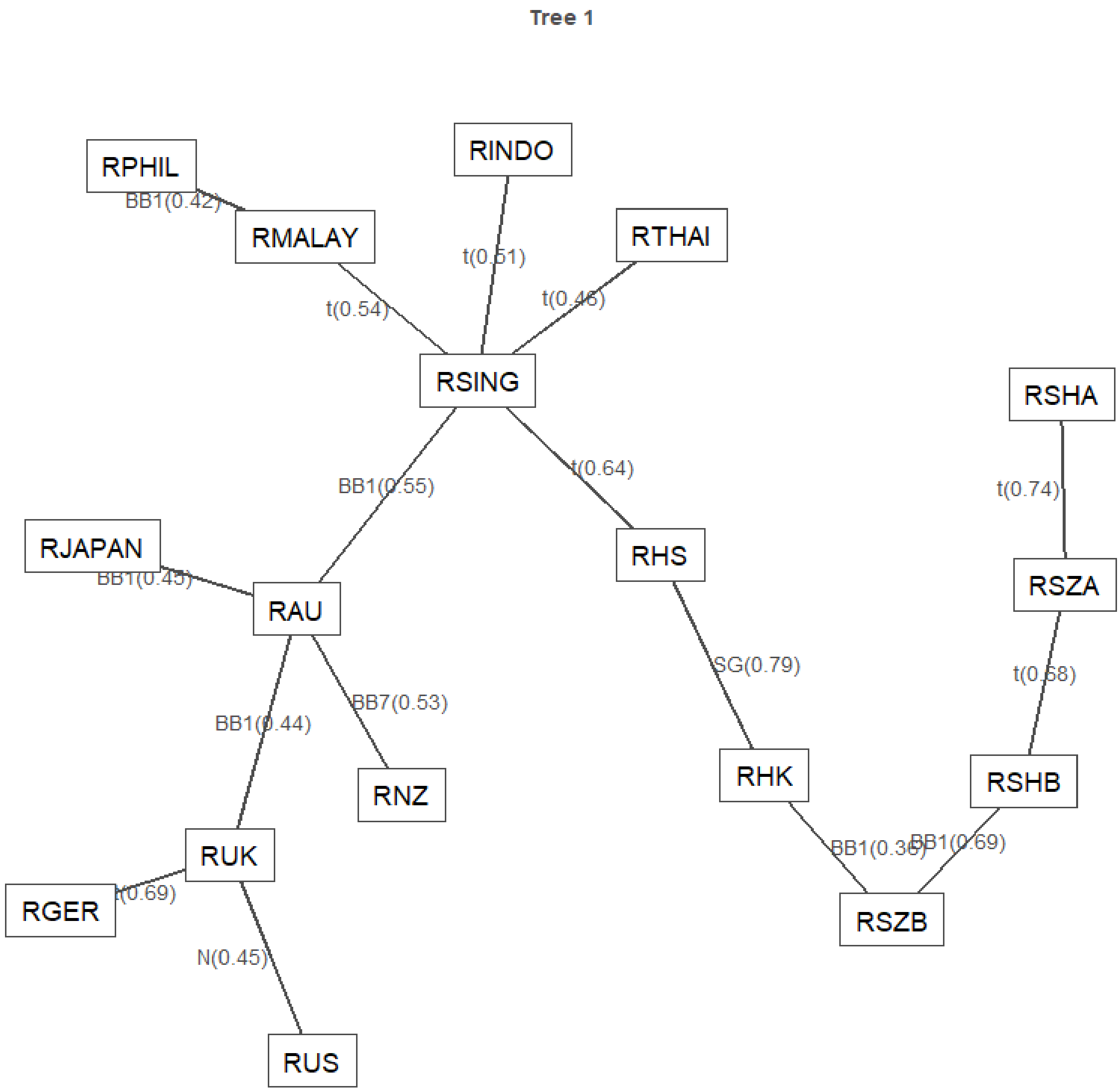


Figure 6-7. Results of R-vine tree 1 (cont.)

(C) Extended-crisis period

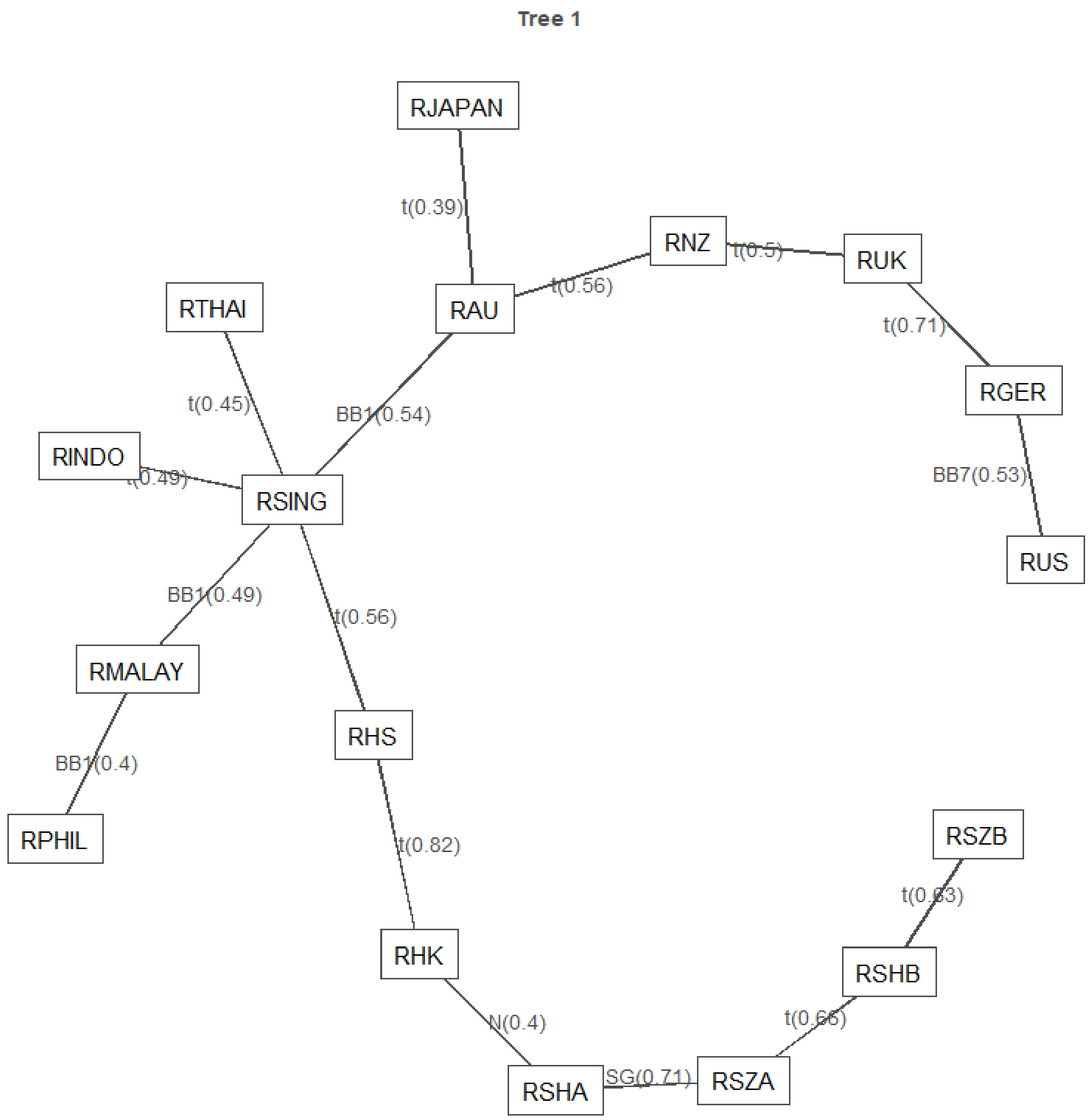


Figure 6-7. Results of R-vine tree 1 (cont.)

(D) Post-crisis period

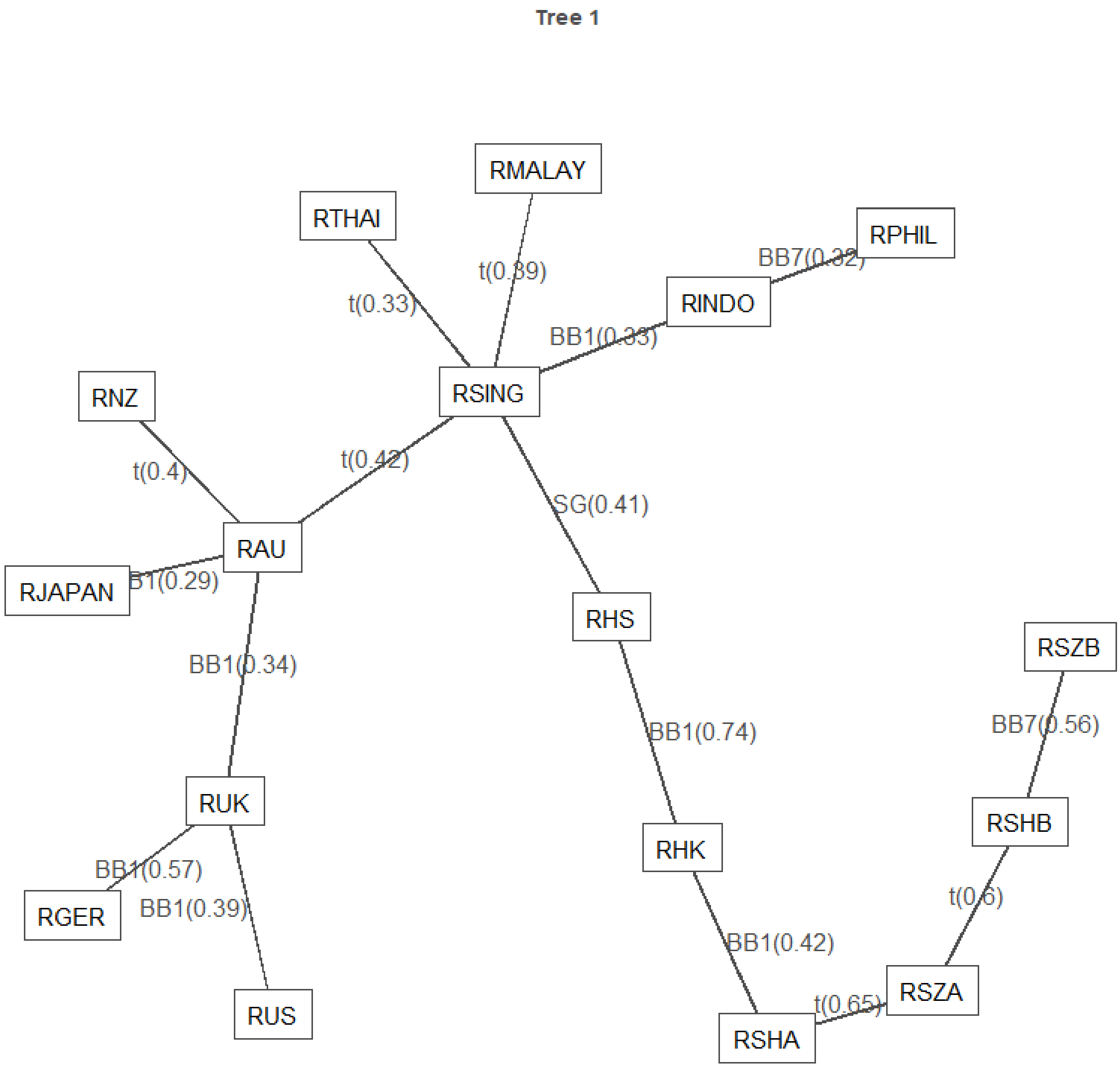


Figure 6-7. Results of R-vine tree 1 (cont.)

Firstly, inter-regional dependencies are evident throughout the four sub-periods. There are three groups shown in the R-vine tree 1.

The first group is the Chinese equities including HK, with HS being the node connecting Chinese markets with the Asian markets through Singapore. It is worth noting that each of China's markets, including HK, has only one edge except for HS. This one-line dependence structure suggests that these Chinese markets are quite isolated from other financial markets. This is consistent with Hu (2010) and Boubaker et al. (2016) who confirmed that the majority of the volatility in China's markets is explained by their own contributions rather than by external shocks. The segmentation of the AS and BS from other financial markets is due to the fact that these markets are accessible to Mainland investors only (the foreign investment in AS and BS is very small in size compared to the domestic investments, due to the fact that the B-share market is very small in size and AS are available to some foreign investors with heavy restrictions). In addition, the segmentation of Mainland Chinese equities from the rest of the world during the crisis periods could also be due to government intervention in order to stabilise the markets, while HS are more connected to the outside because they are traded on the HKSE (Wang & Jiang, 2004). Inequality in economic development and growth can also enlarge the disparity between China and other markets in the region (Chaudhry et al., 2012). China has maintained a super high economic growth in the past 10 years and left behind other markets in the region to become the second-largest economy in the world in 2018, behind the US and ahead of Japan. According to the US *Congressional Research Service Report* "*China's economic rise: History, trends, challenges, and implications for the United States*" published in 2018 also marked the mature phase of China's economy (Morrison, 2018). Hence this unequal economic expansion has contributed to the divergence between the stock markets in China and other markets in the region.

In addition, the results showed that a rearrangement in China's shares connections occurred after the GFC period. In the pre-GFC and GFC periods, SHA connected to SZA, whereas SZA linked with SHB, SHB connected to SZB, and SZB linked with HK. In this structure, SHA was the last node and SZB was the 'first' node of the AS and BS connection. SHA and SZB swapped places, where SHA became the connection node between HK and SZA, while SZB is the last node in the Chinese share connection structure in the extended-crisis period and post-crisis period. This suggests that SHA is more open (Li, 2012; Yao et al., 2018) or that the connection between SHA and HK is more apparent, which could be due to capital liberalisation policies, including the introduction of RQFII 2011 and the SH-HK Stock Connect program in 2014 (Huo & Ahmed, 2017), as discussed in sections 5.5 and 5.6.

The second group consists of the Asian markets including the ASEAN-5 and Japan, where Singapore remains the central node in the Asian markets throughout the four sub-periods. In the pre-GFC and post-crisis periods, Singapore connects directly to Thailand, Indonesia and Malaysia, and indirectly to the Philippines through Indonesia. In the GFC and extended-crisis periods, the node between Singapore and Indonesia has switched to Malaysia. This finding suggests a change in the dependence structure between Singapore and Indonesia. It appears that Malaysia is the connection channel between Indonesia and Singapore during a crisis period. This group connects to Chinese markets through Singapore–HS, and other advanced markets in group three through Singapore–Australia.

Australia is the central node of the last group, which consists of other advanced markets (Japan, NZ, the US, UK and Germany). The US is the last node of the edge of this group, which means it only connects directly with one market in the sample.

Secondly, intra-regional dependence through individual markets is also evident. There is a connection of the central nodes in each group which forms cross-regional linkages. In the pre-GFC and post-GFC periods, Australia connected with Singapore, the central node of the Asian-Pacific markets group through Japan and with Germany and the US through the UK, while Singapore connects to the Chinese equities through HS. In the GFC and extended-crisis periods, Australia connected directly with Singapore without going through Japan, while other cross-regional connected nodes stay the same.

Thirdly, HK, regardless of being a world financial market and governed by a standalone system separate from the Chinese government, is part of the 'Chinese share system' that connects with Mainland AS and BS and with the Asian markets through HS. This structure remains unchanged throughout the four sub-periods over the last 16 years, which is fascinating. Many studies found evidence of market integration between HK and other world financial markets such as the US, UK, Singapore and Japan, and that HK plays a leading role in regional share markets integration in Asia (Li, 2007; Mohammadi & Tan, 2015; Yilmaz, 2010). However, this chapter shows that the regional integration of Chinese AS, BS and HK is actually facilitated through HS. The bivariate analysis revealed that Chinese AS and BS have a strong correlation with the HS and HK markets in every single period. The HS market, on the other hand, has a strong connection with the HK market and other world markets. The results from our bivariate analysis in section 5.5 suggest that Chinese AS and BS, especially AS (even though they are 'closed' markets) are connecting to the world through HS and HK. The results of the GARCH analysis in section 3.7.3 also confirm that HS plays an active role in spreading shocks from Chinese A- and B-share markets to advanced global markets. This could explain why some studies found contradicting results regarding the dependencies between HK and Shanghai or Shenzhen markets when they did not account for HS (Mohammadi & Tan, 2015; Zhang et al., 2009).

Fourthly, **Figure 6-7** shows that the US market connects directly to only one market, which is either the UK or Germany and does not have a direct connection with any other markets in the sample over the four sub-periods, suggesting that the US market is most segmented and least correlated among the advanced markets. Many studies tend to confirm the widely held view of the leadership of the US equity markets and significant relationship between the US and many advanced and emerging markets such as the OECD and the Asian stock markets and the global markets such as Canada, France, and Germany (Royfaizal et al., 2009; Xu & Hamori, 2012). At first glance, the results from this chapter seem to contradict the prevailing view of the leading role of the US market in the global and cross-regional dependencies in the existing literature. However, taking a closer look at the R-vine tree 1, it is noticeable that there is a cross-regional connection with the US through individual markets and this set of markets remained quite stable throughout the four sub-periods. In the pre-GFC period, **Figure 6-7** shows that US linked to Germany and Germany linked to the UK, which linked to Australia. Australia linked to Japan, which linked to Singapore (the central node of the Asian markets), which linked to HS and the Chinese share systems. In the GFC, the cross-regional connection was US–UK–Australia–Singapore–HS. In the extended-crisis period, it was US–Germany–UK–NZ–Australia–Singapore–HS. In the post-crisis period, the cross-regional dependence has the same set of countries in the GFC period;

that is, US–UK–Australia–Singapore–HS. These findings suggest that while the US could be the primary source of the GFC, the shocks from the US market could be transmitted through the cross-regional connection channel – Australia, Singapore and HS – which then spreads through the whole region due to strong inter-regional market linkages. The cross-regional relations could be attributable to the established trading links among these countries and due to globalisation or regionalisation whereby, as found by Bowman, Chan, and Comer (2010), economic fundamentals could explain the reactions of world equity markets to a regional financial crisis. The segmentation between the US and China's equities have been discussed thoroughly in section 5.5.

Table 6-3 presents the estimated Kendall's tau parameters for each pair in the R-vine structure in the four sub-periods. By the size of Kendall's tau parameter, most of the greatest dependencies belong to three groups: 1) among Chinese markets; for example, SHA and SZA (no. 2 and 4 in the first column), SZA and SHB (no. 4 and 3 in the second column), SHB and SZB (no. 3 and 5 in the third column), SZB and HK (no. 5 and 10 in the fourth column), and HK and HS (no. 10 and 1 in the fifth column); 2) between Singapore and Asian markets; that is, Malaysia, Thailand, Indonesia, HS and Japan (no. 7, 9, 6 and 1 in the first row in the 7th, 8th, 9th and 11th columns and no. 11 in the last row of these columns, no. 11 in the first row and no. 12 in the last row of the 12th column); 3) among other developed markets which is evident in the 14th to 16th columns; that is, between Australia and NZ (no. 13 and 15), UK–Germany (no. 15 and 16) and Germany–US (no. 16 and 17). This explains why those studies that focused on the dominant role of the US market in the transmission of shocks during the GFC would find that the US was held as the leading source of external shocks, but would not be able to detect the real transmission mechanism. In addition, this also explains why some studies also found weak stock return correlations between the US market and the Chinese markets (Glick & Hutchison, 2013; Goh, Jiang, Tu, & Wang, 2013; Johansson, 2010).

The takeaway point here is that while the crisis country is an important target for the study of the contagion effect in a global crisis like the GFC, it is not that important how many countries are identified to have a correlation with the crisis country. It is, however, critical to identify the countries and whether they lead or are the central country in their regional dependencies. This is because the relations of two countries could be indirect and established through a channel market, and shocks from a crisis country could travel through multiple transmission channels to reach the seemingly uncorrelated countries. These findings indicate that regional dependence could be more important in spreading the crisis widely than is commonly believed. This finding is supported by the study of Kenourgios and Dimitriou (2015), which found that the GFC could be attributable to the contagion effects occurring at the regional level and regional sectors. In addition, Yu, Fang, et al. (2018) found that the risk contribution from the Shanghai Composite Index to Japan is the highest and to the US is the lowest, suggesting that the regional effect has a clear impact on the external risk contribution on a market. The UK, Australia, Singapore and HS are cross-regionally connected nodes, as shown in this chapter, which underlines that they might be efficient targets to be considered for financial risk management policies in an attempt to stabilise and control volatility transmitted across regions.

The consistency and stability of the joint dependence structure of the Chinese markets, and the inter-regional and intra-regional dependence structures throughout the four sub-periods, suggests that there was not much change in the joint dependence structure of the world financial markets within a region and across regions. Despite the capital reforms, Mainland Chinese equities were 'closed' markets for the past 15 years. Singapore remained the central node of the Asian markets during the past 15 years, indicating that their leading role in the regional dependence, which could be due to their trading power, remains consistent throughout the period in relation to other countries in the region.

Moreover, as shown in **Table 6-3** and **Figure 6-7** there is a strong integration bewteen AS and BS and between HS and HK. There is also evidence of a contagion effect in the GFC period between HK and SZB (doubled from 0.18 to 0.36), HS and Singapore (increased by 1.5 times from 0.42 to 0.64), among Asian markets and among other markets in the sample (for example, Singapore–Thailand increased by 1.5 times, from 0.29 to 0.46, and Australia–Japan increased by 1.25 times, from 0.36 to 0.45). The contagion effect is not evident among AS and BS because the degree of their pre-GFC integration is already high, suggesting a strong correlation prior to the crisis period. Moreover, Chinese equities are more related to Asian markets than to intra-regional markets such as the US, UK and Germany. These findings are consistent with the results from the bivariate analysis in section 5.5 and GARCH analysis in section 3.7.3.

Table 6-3. Estimated empirical Kendall's tau of the R-vine copula

	HS	SHA	SHB	SZA	SZB	INDO	Malay	PHIL	THAI	HK	SING	Japan	AU	NZ	UK	GER
Panel A: Pre-GFC period																
HS																
SHA	0.0003															
SHB	0.0236	-0.0142														
SZA	0.0077	0.0132	-0.0462													
SZB	-0.0042	-0.0118	-0.0325	0.0247												
INDO	-0.0048	0.0027	-0.0302	0.0255	0.0240											
Malay	-0.0146	0.0012	-0.0155	-0.0041	-0.0072	0.0148										
PHIL	0.0328	0.0300	0.0278	0.0591	0.0012	-0.0253	-0.0016									
THAI	0.0232	-0.0548	-0.0006	0.0152	-0.0179	-0.0164	-0.0249	-0.0074								
HK	-0.0166	-0.0178	-0.0321	0.0066	0.0142	-0.0031	-0.0062	0.0320	0.0069							
SING	0.0271	-0.0038	0.0053	-0.0259	-0.0176	0.0750	0.0092	0.0414	0.0272	-0.0667						
Japan	0.0448	-0.0271	-0.0190	0.0038	-0.0367	0.0741	0.0276	0.0094	0.0136	-0.0019	0.0573					
AU	0.0029	-0.0145	-0.0340	0.0447	0.0422	0.0452	0.0523	0.0708	-0.0146	0.0406	0.0316	0.0294				
NZ	0.0243	-0.0356	-0.0197	0.0227	0.0465	0.0318	0.0786	0.0749	0.0799	-0.0543	0.0393	0.0572	0.0178			
UK	0.0313	-0.0103	-0.0338	0.0307	0.0401	0.0874	0.0952	0.0973	0.0742	-0.0673	0.0934	0.0893	0.0522	-0.0759		
GER	0.1182	0.2536	0.0192	0.0229	0.0790	0.1135	0.1415	0.1515	0.1449	-0.0212	0.1596	0.1933	0.0440	0.0771	-0.0146	
US	0.8084	0.6300	0.6089	0.1777	0.4848	0.2192	0.2811	0.2849	0.2997	0.4307	0.4214	0.3740	0.3685	0.3147	0.5635	0.3956
Panel B: GFC period																
SHA	0.0060															
SHB	-0.0089	-0.0399														
SZA	-0.0233	-0.0134	0.0087													
SZB	0.0094	0.0107	-0.0017	-0.0101												
INDO	0.0071	0.0030	0.0073	0.0291	-0.0204											
Malay	0.0351	-0.0179	-0.0606	-0.0253	0.0019	0.0025										
PHIL	-0.0387	-0.0064	0.0037	-0.0198	0.0141	0.0179	0.0419									
THAI	0.0311	0.0186	-0.0439	-0.0302	0.0258	0.0144	0.1646	-0.0192								
HK	-0.0446	-0.0900	0.0351	-0.0369	-0.0437	-0.0598	0.0681	0.0625	0.0390							
SING	-0.0391	-0.0158	-0.0416	-0.0327	-0.0011	0.0546	0.0562	0.0558	0.0365	-0.0235						
Japan	-0.0550	-0.0220	0.0170	0.0802	0.0439	0.1036	0.0037	0.0222	0.0225	-0.0322	-0.1188					
AU	-0.0578	-0.0599	-0.0593	0.0864	0.0451	0.0869	0.0237	0.0063	0.0244	-0.0484	0.0104	0.0038				
NZ	0.1477	-0.0176	-0.0531	0.0200	0.0528	0.0507	0.1048	0.0830	0.0595	0.1079	-0.0703	-0.0128	-0.0365			
UK	0.1535	-0.0122	-0.0151	-0.0373	0.0284	0.0976	0.1399	0.0731	0.0467	0.0124	0.1544	0.0650	0.0981	-0.0613		
GER	0.1542	0.1785	-0.0003	-0.0204	0.0471	0.1445	0.1145	0.2445	0.1443	0.1471	-0.1287	0.1689	0.1622	0.1298	0.0656	

US	0.7487	0.6843	0.6930	0.3560	0.8030	0.5119	0.4179	0.5358	0.4570	0.6352	0.4656	0.5509	0.5308	0.4438	0.7000	0.4298
Panel C: Extended-crisis period																
SHA	-0.0224															
SHB	-0.0304	-0.0157														
SZA	0.0300	-0.0175	0.0187													
SZB	0.0154	-0.0533	-0.0210	-0.0273												
INDO	0.0822	0.0377	-0.0304	-0.0237	-0.0091											
Malay	-0.0022	0.0490	-0.0241	0.0037	-0.0027	-0.0092										
PHIL	0.0458	-0.0357	-0.0389	0.0268	0.0174	0.0303	-0.0444									
THAI	0.0257	0.0561	-0.0067	0.0080	-0.0274	0.0723	-0.0512	-0.0116								
HK	0.0315	0.0094	-0.0299	0.0096	-0.0450	0.0124	-0.0373	-0.0294	0.0191							
SING	-0.0081	0.0594	-0.0100	0.0302	0.0101	0.0099	-0.0768	-0.0327	0.0417	-0.0433						
Japan	0.0281	-0.0393	-0.0312	-0.0421	-0.0134	0.0106	0.1138	-0.0432	-0.0727	-0.0544	-0.0968					
AU	0.0134	0.0265	0.0881	0.0158	0.0643	0.0337	0.0952	0.0672	0.0453	0.0156	0.0049	-0.0187				
NZ	0.1605	0.0011	-0.0322	-0.0187	0.0044	0.0836	0.1150	-0.0437	0.1146	-0.0012	-0.2113	0.0105	-0.0281			
UK	0.1921	0.0306	-0.0373	-0.0250	0.0654	0.0983	0.1093	0.1108	0.0936	0.0464	-0.0298	0.0858	-0.0323	0.0374		
GER	0.2334	0.2568	-0.1317	-0.0372	0.0229	0.1606	0.1977	0.2573	0.1188	0.1703	0.1039	0.0658	0.2238	0.0740	0.1864	
US	0.6349	0.6667	0.7148	0.4027	0.8203	0.4582	0.5612	0.4910	0.4078	0.5018	0.3904	0.5440	0.5596	0.4983	0.7086	0.5428
Panel D: Post-crisis period																
SHA	0.0017															
SHB	0.0225	0.0240														
SZA	0.0058	-0.0158	-0.0082													
SZB	-0.0190	0.0420	0.0018	0.0006												
INDO	0.0321	-0.0211	0.0403	0.0198	0.0393											
Malay	0.0056	0.0178	0.0121	0.0049	0.0448	0.0217										
PHIL	0.0090	0.0088	-0.0057	-0.0548	0.0403	-0.0005	0.0108									
THAI	-0.0430	0.0571	0.0228	-0.0123	0.0175	-0.0336	0.0020	-0.0696								
HK	0.0292	0.0090	0.0164	0.0172	-0.0131	0.0698	-0.0030	0.0095	-0.0072							
SING	0.0269	-0.0093	0.0371	-0.0318	0.0568	0.0209	0.0024	0.0241	0.0195	-0.0081						
Japan	0.0474	-0.0124	0.0022	-0.0463	0.0853	0.0849	0.0135	0.0206	-0.0022	0.0061	-0.0156					
AU	0.0370	-0.0404	-0.0094	0.0230	0.0576	0.0011	-0.0166	-0.0228	0.0547	0.1062	0.0282	0.0039				
NZ	0.1117	-0.0078	-0.0183	-0.0126	0.0715	0.0839	-0.0244	0.0415	0.0395	0.0460	0.0096	0.0292	-0.0320			
UK	0.1504	0.0426	0.0809	-0.0311	0.1187	0.1183	0.0347	0.1376	-0.0719	0.0806	0.0511	0.1083	0.0335	0.0048		
GER	0.2465	0.2540	-0.1113	-0.1202	0.2022	0.1786	-0.0063	0.1115	0.0919	0.1623	0.2082	0.1569	0.1775	0.0206	0.1532	
US	0.5666	0.6057	0.6515	0.4135	0.3238	0.3022	0.7410	0.2893	0.3986	0.4060	0.3363	0.3932	0.4202	0.3482	0.5749	0.3939

Evidence of tail dependencies for individual correlations is abundant and changes in the bivariate dependence structure are recorded over the four sub-periods. **Table 6-4** shows that the Gaussian and Student-t copulas are the most predominant, suggesting that most of the dependencies among the 17 markets in the sample are concentrated in the middle and symmetric for both tails throughout the four sub-periods. However, the Gaussian copula barely appears in the R-vine tree as shown in **Figure 6-7** and instead Student-t dominates, suggesting that Student-t is best able to capture the dependence structures among these 17 markets. **Table 6-4** also shows that reliance on the applications of the Clayton and Rotated Gumbel copulas increased after the pre-GFC period, which indicates that there is an increase in the asymmetric left-tail dependencies over time. This result suggests that advanced and emerging equity markets are more prone to external negative shocks over time. This is consistent with the bivariate analysis results from section 5.5.

Table 6-4. Types of copula fitted of the R-vine structure

	HS	SHA	SHB	SZA	SZB	INDO	Malay	PHIL	THAI	HK	SING	Japan	AU	NZ	UK	GER
Panel A: Pre-GFC period																
SHA	14															
SHB	1	1														
SZA	14	4	1													
SZB	1	1	1	3												
INDO	1	1	1	1	3											
Malay	1	4	1	1	1	14										
PHIL	1	4	3	1	1	1	1									
THAI	3	1	1	4	1	2	1	1								
HK	1	1	1	1	1	1	1	4	3							
SING	4	1	1	2	1	1	1	3	4	1						
Japan	1	1	1	2	2	1	2	4	2	1	2					
AU	2	1	1	4	2	1	4	4	1	1	2	14				
NZ	9	2	1	4	4	14	2	4	4	2	3	2	9			
UK	4	2	1	4	2	4	2	2	2	2	2	2	9	2		
GER	2	4	3	2	2	4	2	9	2	2	2	4	2	9	2	
US	2	2	7	2	2	9	7	2	2	2	9	2	7	9	2	7
Panel B: GFC period																
SHA	1															
SHB	2	1														
SZA	1	1	2													
SZB	3	4	1	2												
INDO	3	3	1	3	1											
Malay	14	1	1	2	4	14										
PHIL	2	1	4	1	4	3	1									
THAI	1	4	1	1	1	4	1	1								
HK	1	1	1	2	1	1	2	1	14							
SING	2	2	2	1	1	4	4	1	3	1						
Japan	2	2	14	14	4	2	2	4	2	2	1					

AU	1	1	1	3	4	2	9	1	4	1	3	4				
NZ	4	1	1	4	1	2	7	3	14	3	1	1	1			
UK	2	2	1	2	14	3	4	1	2	4	4	1	2	1		
GER	2	2	1	1	1	2	4	1	1	2	1	1	1	2	4	
US	2	2	7	7	14	2	7	2	2	2	7	7	9	7	2	1
Panel C: Extended-crisis period																
SHA	1															
SHB	1	1														
SZA	14	1	1													
SZB	3	1	1	1												
INDO	2	1	1	1	1											
Malay	1	1	1	3	1	1										
PHIL	3	1	1	14	4	3	2									
THAI	4	2	1	14	1	4	2	1								
HK	2	1	1	2	1	1	2	1	4							
SING	1	1	1	1	2	4	2	2	3	2						
Japan	4	1	1	1	2	4	2	1	2	1	1					
AU	14	1	4	4	2	2	2	4	2	2	14	1				
NZ	1	3	2	1	3	2	2	1	2	1	1	2	2			
UK	1	2	2	1	2	4	2	2	1	1	1	4	2	14		
GER	2	2	2	2	2	4	2	4	9	2	1	2	9	2	1	
US	2	2	14	1	2	2	2	2	7	7	2	7	2	2	2	9
Panel D: Post-crisis period																
SHA	14															
SHB	14	4														
SZA	2	1	1													
SZB	1	1	3	1												
INDO	3	1	1	4	14											
Malay	14	4	4	4	3	4										
PHIL	2	1	1	2	1	2	3									
THAI	1	4	4	1	4	2	4	2								
HK	1	3	4	1	1	9	2	4	2							
SING	1	1	9	1	14	3	14	14	2	1						
Japan	7	1	4	1	2	1	2	2	1	2	1					
AU	2	1	2	4	4	2	1	2	2	1	1	4				
NZ	7	2	1	2	4	2	2	1	14	4	4	2	2			
UK	2	9	2	2	4	2	14	1	1	1	2	2	2	3		
GER	2	2	2	2	7	2	2	1	2	2	2	2	2	4	2	
US	9	2	2	7	2	9	7	7	2	14	7	2	2	7	7	7

The R-vine tree 1 from **Figure 6-7** shows that symmetric tail dependence (Student-t copula) is dominant in the pre-GFC and extended-crisis periods, whereas there is greater application of different tail dependencies (BB1 and BB7) and asymmetric left-tail dependence (Survival Gumbel) in the GFC period and post-crisis period. In the post-crisis period, there are six Student-t copulas, nine BB1/BB7 copulas, and one Survival Gumbel copula. This result indicates that tail dependencies are strongly evident for many pairs across the four sub-periods including non-crisis and crisis periods, which is consistent with the existing literature (Allen et al., 2017; Tófoli et al., 2012).

Figure 6-8 presents the results of the R-vine tree 2 conditional dependence structure. In the pre-GFC and GFC periods, HS and SZB relate to each other conditional on HK. In the extended-crisis period, given HK as a condition, there is a relationship between HS and SZA. In the post-crisis period, HS and SHA relate to each other conditional on HK. This finding suggests that HK plays a role in facilitating market integration between HS and Mainland AS and BS. Moreover, R-vine tree 2 also highlights the conditional regional dependence structure such as in the pre-GFC period where HS connected to Indonesia and Japan are conditional on Singapore, Singapore connected to Australia is conditional to the Japan market, and so on. When the primary dependence is taken into account for each group, Student-t copulas were still dominant, indicating that symmetric tail dependence was the most common conditional dependence structure.

These findings highlighted the importance of studying joint dependence structure under a multivariate context and the usefulness of vine copulas, especially R-vines, in capturing a complicated non-linear, high-dimensional dependence structure in a large sample such as in this chapter.

(A) Pre-GFC period

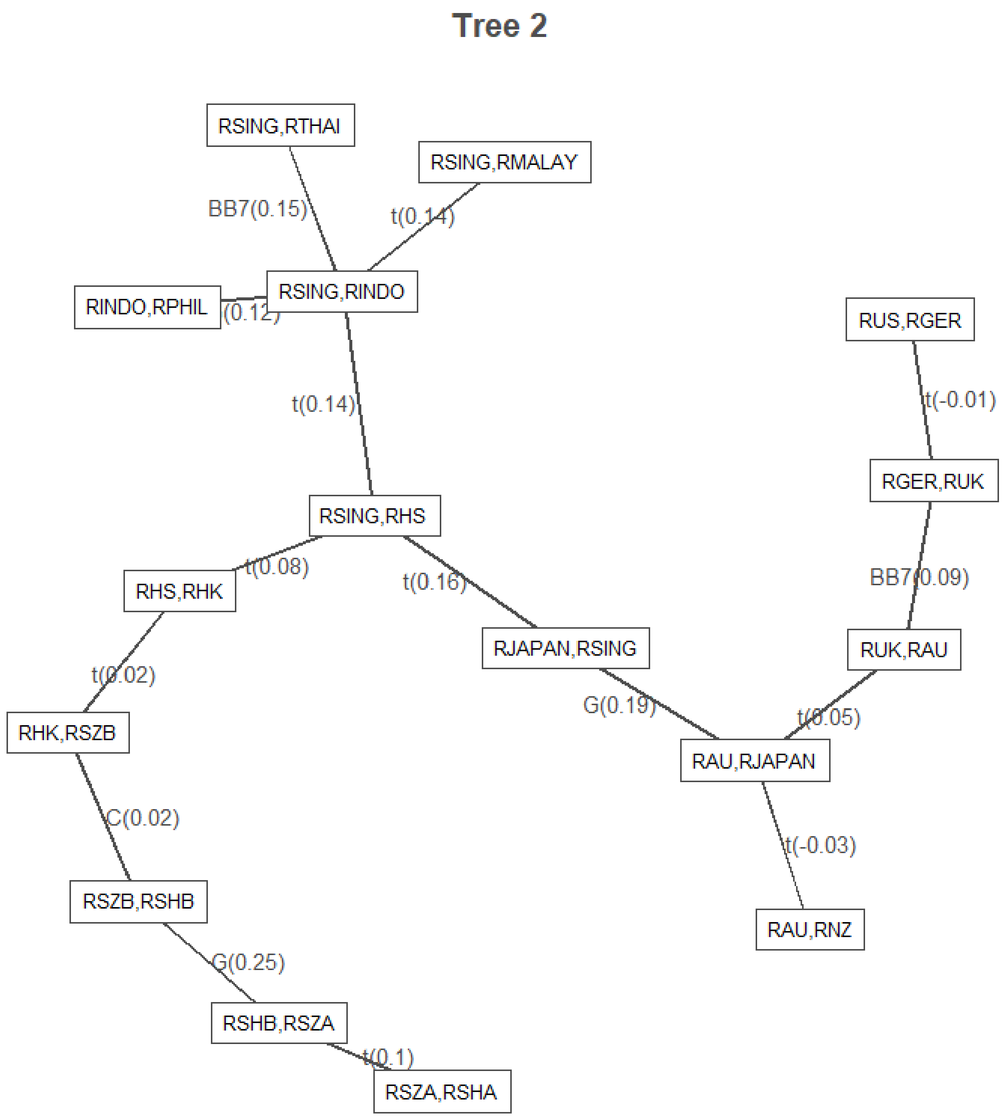


Figure 6-8. Results of R-vine tree 2

(B) GFC period

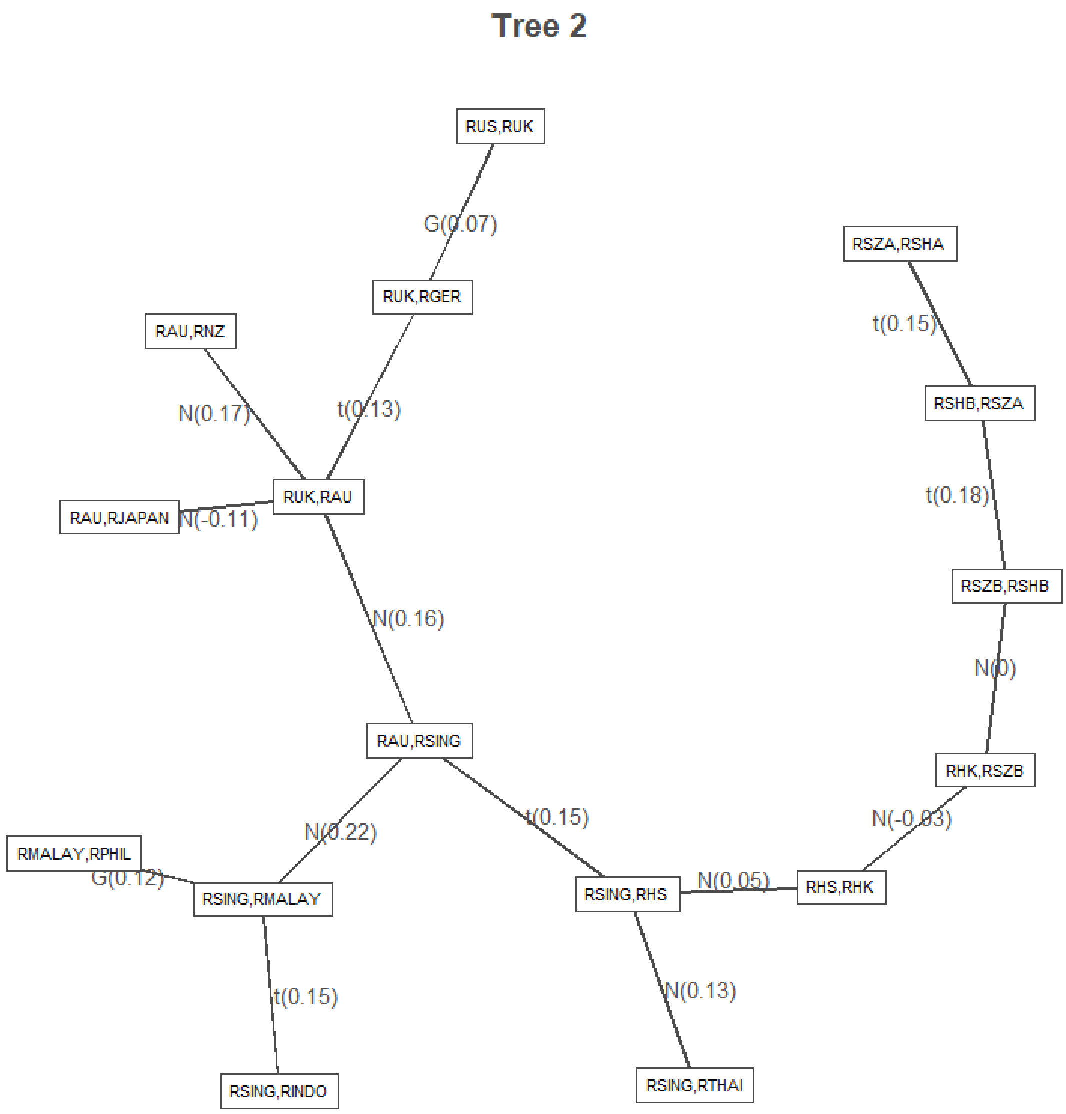


Figure 6-8. Results of R-vine tree 2 (cont.)

(C) Extended-crisis period

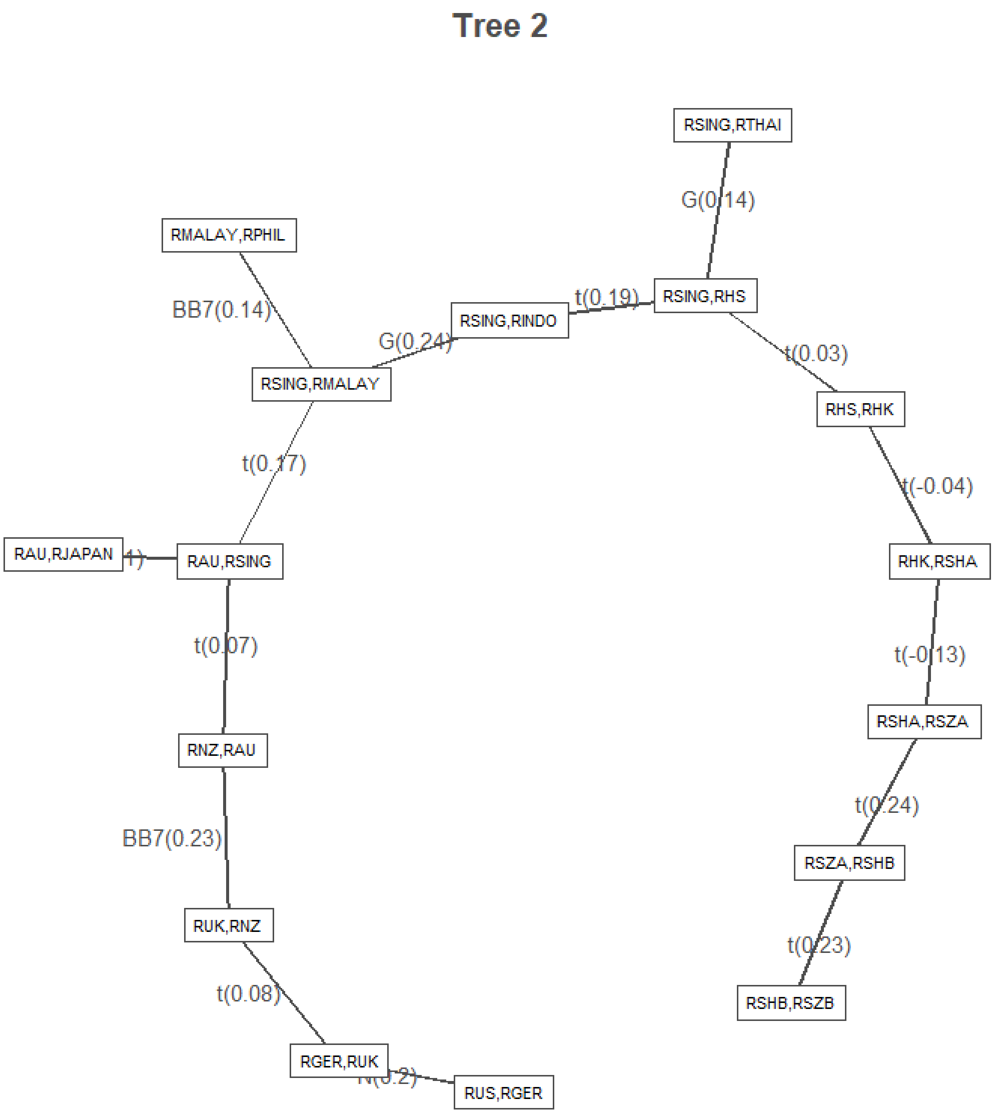


Figure 6-8. Results of R-vine tree 2 (cont.)

(D) Post-crisis period

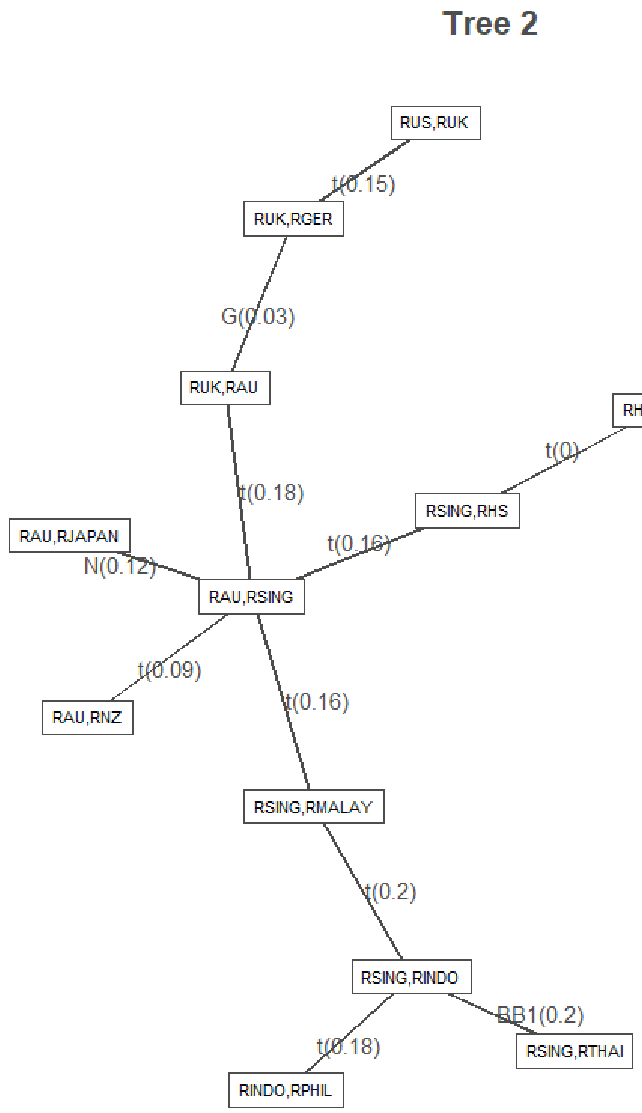


Figure 6-8. Results of R-vine tree 2 (cont.).

6.7. Conclusion and recommendations

This chapter uses R-vine and C-vine copulas to capture the multivariate dependence structures of the 17 markets in the sample over four sub-periods. The C-vine analysis confirms that HS are the centre of the dependence structure and has the highest individual dependence with all other markets in the sample in all four sub-periods. R-vines are found to be more flexible than C-vines in capturing complex multivariate dependence structures constructed from a combination of various pair-wise copulas, revealing more meaningful findings. There are four major findings from the R-vine analysis.

Firstly, inter-regional dependence is evident with three clustered groups throughout the four sub-periods: 1) Chinese equities (AS, BS, HS and HK) as one straight line with no central node; 2) the Asian markets (Singapore, the Philippines, Malaysia, Indonesia, Thailand and Japan, with Singapore being the central node); and 3) other advanced markets (Australia, NZ, US, UK and Germany, with Australia being the central node).

Secondly, intra-regional dependence was evident and formed by the connection of the central nodes in each group, which are UK–Australia–Singapore–HS. This structure remained consistent for the past 15 years, which could be due to the economic development and the trading power in these countries remaining consistent over this time period in relation the other countries in the region.

Thirdly, the Chinese shares including HK and HS were captured by a D-vine structure, in which there is a single straight line connection with no central node, where one node has one or two edges. This indicates that Chinese markets, including HK, are strongly correlated with one another, but are quite isolated from the rest of the world. This is understandable, as Mainland Chinese share markets are government policy markets and are under 'close' watch by the government, as discussed in sections 3.9 and 4.6. Moreover, the R-vine analysis shows that HS are the connection node between the Chinese share markets and the Asian markets. This finding shows that HS play a dominant role in facilitating the incoming capital into Mainland Chinese share markets from foreign investors, which forms the regional market integration of these Chinese shares including AS, BS and HK. The bivariate analysis from Chapter 5 shows a strong relationship between HS and AS/BS and between the HS and HK market throughout the four sub-periods, possibly due to the fact that they are all Chinese companies and that herding is evident in HK, Shanghai and Shenzhen markets (Teng & Liu, 2014; Yao et al., 2014), as mentioned in Chapter 5. Intuitively, one would expect HS to be more related to AS and BS and connect with global markets through the HK market because evidence of regional and global integration of the HK share market in the existing literature is abundant. However, this is not the case for Chinese equities. The R-vine trees show that HK is more related to Chinese AS and BS, while HS are more related to the regional markets. Even though Mainland China and HK are run under two government systems, their share markets are related to each other more than commonly thought. In addition, this structure has remained consistent over the past 15 years, even in two crisis periods (GFC and extended-crisis periods), suggesting that these Chinese share markets are quite segmented. This underlying mechanism can only be revealed under the multivariate dependence analysis when studying the AS, BS and HS separately and concurrently with global markets. These findings suggest that future studies should consider both HS and HK markets when evaluating the regional and global dependence structure of Mainland Chinese shares.

Fourthly, in the last group, in both crisis and non-crisis periods, the US appeared to be the most isolated market where it had only one edge that connected to either the UK (GFC and post-crisis periods) or Germany (pre-GFC and extended-crisis periods). This chapter seems to contradict the prevailing opinion in the literature that a contagion effect is directly evident among the US and many global markets. The findings of this thesis showed strong inter-regional clustering, intra-regional connections and clear evidence of the isolation of the US market, which suggests that shocks from the US spread to other regions through cross-regional connected nodes (the UK, Australia, Singapore and HS). Due to the strong regional correlation, Singapore spread the crisis to the Asian markets and Australia spread it to NZ and Japan, while HS spread to other Chinese markets including HK. This finding demonstrates a domino effect across regions and within a region during a crisis where regional market integration plays an important role. These findings suggest that in evaluating how widely a country's crisis can be spread, it is necessary to identify which crisis-impacted country is the central node in to a regional dependence. Future studies which further consider the impact of regional dependencies in spreading a crisis globally could be interesting.

In addition, R-vines have demonstrated the ability to capture different pair-wise dependence structures, creating a complex multivariate dependence structure constructed from a combination of various pair-wise copulas. This chapter also found evidence of a contagion effect between Chinese equities and other advanced and emerging markets, which is consistent with the findings from the bivariate analysis in Chapter 5.

Chapter 7 Summary and conclusion

7.1. Summary

7.1.1. Introduction

Since the GFC, which commenced in late 2007, despite the US economy subsequently showing some signs of recovery, concern over the global economy and stock markets has been stirred by various events, coupled with fear over the instability in China's economy. Compared to the pre-GFC period, attention from investors, analysts and economists to the movement in China's stock market has been growing considerably. In August 2015, global stock markets experienced a considerable fall, due to China's market stock crash. In late 2017, another fall occurred in global stock markets, due to a massive sell-off in the bond market in China. These events raised a flag about the stability of global markets. A big question that interests many analysts and investors is how far the impact can spread if the markets in China experience substantial falls. To answer this question, having a thorough understanding of the nature of cross-equity linkages between China and other global markets is required, which is a key aim of this study.

It is worth noting that, due to economic reforms and a high level of government control, China's stock markets have three major share types, namely AS, BS and HS with different market players and operational features. AS and BS are listed on the Mainland China stock markets, (SHSE and SZSE). Both AS and BS are denominated in Renminbi, but BS can be traded in US dollars or HK dollars. HS are listed on the HKSE denominated in HK dollars and traded the same way as other equities on the HKSE. Generally, AS are traded by domestic Chinese investors, while B-share and HS markets are for foreign investors. Thanks to the reforms in capital deregulation introduced from 2011 to 2016 (RMB QFII, SH-HK Stock Connect program 2014 and Shenzhen-Hong Kong Connect scheme 2016), international investors are allowed to trade AS, and domestic Chinese investors are allowed to trade BS with restriction. Shanghai and Shenzhen stock markets are emerging markets, while the HK market is an advanced market with stricter reporting regulations and more complex financial products such as derivatives. HS and BS are traded mostly by sophisticated foreign institutional investors, while AS are predominantly traded by domestic retail Chinese investors with less knowledge (Credit Suisse, 2015). Therefore, HS and B-share investors are more rational, while A-share investors can be subject to a higher degree of irrational trading bias such as herding (Fu, 2010; Mahmud & Tiniç, 2015). Further, AS and BS are considered 'policy' markets because they are under the close watch of the government and there were many cases of government intervention in the markets during a crisis or a stock crash to stabilise the markets, as discussed in Chapter 3.

Volatility spillover, contagion effect and recoupling hypothesis are major phenomena documented in the literature in various crises such as the AFC 1997, GFC 2008 and the European debt crisis 2012, as mentioned in sections 1.4.2 and 1.4.3. The literature that has examined these phenomena for major markets such as the US, UK, Singapore, and Germany is abundant, as mentioned in the literature reviews conducted throughout the thesis such as in sections 1.4, 3.2, 4.2., 5.2.1, and 6.2. While many studies have examined shock transmissions and the volatility dependence of major stock markets in China; that is, Shanghai, Shenzhen and Taiwan, studying three major share types in Mainland China including A-, B- and H-share markets simultaneously has received little attention. To close this gap, this thesis evaluated cross-market linkages between AS, BS and HS and other emerging and advanced markets which are neighbouring trading partners of China and which hold a significant economic position globally or regionally, including the ASEAN-5, Japan, HK, the US, UK, Germany, Australia and NZ. Together, there are 17 markets studied in this thesis (five share markets in China and 12 other markets). In addition, the combination of these emerging and advanced markets in the sample is to ensure a broad view of the regional and global dependence of China's markets.

The remainder of this chapter is structured as follows. Section 7.1.2 highlights how the thesis met the thesis objectives. Section 7.1.3 describes the major motivation of the thesis. Section 7.1.4 summarises key findings. Section 7.1.5 concludes. Section 7.2 discusses some of the main limitations of this thesis and recommends future research. Section 7.3 presents the contribution of the whole thesis.

7.1.2. Meeting the thesis objectives

As mentioned in section 1.1 page 17, this thesis examined four main objectives of market interdependencies in the literature between the selected countries: 1) to investigate the asymmetries and leverage effect in the distributional volatility of each time series and to detect volatility spillover between China and other markets in the sample using a univariate GARCH and EGARCH model; 2) to assess the dynamic multivariate dependence of these 17 markets using a multivariate time-varying DCC-EGARCH model; 3) to evaluate the joint tail dependence between China and other markets using bivariate copulas; and 4) to study the multivariate joint tail dependence structure of all studied markets using vine copulas.

This thesis examined each of these objectives using four different models on the same dataset in four sub-periods including non-crisis periods (pre-GFC period from 1 May 2002 to 26 February 2007; post-crisis period from 7 June 2012 to 31 July 2017) and crisis periods (GFC period from 27 February 2007 to 29 May 2009; extended-crisis period from 30 May 2009 to 6 June 2012). The complete description of the data of this thesis, the four sub-periods and the preliminary analysis are presented in Chapter 2. As expected, the daily returns of all markets are characterised with non-normality, skewness, excess kurtosis, serial correlations and heteroskedasticity.

The modelling of the associations between these financial markets in the thesis started with simple GARCH and EGARCH models in Chapter 3, which accounted for prominent distributional properties of the studied markets. Chapter 3 examined the leverage effect and the asymmetry in volatility for each market using the EGARCH model and the volatility spillover between two markets using the EGARCH model with an added auxiliary term of spillover effect. The thesis then assessed the dynamics of the multivariate dependence structure of the 17 studied markets using a time-varying DCC-EGARCH model in Chapter 4. Chapter 5 quantified the joint tail and general dependence structure of each pair of markets using seven bivariate copulas. Chapter 6 assessed the general and tail dependence structure of 17 markets under a multivariate context using vine copulas (R-vine and C-vine). Significant phenomena in cross-market linkages which were documented in the existing literature, including contagion effect, recoupling hypothesis and volatility spillover, were also addressed in the discussion of chapters 3 to 6. The research questions for each chapter are mentioned in section 1.5 and the hypotheses section in each chapter.

7.1.3. Motivation

The motivation of this thesis can be summarised on two primary grounds. First is the current economic situation where China has risen to be the second-largest economy in the world and is one of the biggest trading partners of many global economies such as the US, UK, Germany, Japan and Singapore, as mentioned in section 1.3. The literature recorded an increase in the regional integration of Chinese equities, as mentioned in section 1.4. Higher market integration not only reduces diversification benefits, but also introduces additional exposures from cross-market dependencies, especially during heightened volatility periods through contagion effect and volatility spillover, which occurred in the AFC 1998 and GFC 2008, as discussed in the literature review sections throughout this thesis. Given the increased volatility in the global markets due to wars, political instability in many regions and natural disasters, in addition to the increased volatility from China's markets and economy due to rapid expansion and uncertainty in the long-term economic growth, it is necessary to examine the role of China in global markets regarding volatility spillover and contagion effect. Secondly, while the need is visible, the literature concerning relations among three major share types in Mainland China has received little attention, as discussed in the literature review sections in chapters 3, 4, 5 and 6. These reasons created a strong motivation for this thesis.

7.1.4. Major findings

There are various findings from this thesis, and the most significant ones are summarised as follows. The univariate analysis using GARCH and EGARCH models found that the leverage effect was evident in many emerging and advanced markets but differed among China's markets. The leverage effect was found to be significant for HS in all sub-periods, while AS and BS were more prone to bad news than good news during market turbulence (crisis periods). Volatility spillover is clearly evident among AS, BS, HS and HK throughout the whole sample period, possibly due to herding behaviour. Evidence of volatility spillover between the stock markets in China and other emerging and advanced markets in the samples is abundant, but generally, the dependence level is trivial. Volatility spillover from China to some Asian emerging markets including Indonesia, the Philippines, Malaysia and Thailand increased since 2015, which could be explained by the 'cash pump' from China to those countries' major infrastructure projects via the two Chinese banks – the New Development Bank and Asian Infrastructure Development Bank.

A significant connection among China's AS, BS, HS and HK was strongly and consistently evident in four different models. Market interdependence between AS, BS and HS was generally stronger, if not much stronger, than with regional markets, indicating that China's share markets are more vulnerable to local shocks than regional shocks. The findings also suggested that Mainland China's share markets were strongly correlated with one another, and in fact were quite segmented from the rest of the world, despite capital liberalisation policies. Chapter 4 even found evidence that while HS behaved like HK during the non-crisis periods, which is strongly connected with major financial markets in the region, HS experienced disparity with those global markets during the GFC period. In fact, recoupling and strong synchronisation between HS and Mainland China's AS and BS were documented during this period. Chapter 6 found that all Chinese stock markets, including AS, BS, HS and HK, were captured by a D-vine structure in which they were connected in one line, and this structure remained unchanged over the past 15 years. Even though China became the second-largest economy in the world in 2018 and the market capitalisation was more than US$8 billion – exceeding the US in 2015 – these findings provided clear evidence of isolation between China's markets and other global markets. The R-vine tree in Chapter 6 revealed that HS was a bridging channel between China's shares, including HK and the Asian markets. The C-vine analysis confirmed that HS was the centre of the dependence structure and had the highest individual dependence with all other markets in the sample, in all four sub-periods. These findings highlighted the critical and dominant role of HS in facilitating the regional integration of Chinese shares, including AS, BS and HK. This mechanism and structure could not be detected using GARCH models and was captured in the multivariate analysis using vine copulas in Chapter 6.

Regional integration was evident in all four models, and there was clear evidence of regional clustering found in Chapter 6. Three clustered groups which remained consistently throughout the four sub-periods are: 1) Chinese equities (AS, BS, HS and HK) as one straight line connection; 2) the Asian markets (Singapore, the Philippines, Malaysia, Indonesia, Thailand and Japan, with Singapore being the central node); and 3) other advanced markets (Australia, NZ, US, UK and Germany, with Australia being the central node). Regional integration for Mainland China's equities (such as HK, Japan and Singapore) was generally higher than intra-regional integration (such as the US, UK and Germany), indicating that the geographic factor could play a significant role in market interdependencies. An increase in the connection between Mainland China's equities and other markets in the region was documented in the post-crisis period, but the increase was trivial.

While GARCH models could not detect the structure of the intra-regional dependence among the studied markets, Chapter 6 found that the dependence across regions was formed by the connection of the central nodes in each group, which are UK–Australia–Singapore–HS. This structure remained consistent for the past 15 years, which could be due to the economic development and the trading power in these countries remaining consistent over this period in relation to other countries in the region, as discussed in section 5.5.

Importantly, segmentation between the US and China's equities was consistently evident in all four models. This finding shed light in two areas. First, while the US and China are the two largest economies in the world, and have solidly established trade and investment links, they appeared to be insulated from the negative shocks from each other. Taking a closer look into their trade profiles and economic policies, it was noted that China is the world's largest holder of national reserve assets, including gold and US dollars. A significant source of China's economic growth was driven by manufacturing and exporting finished goods products instead of commodities and raw resources materials. As discussed in section 5.5.2, these economic factors might hinder the external shocks from other global markets such as the US from impacting the Chinese economy significantly. Also, the Chinese government is keeping a close watch on Mainland China's share markets, and intervention has been executed in many catastrophic events to halt and stable the market. Therefore, even though there were several liberalised capitalisation policies implemented in Mainland China's markets since 2011, the findings of this thesis supported the contention that economic and trade policies might have some positive effects on protecting China's markets from global fluctuations. On the other hand, the US has had a net trade deficit (imports more than exports) with China, which created a cushion for the US's economy against the turbulence in China's economy.

Secondly, in both crisis and non-crisis periods, the US appeared to be the most isolated market, where it had only one edge that connected to either the UK (GFC and post-crisis periods) or Germany (pre-GFC and extended-crisis periods). This finding also shed light on the transmission mechanism from the sub-prime crisis to the GFC. While the crisis from the US was not transmitted directly to markets out of the region, given strong inter-regional clustering and intra-regional connections, the findings from this thesis indicated that shocks from the US spread to other regions through cross-regional connected nodes (the UK, Australia, Singapore and HS), from which they then affected the countries in each region through inter-regional linkages. The severity of the impact on a country, therefore, might be dependent on the amount of volatility transmitted from the US to the central market in the region through the intra-regional connection, and the vulnerability of the affected country to the transmitted shocks, as discussed in section 6.6.

Contagion effect and recoupling-decoupling in market returns were recorded between China's markets and other advanced and emerging markets during the GFC period. This finding implies increased systematic risk during the crisis. In addition, while regional integration of Chinese equities was on a weak upward trend, there was a clear shift in the tail joint dependence structure, from the right tail dependence between the stock markets in China and other studied countries in the pre-GFC period to the left tail dependence in extended-crisis and post-crisis periods, suggesting higher systematic risks. It also means that there was a higher risk of co-crashes in the extreme movements between these markets.

Distinct distributional features and co-movement behaviours were recorded for AS, BS and HS throughout the thesis and between the crisis and non-crisis periods, which were found for leverage effect, asymmetries in volatility of marginal distributions, volatility spillover and dynamic correlations. This infers that in these markets, the degree and extent of regional and global integration in terms of returns and shock transmission depends on the share classification. Therefore, from both empirical and theoretical perspectives, the findings from this study suggested that accounting for heterogeneity in the joint dependence structure of AS, BS and HS is necessary to examine their regional and global linkages in different economic states, and validated the needs to study these Chinese share markets separately.

In addition, the findings from Chapter 6 showed that R-vines had demonstrated the ability to capture different pair-wise dependence structures, creating a complex multivariate dependence structure such as a combination of C-vine and D-vine paths constructed from a combination of various pair-wise copulas.

7.1.5. Conclusion

In brief, the results from the four different models summarised above suggested that Chinese equities, including HK, were strongly connected. Even though the correlation between China's markets and other markets in the region in terms of volatility and returns is evident, the dependence level is weak. The vine copulas in Chapter 6 found that China's markets are connected in one line, suggesting that China's markets are quite segmented from the rest of the world. These 'closed' markets connected with other (Asian) countries through HS. This structure has remained stable for the last 15 years, highlighting the role of HS in facilitating innovations between Chinese equities and other markets in the regions. Chapters 4 and 5 also supported the existence of segmentation between China and other markets in the region. Literature concerning decoupling, as discussed in section 1.4.2, suggested that unequal economic growth can diminish integration among emerging markets, which could explain weak correlation between China and other emerging markets in the region. In addition, while the strong connection among Chinese equities was slightly weaker in the post-crisis periods, and regional integration was slightly more robust in this period – which could be attributable to the capital liberalisation policies and consistent with the decoupling-recoupling hypothesis – it is worth noting that the increase was small. Regardless, investors should be aware that HS might transmit innovations between Asian markets and Chinese markets, especially during a heightened volatility period. Moreover, higher market integration can reduce the diversification benefits and introduce an additional risk factor, which should be considered in hedging strategies.

All four models found segmentation or lack of direct relations between the US and Mainland Chinese equities. While recoupling was also recorded between SZB and the US in the GFC, SZB is a very small market compared to AS. Therefore, this finding cannot overrule the existence of segmentation between these markets that was found in all four different models. In addition, the economic and trade policies implemented in China and the US which were designed to protect them from increased volatility from global markets, together with government intervention and strict control in foreign capitals inflows, are factors which could explain the segmentation between these markets. This finding also suggested that market sentiments could explain the global stock crash in August 2015 and late 2017, which were claimed to be due to the massive sell-off in China's stock markets. Hence, this finding could explain why the crash was only short term and quickly reverted to the pre-crash level. The multivariate copula model in Chapter 6 revealed that the innovations between the US and Chinese equities were transmitted through intra-regional links.

There is consistent evidence from the GARCH analysis to the bivariate and multivariate copula analyses that regional dependence for Chinese equities (for example, with Asian markets) was more potent than intra-regional dependence (for example, with the US, UK and Germany), which implied that geographic location plays a considerable role in market interdependencies. This finding might also explain the segmentation between the markets in China and the US.

More importantly, the contagion effect and recoupling hypothesis between Chinese equities (AS, BS and HS) and other advanced and emerging markets at general and tail dependencies were evident. The copula models revealed that the joint dependence structure was commonly described by a Student-t copula, indicating significant tail dependence between China's markets and other markets in the sample. A clear shift to left-tail dependence during the crisis periods was found, indicating the existence of higher symptomatic risks. This finding highlighted the importance of tail dependence in both practical and theoretical settings in the contemporaneous context.

Finally, heterogeneity was found for AS, BS and HS from the distributional properties of volatility including volatility persistence, leverage effect to the extent of joint dependence structures, behaviours and the degree of regional and global integration. The results validated the need to study cross-equity linkages AS, BS and HS separately and simultaneously, and the need to treat these shares differently when forming investment and hedging strategies.

7.2. Limitations and recommendations

Firstly, a key aim of this thesis was to describe the joint dependence structure and quantify the tail dependence between China's markets and other markets in the sample in non-crisis and crisis periods. While some explanations of the causes of the documented phenomenon were discussed, it was not within the scope of the thesis to undertake a detailed market sentiment analysis which might further explain the transmitted volatility from China's markets to global financial centres. This creates an opportunity for future research, espescially taking into consideration the effect of the corona virus pandemic i.e. COVID-19 that is currently happening around the world.

Secondly, to make the scope of the thesis manageable, the sample covered 17 advanced and emerging markets. While this scope was extensive in that it represented about 60% of the total market capitalisation of all global markets, the models could also be applied to other markets to expand the literature. This thesis found there is a clustering of Asian countries (except for China), so future research can use the models in this thesis to examine this phenomenon in other major economic regions such as Europe, America, Middle East and Africa.

Thirdly, the thesis used daily data to capture simultaneous dependence at return and volatility levels, following conventional approaches in the existing literature. Even though weekly data can reduce daily noise in stock returns volatility, it can also eliminate simultaneous dependence occurring at the daily level. Similarly, high frequency data such as intraday might be useful to study market sentiment and short-term reactions, but it can introduce extra noise from high frequency levels. For this reason, using daily data is deemed appropriate to the thesis objectives. Nonetheless, the models used in this study could be applied to weekly and higher frequency data in future studies for comparison purposes.

Fourthly, the study period covered a 15-year period which included the periods before and after the peak of the GFC. Therefore, the results provided an essential understanding of the differences in the joint dependence behaviour of the sampled markets in the crisis and non-crisis periods. However, this study was based on empirical data, and what happened in the past might not necessarily repeat in the future. Hence, for forecasting purposes, further study could use the data with allowance for new risk factors.

7.3. Contribution and potential policy implications

The contribution of this thesis to the existing literature of cross-equity volatility dependence regarding asymmetries, tail dependence and regime-dependence behaviour from both theoretical and practical aspects such as portfolio selection, risk management, hedging and option valuation is noteworthy, as summarised in this section.

Part of the significance of this thesis is that it closes the gap in the existing literature, whereby the modelling of cross-linkages and the tail dependence of AS, BS and HS with other global markets has received little attention to date. Tail dependence is a critical topic in the current situation since China is the second-largest economy in the world, while the instability of China's long-term growth rate has been a concern, in addition to globalisation, regionalisation and increased unpredictability in the global markets due to increased political and economic tension in many regions.

This thesis is also significant for shedding light on the GFC transmission mechanism, the hidden role of the HS market in regional integration of Chinese equities, segmentation between the US and China, and clustering of markets in the same region, as mentioned above. The thesis evaluated important concepts in the modelling of market interdependencies during a crisis, including volatility spillover, contagion effect and decoupling-recoupling hypothesis. This understanding is beneficial to risk managers and policymakers. Assessing general and tail dependence at regional and global levels provides vital implications in quantifying the downside risk of a co-crash, constructing an optimal and efficient global stock portfolio and forming hedging strategies for various audiences including global investors, policymakers and risk managers.

One of the major findings of this thesis is the weak dependence, if not segmentation, between the US and Chinese equities. This finding is consistent across four different models. As discussed in section 5.5, despite having strong trade and economic interactions, there is no evidence from the four models to suggest that these markets strongly impact each other. There are studies concerning the effectiveness of the policies that emerging markets such as BRICS utilise to insulate them from adverse shocks from advanced markets such as the US (for example, holding substantial reserve assets, including US dollars and gold, and reduction in the reliance on foreign capitals at an aggregate level, as discussed in section 1.4.2). The findings from this thesis cautiously indicated that such policies, along with government intervention, might have had some positive effect in insulating China and the US from negative shocks from each other over the past 15 years. Even though recoupling still occurred at certain points during crisis periods, this was short term, as discussed in section 1.4.2 and section 5.5. Moreover, since China's economic performance relies on exporting finished goods, this could protect China better in absorbing negative impacts from the US markets compared to a country that has relied significantly on commodity prices such as Brazil or Russia (Aloui et al., 2011). Taken together, trade and economic profiles could be prevailing explanatory factors for the insulation of China from other markets in general. The findings from this thesis could be an indication of the effectiveness of these policies, in which China–US is a good case study worthy of future research focusing on explicit explanations of cross-market dependencies in times of both normal and extreme movements using trade profiles and policies.

Another novel feature of this thesis is that the findings also suggest higher integration between China and other markets in the sample in the post-crisis period, which is consistent with the decoupling-recouping hypothesis of Dooley and Hutchison (2009), especially for tail dependence (even though the degree of the dependencies is still weak). This finding suggests that policymakers, while maintaining the policies designed to minimise regional exposures, should at the same time closely monitor the dependencies of their countries with China, especially those on the cross-regional linkages found in Chapter 6 (HS–Singapore–Japan–Australia–US). Literature concerning market integration suggested that internal exposures such as political issues, poor economic development, high unemployment rate, substantial government budget deficit and trade coordination policies can intensify the vulnerability of a country with a weaker economy to adverse shocks to a country with a more robust economy, as discussed in section 5.5.2. Therefore, markets that were connected to the central node in each region which was found in Chapter 6 – Malaysia, the Philippines, Thailand and NZ – should watch out for those factors and have a policy in place to evaluate, quantify and manage the external exposures that they have from their central node country.

The findings from this thesis also have important implications for policy makers at an international financial market perspective. The results from this thesis regarding the contagion and spillover effect and inter-regional integration among markets should sound an alarm for policy markets in those countries. It has been found in the literature that the risk premium of a financial market could be driven significantly by a regional component, such as was found in the case of the Greek stock index futures market (Floros et al., 2013). Taken together, the findings from this thesis suggest that the regional component might play a major role in market integration in the region and escalate the transmission of risks from one region to another. This finding necessitates a continuing enforcement of the immunisation system of the major stock markets within their region, which is facilitated by strong trade profiles, economic policies regarding reserve asset position, export orientation, use of overseas capital and political and economic stability to minimise the impact of the innovations from stock returns and volatility in other markets, especially the ones in the inter- and intra-regional links. For example, Malaysia, Indonesia, the Philippines and Thailand might be facing greater exposure to shock and volatility contagion from China's markets due to the unequal economic development, lower reserve assets compared to other Asian markets in the sample, higher internal exposures as mentioned above, and geographical proximity which could result in the receipt of shocks from China transmitted through Singapore. Australia could also be in an alarm zone due to strong connections with the US, while having significant reliance on China's demands for resources, commodity-oriented exports and low reserve assets, as discussed in various sections such as 1.3.1, 2.3.1, 4.6 and 5.5. For this reason, it is recommended that those countries consider these factors carefully in forming a stronger insulation system to protect them from the external shocks from China and other global markets in general.

The results of the thesis support the popular view in the existing literature that financial markets are non-normally distributed with skewness and excess kurtosis, implying a higher downside risk than for a normal distribution assumption. In addition, the results from the thesis confirm tail dependencies between the stock markets in China and various emerging and advanced markets in the sample. This finding implied that extreme co-movement in both downside and upside market conditions is evident, which should be taken into account when forming related risk management policies and strategies at national and regional levels.

Understanding the dynamics of co-behaviours of returns and volatility in the stock markets in China and other major advanced and emerging markets, especially during a crisis, is necessary to form effective policies for hedging and risk management for these global stock markets. The results from the thesis suggest that globalisation and capital liberalisation in China might have had some positive impact on the regional linkages of Mainland Chinese AS, BS and HK stock markets, including HS. While the benefits of economic globalisation and capital liberalisation are undeniable, the risks are also visible, such as increased systematic risk – especially in a crisis period due to contagion and spillover effects. This finding is useful for forming policies to maximise the benefits and managing the risk of their stock markets. In addition, pricing and evaluating risks during a crisis period should account for extra premiums compared to non-crisis periods, due to contagion and spillover effects.

Another contribution of this thesis is that the results provide a useful comparison for assessing covariance and co-movements between markets and the transmission of shocks across markets using different methodologies. The results from this thesis also documented multiple aspects of volatility and return dependence that help explain volatility asymmetry using univariate and multivariate models, time-varying dependence behaviour in stock returns and asymmetries in tail dependence at cross-market levels. The volatility of each time series was subject to the leverage effect, and the general and tail dependencies across these markets in the sample also exhibited asymmetries.

This study was applied directly to markets which provided valuable insights to not only domestic, but also global investors. International diversification is a well-known application in portfolio construction. Theoretically, systematic risk reduction can be attained by holding assets in various countries that have low correlations of returns. However, the benefits from international diversification need to be considered, given the increased market interdependence due to globalisation and higher economic integration. Thus, this study has a very wide spread of interested audiences and provides benefits in both theoretical and practical settings.

Appendix

Appendix A. Breusch-Godfrey LM test statistic and p-values for the autocorrelation and serial correlation Lagrange multiplier test for each pair of markets

Panel A: Pre-GFC period

	HS	SHA	SHB	SZA	SZB	INDO	MALAY	PHIL	THAI	AU	HK	JP	NZ	SING	US	GER	UK
HS	3.2711	3.6491	15.9629***	2.0844	5.4754	4.0492	13.6238**	1.7816	4.9591	4.8124	25.9268***	8.9576	2.8599	5.8159	6.2429	8.1145	10.5997*
SHA	2.8086	3.9978	25.4528***	4.5019	13.9921**	7.0974	17.7331***	3.2066	6.6883	5.3089	15.1554***	2.7729	2.7541	6.7749	5.7944	6.8361	11.2019**
SHB	3.0697	3.7770	4.9706	1.4161	3.9680	6.9934	18.1385***	3.7174	6.4816	5.3957	15.0458**	2.8434	2.7746	6.8581	5.7567	6.6258	11.3126**
SZA	3.0471	3.7120	21.0603***	1.7197	11.3119**	7.3133	18.4288***	3.6807	6.5787	5.2859	15.7237***	2.7606	2.7558	6.9569	5.6944	6.5694	11.1150**
SZB	2.5407	4.1997	8.2943	1.5407	4.3897	6.2283	16.5092***	3.3447	5.9950	5.2509	14.5169**	2.8634	2.8016	6.7001	5.7328	7.5836	12.0360**
INDO	4.4471	3.5327	16.1762***	2.1096	5.4870	2.3987	18.3738***	1.6801	6.4609	6.2639	21.8791***	3.9085	2.6619	8.4424	5.3388	6.0084	9.7539*
MALAY	3.3015	3.3893	15.4269***	1.6362	5.0177	5.0838	5.6712	1.6653	4.2602	5.2128	16.9326***	4.8127	2.6954	6.5998	6.9003	7.4832	10.3857*
PHIL	3.9766	3.6860	16.2053***	2.3315	5.6380	6.2718	22.5513***	1.2370	5.6098	5.5502	21.7108***	4.0733	2.3888	6.6779	6.0175	6.9269	11.4502**
THAI	3.0885	3.4369	14.8877**	2.1819	4.8282	3.2747	17.7829***	1.4780	4.1654	5.1836	14.2441**	5.0917	2.7610	6.4143	5.4162	6.1924	9.9987*
AU	2.9693	3.1990	14.0790**	1.5052	4.3929	3.9466	14.6620**	1.8543	4.0132	4.6140	16.4358***	5.1004	3.4349	6.2086	5.1442	5.2176	8.5484
HK	3.6426	4.6496	13.4477**	1.7094	4.8593	3.7448	16.0791***	2.1506	4.7120	5.2008	8.3040	7.8524	3.3631	5.8068	5.9962	8.1637	11.0640*
JP	5.9993	3.6730	16.6661***	2.1706	6.0726	7.3368	19.0081***	2.8078	4.9518	6.5947	24.2353***	2.3690	2.8197	8.4572	5.9188	6.4209	10.3884*
NZ	3.2128	3.4745	15.0560**	1.8782	5.0682	5.5670	18.9128***	3.2189	4.4330	4.5294	17.6016***	3.3318	2.4620	6.1321	5.9674	6.3948	10.2129*
SING	3.1281	3.4782	15.3299***	1.9118	5.0089	3.6061	12.3440**	1.2565	4.4292	5.1059	17.8050***	8.9202	2.6444	5.4561	5.4725	6.8160	8.9020
US	8.7235	3.6742	16.0511***	2.2350	5.6547	5.9527	16.3588***	2.0181	4.4287	7.9030	14.2056**	10.6562*	1.1459	5.4443	8.2717	26.8990***	55.3746***
GER	5.6817	3.4721	15.6012***	2.0493	5.5150	4.2037	14.1160**	1.5224	4.5280	13.7540**	16.0387***	15.3558***	2.3758	5.3649	5.9120	6.3272	21.8254***
UK	5.9498	3.7862	15.3494***	2.0778	5.4346	4.1531	14.8862**	1.6909	4.6911	11.0686**	13.4897**	9.9609*	3.1194	5.1412	5.6941	5.2197	7.1030

Panel B: GFC period

	HS	SHA	SHB	SZA	SZB	INDO	MALAY	PHIL	THAI	AU	HK	JP	NZ	SING	US	GER	UK
HS	9.4102*	6.6882	7.7257	4.0209	2.5986	5.1763	1.0566	4.7652	6.2869	4.4328	11.2704**	41.9016***	7.3842	13.9902**	4.5536	13.6289**	11.8094**
SHA	10.2654*	4.1669	18.8649***	6.6233	16.0874***	5.5084	1.3711	5.5171	13.5267**	5.9667	13.2049**	16.7917***	11.9066**	7.9108	7.2875	12.3227**	12.0492**
SHB	10.2884*	8.3535	4.1829	4.8009	4.8572	5.1720	0.7936	5.2803	13.1326**	5.6793	11.9160**	17.0974***	12.2566**	7.9851	7.2678	12.4790**	11.5683**
SZA	10.0826*	4.2562	20.7088***	4.1034	15.8178***	5.2347	1.0612	5.6515	13.6058**	5.4224	12.6447**	16.2344***	11.5681**	7.7597	7.4700	12.8137**	11.7711**
SZB	9.5210*	8.1367	4.3373	4.5075	2.4471	4.9065	0.8578	5.7175	12.8455**	5.5698	11.7839**	16.9643***	12.2734**	7.6744	6.8798	11.6912**	10.2921*
INDO	16.0391***	5.9855	6.3052	3.9745	2.6838	0.8978	4.3441	6.2165	2.6857	4.8850	12.6891**	41.4652***	8.1830	7.7155	7.0744	13.0979**	11.5911**
MALAY	9.7285*	5.4934	8.4101	4.2116	3.0622	4.3760	1.4119	5.0482	8.1893	5.2905	11.0025*	26.9937***	9.8997*	8.4839	4.9169	14.7251**	12.1271**
PHIL	11.6933**	5.7262	7.3693	3.9683	2.7576	3.0657	0.5431	4.6293	5.0571	6.5119	11.3690**	22.2312***	12.7631**	7.1881	6.8842	12.5634**	13.4202**
THAI	11.4979**	5.2389	6.7736	3.7636	2.5741	1.5222	1.8138	5.0445	1.3989	4.9644	11.0741**	38.5503***	8.7733	7.2160	6.4659	13.1265**	11.7410**
AU	20.4259***	6.6313	6.6979	3.8310	1.8958	1.0417	2.0249	7.7876	3.1115	3.8836	14.1258**	74.0077***	5.5026	7.1271	6.4646	13.9392**	12.2147**
HK	9.2598*	7.3309	6.8599	3.9358	2.5730	4.5417	0.6852	4.2485	7.1078	4.8857	10.9735*	35.6829***	7.6174	11.2798**	4.1839	13.5669**	12.0908**
JP	9.6965*	4.5568	10.8014*	4.5819	4.9825	9.6110*	1.9150	4.3070	10.1102*	16.0076***	12.6225**	9.7109*	12.2747**	11.3275**	8.3128	11.2184**	10.4304*
NZ	20.1448***	6.7176	6.0383	3.6700	1.9989	1.8131	2.7091	8.8439	2.9805	7.1877	14.8148**	58.1396***	5.5051	8.3269	6.7176	13.0240**	12.0641**
SING	26.7288***	7.0387	6.9749	3.9585	2.3685	1.5968	5.5520	9.2787*	3.4330	7.9544	16.5257***	69.6881***	7.5204	6.9068	6.0407	13.0815**	13.2380**
US	24.5122***	6.0274	8.6686	4.4440	3.6407	1.0604	3.5970	7.1646	3.8429	22.8510***	14.1814**	64.2921***	6.8459	11.1063**	3.0006	19.1073***	27.0440***
GER	30.5340***	5.9914	6.6348	3.6916	1.9009	2.2359	5.5145	10.6527*	3.8441	25.4065***	19.4387***	90.9506***	9.6154*	12.6609**	11.0166*	12.0593**	15.6012***
UK	34.9720***	5.8162	7.0932	3.6704	2.1410	2.2479	5.8882	10.5521*	3.9620	24.4759***	20.1001***	82.3001***	6.6563	13.5997**	10.1237*	12.7186**	11.3594**

Panel C: Extended-crisis period

	HS	SHA	SHB	SZA	SZB	INDO	MALAY	PHIL	THAI	AU	HK	JP	NZ	SING	US	GER	UK
HS	4.2037	0.2970	4.0179	3.8962	0.8291	10.8822*	9.8695*	8.3126	9.6767*	3.3842	5.6634	26.4458***	2.2727	5.0951	12.3086**	7.7112	6.2608
SHA	3.9987	1.4486	5.3983	2.7995	1.8956	12.5675**	12.7763**	5.5186	11.3283**	5.2108	4.1951	17.4034***	6.0512	5.5505	6.3229	4.6304	4.1491
SHB	3.9169	0.2202	3.9174	3.0330	1.1974	11.8055**	13.1837**	6.2520	11.5045**	5.1044	4.1222	16.7232***	5.8041	4.9312	6.0124	4.5758	4.3661
SZA	4.0879	0.9502	5.6769	2.9669	3.2786	12.0872**	13.2178**	5.8098	11.9531**	5.1387	4.0719	16.1311***	6.4788	5.7083	5.3563	4.4600	4.1153
SZB	3.7872	0.2235	5.7756	3.9921	4.1275	12.1142**	11.6737**	6.4616	11.1942**	5.0669	4.1217	16.7140***	4.8853	4.8761	8.0374	5.0374	4.5510
INDO	3.8596	0.1511	4.5438	4.0628	1.2772	9.3291*	9.2761*	12.0963**	11.8504**	3.2951	4.3327	26.8531***	3.3893	5.3866	6.4023	4.4733	3.9652
MALAY	3.7613	0.1575	4.5869	4.0494	1.1158	10.4734*	10.2952*	9.1223	10.6909*	4.0291	4.5017	28.7578***	2.8205	5.8465	8.2468	5.9381	4.5431
PHIL	4.3162	0.2253	4.7316	4.4240	1.4960	11.2461**	12.5234**	5.1123	10.8779*	6.7530	4.4144	20.1827***	8.0732	5.9722	6.4686	4.5256	3.8626
THAI	3.7163	0.1078	4.3626	3.3631	1.2186	12.5284**	11.9338**	5.5901	10.1534*	5.4989	4.1743	22.5591***	8.1193	8.2400	3.7278	3.8584	3.8470
AU	10.9203*	0.1913	4.3532	4.2866	0.9018	10.6888*	8.7929	7.8752	11.1044**	2.6026	10.3883*	42.0180***	1.9711	3.5261	12.6486**	5.7045	5.1033
HK	5.3224	0.3366	4.0303	3.8705	0.8177	12.1031**	10.7652*	7.0007	9.3703*	5.4220	4.8596	22.5887***	3.9256	6.8964	9.7884*	6.0545	4.8703
JP	6.1168	0.3742	5.4891	4.6368	2.8815	14.0703**	16.6003***	6.0310	10.5987*	9.9264*	4.9078	3.8476	8.1396	7.9215	6.4912	5.1801	4.0426
NZ	15.0749***	0.1415	4.6288	4.2463	0.7084	13.0459**	7.8702	6.2444	9.3365*	1.9433	13.6998**	40.7392***	9.9570*	5.1728	6.5165	4.1232	4.0568
SING	13.9302**	0.2749	3.9898	4.0746	0.7889	9.2656*	10.5150*	12.0219**	11.5469**	2.4496	13.4256**	36.5631***	1.6875	3.7658	7.9517	5.3087	4.5124
US	15.5991***	0.3839	3.6714	3.5077	0.5545	13.9210**	5.8577	4.4935	8.7980	9.8575*	15.3518***	49.3509***	1.2527	11.8366**	3.8316	10.9718*	9.8522*
GER	13.4088**	0.3574	4.3732	3.7589	1.0086	10.5620*	7.4450	4.9767	8.4128	5.3354	13.4448**	51.3887***	1.2424	8.0372	3.3074	6.0983	5.6893
UK	22.8401***	0.6326	3.8723	3.8517	0.9561	10.5146*	8.3990	5.4432	9.6036*	10.0237*	18.8762***	54.0220***	0.8751	9.2724*	6.1248	4.4196	9.3017*

Panel D: Post-crisis period

	HS	SHA	SHB	SZA	SZB	INDO	MALAY	PHIL	THAI	AU	HK	JP	NZ	SING	US	GER	UK
HS	7.0794	9.5891*	46.1095***	14.7009**	21.0065***	13.7700**	21.1110***	11.6484**	6.1290	16.1441***	8.5318	54.6870***	7.4188	7.4630	25.7610***	9.6304*	25.1253***
SHA	6.7073	6.9644	50.4513***	15.5395***	24.3952***	13.1375**	19.8959***	12.4197**	5.5634	17.3128***	8.9802	39.8238***	7.0149	9.8039*	23.9985***	10.0344*	25.1329***
SHB	6.5540	6.3847	39.5014***	13.8742**	20.5098***	13.2452**	19.4001***	12.5478**	5.3959	16.7317***	7.8568	40.0508***	7.0877	9.0071	23.8890***	9.7360*	25.2173***
SZA	6.6052	14.0639**	52.8174***	13.7536**	27.5685***	13.2582**	19.7177***	12.6215**	5.6946	17.1369***	9.0190	41.3640***	6.9314	9.8590*	23.1462***	9.9138*	25.0362***
SZB	6.5386	6.8552	39.1411***	13.3540**	18.5346***	12.9630**	19.3668***	12.3839**	5.1822	16.8531***	7.4250	39.6555***	6.8668	8.7965	24.3644***	9.7931*	25.2885***
INDO	7.8187	10.6001*	50.5166***	15.0528**	23.1538***	9.5840*	14.1801**	11.1933**	2.2323	14.7256**	8.1630	44.9060***	7.0087	5.5240	27.2048***	9.7523*	24.9009***
MALAY	8.8252	10.5724*	49.4499***	14.8355**	23.4234***	12.0431**	12.6884**	11.7124**	3.5903	15.4215***	7.1242	44.1195***	6.9524	5.3322	24.9740***	9.6002*	25.4304***
PHIL	6.5234	10.2399*	50.3244***	14.9704**	23.4122***	15.0178**	18.6814***	11.5928**	6.5751	16.3527***	8.1465	35.5733***	7.0900	7.0705	27.7586***	9.9159*	25.8607***
THAI	7.3749	11.5495**	51.5862***	15.3845***	24.7032***	11.3690**	19.4590***	12.7757**	3.3404	15.9229***	8.0592	45.5760***	7.0506	5.9937	25.4014***	9.7723*	25.2763***
AU	10.5088*	10.4784*	50.1295***	15.5785***	23.3436***	11.9452**	14.4905**	11.4105**	4.4444	15.7159***	7.0916	52.4541***	6.7918	5.9314	25.8515***	10.1205*	25.7056***
HK	6.5618	7.4652	44.3451***	14.0535**	19.8828***	13.6895**	21.0014***	11.9473**	6.6781	16.1723***	7.3355	47.7047***	7.2267	8.5541	25.1540***	9.6128*	25.1274***
JP	6.6882	11.6008**	52.2516***	15.5805***	25.2526***	14.3923**	18.9713***	13.3008**	6.4568	17.1984***	9.7540*	10.4242*	6.8992	9.2259	28.1374***	10.4491*	26.4504***
NZ	7.4894	10.5247*	50.9335***	14.7140**	24.0768***	12.8077**	17.1603***	11.3901**	4.0024	17.1149***	7.9940	40.0683***	7.5512	6.3572	24.9725***	9.9037*	25.3273***
SING	7.6482	8.8899	48.4040***	14.2222**	22.1184***	12.4817**	17.3374***	11.1085**	5.6088	15.1157***	6.6004	54.3138***	7.8991	7.1476	26.7874***	10.0553*	25.3233***
US	16.6743***	8.8774	43.9380***	12.9394**	21.7150***	8.2494	11.7962**	9.2791*	3.0853	15.7249***	9.1323	92.1049***	9.1686	7.2811	22.3785***	18.3785***	34.8250***
GER	15.6124***	10.6163*	48.7481***	14.8238**	22.9106***	10.3771*	12.6752**	10.1374*	4.4928	11.2757**	9.9746*	76.0190***	5.8172	6.3329	23.3078***	10.1456*	24.8050***
UK	18.0994***	10.5851*	49.2538***	15.2413***	23.1704***	10.0823*	11.7253**	10.0921*	4.5145	14.2687**	9.3611*	73.7271***	6.4427	6.1344	23.4936***	9.7304*	24.4644***

Appendix B. Summary of results of the best-fitting copula for a bivariate distribution between HS and other markets in the four sub-periods

Panel A: Pre-GFC period: HS versus other markets 2002-2008

	Copula name	Kendall's tau	Estimated copula parameter	Estimated second parameter	Tau	Lower tail dependence parameter	Upper tail dependence parameter	AIC
HK	t	0.48	0.69	5.78	0.48	0.30	0.30	-566.85
SING	BB7	0.42	1.67	0.75	0.42	0.40	0.48	-459.83
JAPAN	t	0.34	0.51	5.69	0.34	0.19	0.19	-273.68
AU	BB7	0.30	1.34	0.51	0.31	0.26	0.33	-239.42
INDO	t	0.29	0.44	3.39	0.29	0.26	0.26	-242.67
THAI	t	0.27	0.41	4.45	0.27	0.19	0.19	-181.28
MALAY	t	0.26	0.39	7.70	0.25	0.08	0.08	-144.23
GER	t	0.23	0.36	4.93	0.23	0.15	0.15	-152.08
UK	BB7	0.21	1.24	0.36	0.24	0.15	0.25	-154.53
PHIL	t	0.17	0.27	5.33	0.17	0.10	0.10	-91.72
US	BB7	0.16	1.17	0.23	0.17	0.05	0.19	-81.97
SZB	t	0.15	0.23	6.91	0.15	0.06	0.06	-56.81
NZ	t	0.13	0.20	4.04	0.13	0.13	0.13	-72.99
SHB	t	0.11	0.17	9.52	0.11	0.02	0.02	-28.63
SHA	t	0.10	0.16	10.37	0.10	0.01	0.01	-25.38
SZA	t	0.10	0.15	13.64	0.10	0.01	0.01	-19.20

Panel B: GFC period: HS versus other markets

	Copula name	Kendall's tau	Estimated copula parameter	Estimated second parameter	Tau	Lower tail dependence parameter	Upper tail dependence parameter	AIC
SHA	Survival Gumbel	0.80	4.75	0.00	0.79	0.84	-	-936.26
SHB	t	0.64	0.84	5.54	0.64	0.48	0.48	-500.60
SZA	BB1	0.51	0.66	1.53	0.51	0.50	0.42	-306.41
SZB	t	0.48	0.68	5.55	0.48	0.31	0.31	-255.74
INDO	t	0.47	0.67	4.19	0.47	0.36	0.36	-253.77
MALAY	BB7	0.43	1.51	1.03	0.43	0.51	0.42	-228.79
PHIL	BB1	0.40	0.62	1.28	0.40	0.42	0.28	-185.66
THAI	t	0.40	0.59	6.92	0.40	0.19	0.19	-177.04
HK	BB7	0.37	1.46	0.66	0.37	0.35	0.39	-159.76
SING	BB1	0.37	0.41	1.32	0.37	0.27	0.31	-148.99
JAPAN	BB1	0.35	0.47	1.25	0.35	0.31	0.26	-141.19
AU	BB1	0.33	0.44	1.23	0.33	0.28	0.24	-122.40
NZ	t	0.31	0.46	6.10	0.31	0.15	0.15	-99.54
UK	Survival Gumbel	0.29	1.40	0.00	0.28	0.36	-	-91.47
GER	t	0.27	0.41	5.40	0.27	0.15	0.15	-79.76
US	BB7	0.18	1.22	0.23	0.19	0.05	0.24	-44.27

Panel C: Extended-crisis period: HS versus other markets

	Copula name	Kendall's tau	Estimated copula parameter	Estimated second parameter	Tau	Lower tail dependence parameter	Upper tail dependence parameter	AIC
SHA	t	0.82	0.96	8.00	0.82	0.67	0.67	-1337.18

SHB	t	0.56	0.77	10.95	0.56	0.24	0.24	-482.04
SZA	t	0.48	0.68	6.79	0.48	0.26	0.26	-338.38
SZB	t	0.48	0.67	8.99	0.47	0.19	0.19	-309.68
INDO	t	0.46	0.67	8.75	0.46	0.19	0.19	-311.52
MALAY	t	0.43	0.61	4.37	0.42	0.31	0.31	-251.82
PHIL	t	0.39	0.57	9.57	0.38	0.12	0.12	-202.09
THAI	t	0.38	0.55	5.64	0.37	0.21	0.21	-186.01
HK	Gaussian	0.37	0.54	0.00	0.36	-	-	-178.05
SING	Gaussian	0.35	0.53	0.00	0.35	-	-	-167.30
JAPAN	BB7	0.34	1.27	0.70	0.33	0.37	0.28	-173.84
AU	t	0.30	0.47	9.28	0.31	0.08	0.08	-133.73
NZ	t	0.28	0.43	10.48	0.28	0.06	0.06	-106.15
UK	t	0.28	0.42	17.08	0.28	0.01	0.01	-96.56
GER	t	0.26	0.40	8.00	0.26	0.08	0.08	-95.79
US	BB7	0.21	1.27	0.22	0.21	0.04	0.28	-66.35

Panel D: Post-crisis period: HS versus other markets 2015-2017

	Copula name	Kendall’s tau	Estimated copula parameter	Estimated second parameter	Tau	Lower tail dependence parameter	Upper tail dependence parameter	AIC
HK	BB1	0.74	1.00	2.54	0.74	0.76	0.69	-1726.69
SING	Survival Gumbel	0.41	1.70	0.00	0.41	0.50	-	-443.49
AU	BB7	0.34	1.32	0.71	0.34	0.38	0.31	-319.01
SHA	BB1	0.33	0.38	1.27	0.34	0.23	0.27	-287.40
SZB	BB7	0.31	1.38	0.50	0.31	0.25	0.35	-258.51
MALAY	t	0.30	0.46	5.93	0.30	0.15	0.15	-230.02
INDO	t	0.30	0.45	6.73	0.30	0.13	0.13	-211.25
THAI	t	0.28	0.43	5.39	0.28	0.16	0.16	-199.36
PHIL	t	0.28	0.43	5.23	0.28	0.16	0.16	-199.75
UK	BB1	0.28	0.39	1.16	0.28	0.22	0.18	-198.31
JAPAN	BB1	0.27	0.36	1.17	0.28	0.19	0.20	-193.88
SHB	BB7	0.26	1.31	0.41	0.27	0.18	0.30	-200.23
SZA	t	0.25	0.39	6.38	0.25	0.11	0.11	-161.94
GER	Survival Gumbel	0.24	1.31	0.00	0.23	0.30	-	-142.67
NZ	BB7	0.17	1.12	0.35	0.19	0.14	0.14	-101.14
US	BB7	0.14	1.12	0.24	0.16	0.06	0.14	-66.66

Note: The p-values of the independence tests are not reported for brevity, as they are mostly insignificant. The number of observations for each period is 870 in the pre-GFC period, 410 in the GFC period, 539 in the extended-crisis period and 912 in the post-crisis period. Seven copulas are fitted for each pair of markets, between each of China’s markets (AS, BS and HS) and other markets in the sample. The best-fitting copula is selected by the lowest AIC. The lower tail and upper tail dependence are equal for the symmetric tail copula such as a Student-t-copula. The lower tail and upper tail dependence are different for a tail dependence copula with different levels such as a BB1 (rotated Gumbel) or Joe copula. Tail dependence parameters equal zero for tail independence copulas such as Frank and Gaussian copulas. For the symmetric tail dependence copula, such as lower tail dependence Clayton or upper tail dependence Gumbel, the parameters for the tail independence will take a value of zero. For the t-copula, the second parameter is found by a crude profile likelihood optimisation over the interval [2, 10].

Appendix C. Summary of results of the best-fitting copula for a bivariate distribution between SHA and other markets in the four sub-periods

Panel A: Pre-GFC period: SHA versus other markets

	Copula name	Kendall's tau	Estimated copula parameter	Estimated second parameter	Tau	Lower tail dependence parameter	Upper tail dependence parameter	AIC
SZA	t	0.81	0.95	2.59	0.81	0.79	0.79	-2125.19
SHB	t	0.61	0.81	3.25	0.60	0.54	0.54	-919.89
SZB	BB1	0.57	0.17	2.11	0.56	0.15	0.61	-802.72
HK	BB1	0.15	0.13	1.11	0.15	0.01	0.13	-52.93
HS	t	0.10	0.16	10.37	0.10	0.01	0.01	-25.38
SING	BB7	0.09	1.10	0.12	0.11	0.00	0.12	-27.48
INDO	t	0.08	0.13	12.36	0.08	0.01	0.01	-15.75
NZ	t	0.07	0.11	7.18	0.07	0.03	0.03	-19.98
JAPAN	Gumbel	0.07	1.08	0.00	0.08	-	0.10	-14.90
MALAY	t	0.07	0.11	7.51	0.07	0.03	0.03	-20.42
AU	Gumbel	0.06	1.08	0.00	0.07	-	0.10	-14.57
THAI	t	0.05	0.09	7.92	0.06	0.02	0.02	-15.20
GER	t	0.05	0.09	7.31	0.06	0.03	0.03	-18.37
US	t	0.03^	0.05	6.09	0.03	0.04	0.04	-15.21
UK	t	0.03^	0.05	7.26	0.03	0.03	0.03	-13.76
PHIL	t	0.01^	0.01	6.64	0.01	0.03	0.03	-13.73

Panel B: GFC period: SHA versus other markets

	Copula name	Kendall's tau	Estimated copula parameter	Estimated second parameter	Tau	Lower tail dependence parameter	Upper tail dependence parameter	AIC
HS	Survival Gumbel	0.80	4.75	0.00	0.79	0.84	-	-936.26
SHB	t	0.75	0.92	5.93	0.74	0.61	0.61	-765.38
SZA	t	0.65	0.85	3.74	0.64	0.56	0.56	-510.68
SZB	t	0.62	0.83	2.92	0.62	0.57	0.57	-472.38
INDO	t	0.35	0.52	5.03	0.35	0.21	0.21	-132.63
MALAY	t	0.22	0.33	8.62	0.21	0.05	0.05	-44.26
PHIL	t	0.22	0.33	7.23	0.21	0.08	0.08	-47.48
THAI	t	0.19	0.30	4.81	0.19	0.13	0.13	-45.93
HK	t	0.19	0.29	10.31	0.19	0.03	0.03	-35.32
SING	t	0.17	0.26	8.32	0.17	0.04	0.04	-28.47
JAPAN	Clayton	0.16	0.37	0.00	0.16	0.15	-	-30.60
AU	t	0.16	0.25	3.60	0.16	0.16	0.16	-42.35
NZ	t	0.14	0.22	8.95	0.14	0.03	0.03	-20.17
UK	Gumbel	0.12	1.13	0.00	0.11	-	0.15	-14.08
GER	t	0.10	0.15	6.44	0.10	0.05	0.05	-12.92
US	Gumbel	0.02^	1.05	0.00	0.05	-	0.07	-2.63

Panel C: Extended-crisis period: SHA versus other markets

	Copula name	Kendall's tau	Estimated copula parameter	Estimated second parameter	Tau	Lower tail dependence parameter	Upper tail dependence parameter	AIC
HS	t	0.82	0.96	8.00	0.82	0.67	0.67	-1337.18

SZA	Survival Gumbel	0.71	3.43	0.00	0.71	0.78	-	-889.08
SHB	t	0.65	0.85	3.28	0.65	0.59	0.59	-695.99
SZB	BB1	0.62	0.90	1.79	0.61	0.65	0.53	-627.99
HK	Gaussian	0.40	0.58	0.00	0.40	-	-	-216.24
INDO	t	0.26	0.39	11.52	0.25	0.04	0.04	-81.75
AU	t	0.26	0.39	6.46	0.25	0.11	0.11	-86.80
SING	BB1	0.26	0.37	1.13	0.25	0.19	0.15	-89.31
MALAY	t	0.23	0.34	10.11	0.22	0.04	0.04	-64.76
PHIL	t	0.21	0.32	4.73	0.21	0.14	0.14	-69.60
THAI	t	0.20	0.31	9.68	0.20	0.04	0.04	-52.32
JAPAN	t	0.20	0.30	6.43	0.19	0.08	0.08	-48.00
NZ	Survival Gumbel	0.17	1.23	0.00	0.19	0.25	-	-58.26
UK	Survival Gumbel	0.17	1.19	0.00	0.16	0.21	-	-38.39
GER	Survival Gumbel	0.13	1.15	0.00	0.13	0.17	-	-28.25
US	Survival Gumbel	0.09	1.11	0.00	0.10	0.13	-	-16.52

Panel D: Post-crisis period: SHA versus other markets

	Copula name	Kendall's tau	Estimated copula parameter	Estimated second parameter	Tau	Lower tail dependence parameter	Upper tail dependence parameter	AIC
SZA	t	0.65	0.85	3.93	0.65	0.56	0.56	-1188.72
SHB	t	0.59	0.80	4.33	0.59	0.47	0.47	-929.54
SZB	t	0.55	0.77	4.24	0.56	0.44	0.44	-824.78
HK	BB1	0.41	0.38	1.44	0.42	0.28	0.38	-450.89
HS	BB1	0.33	0.38	1.27	0.34	0.23	0.27	-287.40
AU	Survival Gumbel	0.17	1.20	0.00	0.16	0.21	-	-74.36
SING	Survival Gumbel	0.16	1.21	0.00	0.18	0.23	-	-92.08
JAPAN	BB1	0.15	0.20	1.06	0.14	0.04	0.08	-48.38
THAI	t	0.14	0.22	5.44	0.14	0.08	0.08	-62.96
INDO	Survival Gumbel	0.12	1.13	0.00	0.11	0.15	-	-33.45
MALAY	t	0.12	0.19	6.81	0.12	0.05	0.05	-46.41
PHIL	t	0.10	0.16	5.92	0.10	0.06	0.06	-41.42
UK	t	0.10	0.16	5.85	0.10	0.06	0.06	-41.74
NZ	t	0.09	0.13	7.26	0.09	0.04	0.04	-26.87
GER	t	0.06	0.09	5.12	0.06	0.06	0.06	-31.60
US	Survival Gumbel	0.04^	1.05	0.00	0.05	0.07	-	-9.23

Note: In panels A, B and D, ^ represents the p-value of the independence test as higher than 0.05, which indicates that the null hypothesis of independence cannot be rejected at the 5% significance level. This implies that the pair is not dependent. The rest have p-values less than 0.05, which indicates that the null hypothesis of independence is rejected at the 5% significance level, suggesting the pair is dependent.

Appendix D. Summary of results of the best-fitting copula for a bivariate distribution between SHB and other markets in the four sub-periods

Panel A: Pre-GFC period: SHB versus other markets

	Copula name	Kendall's tau	Estimated copula parameter	Estimated second parameter	Tau	Lower tail dependence parameter	Upper tail dependence parameter	AIC
SZA	t	0.63	0.83	4.63	0.62	0.49	0.49	-991.92
SZB	BB1	0.61	0.27	2.28	0.61	0.33	0.65	-1001.36
SHA	t	0.61	0.81	3.25	0.60	0.54	0.54	-919.89
HK	t	0.15	0.25	10.96	0.16	0.02	0.02	-57.00
HS	t	0.11	0.17	9.52	0.11	0.02	0.02	-28.63
SING	Gumbel	0.08	1.10	0.00	0.09	-	0.12	-22.85
MALAY	t	0.07	0.11	7.01	0.07	0.04	0.04	-24.70
AU	Gumbel	0.07	1.08	0.00	0.07	-	0.10	-14.94
THAI	t	0.07	0.11	7.39	0.07	0.03	0.03	-17.43
JAPAN	Gumbel	0.06	1.07	0.00	0.07	-	0.09	-13.99
NZ	Gumbel	0.06	1.07	0.00	0.06	-	0.08	-7.91
INDO	t	0.06	0.10	8.28	0.06	0.02	0.02	-14.69
GER	t	0.03^	0.05	6.34	0.03	0.04	0.04	-15.71
UK	t	0.03^	0.05	6.05	0.03	0.04	0.04	-18.24
US	t	0.02^	0.03	7.18	0.02	0.02	0.02	-9.66
PHIL	t	0.00^	0.01	6.23	0.00	0.03	0.03	-15.18

Panel B: GFC period: SHB versus other markets

	Copula name	Kendall's tau	Estimated copula parameter	Estimated second parameter	Tau	Lower tail dependence parameter	Upper tail dependence parameter	AIC
SHA	t	0.75	0.92	5.93	0.74	0.61	0.61	-765.38
SZB	BB1	0.69	0.67	2.40	0.69	0.65	0.67	-635.63
SZA	t	0.68	0.88	3.15	0.68	0.63	0.63	-589.67
HS	t	0.64	0.84	5.54	0.64	0.48	0.48	-500.60
HK	BB1	0.32	0.43	1.20	0.32	0.26	0.22	-107.91
MALAY	BB7	0.22	1.19	0.38	0.23	0.16	0.21	-57.57
SING	Survival Gumbel	0.22	1.27	0.00	0.21	0.27	-	-48.80
PHIL	Survival Gumbel	0.20	1.26	0.00	0.21	0.27	-	-51.74
INDO	t	0.19	0.30	9.19	0.19	0.04	0.04	-36.08
AU	Survival Gumbel	0.18	1.22	0.00	0.18	0.24	-	-39.50
JAPAN	Clayton	0.14	0.32	0.00	0.14	0.12	-	-25.66
THAI	t	0.13	0.21	4.09	0.13	0.13	0.13	-31.42
NZ	Survival Gumbel	0.13	1.16	0.00	0.14	0.18	-	-21.85
UK	Gumbel	0.12	1.15	0.00	0.13	-	0.17	-19.46
GER	t	0.11	0.18	5.22	0.11	0.08	0.08	-19.50
US	Gumbel	0.05^	1.08	0.00	0.08	-	0.11	-8.92

Panel C: Extended-crisis period: SHB versus other markets

	Copula name	Kendall's tau	Estimated copula parameter	Estimated second parameter	Tau	Lower tail dependence parameter	Upper tail dependence parameter	AIC

SZA	t	0.67	0.86	4.09	0.66	0.56	0.56	-712.22
SHA	t	0.65	0.85	3.28	0.65	0.59	0.59	-695.99
SZB	t	0.63	0.84	4.43	0.63	0.52	0.52	-658.25
HS	t	0.56	0.77	10.95	0.56	0.24	0.24	-482.04
HK	t	0.31	0.47	8.00	0.31	0.10	0.10	-129.22
INDO	Gaussian	0.21	0.33	0.00	0.21	-	-	-57.27
SING	Survival Gumbel	0.20	1.24	0.00	0.19	0.25	-	-53.72
AU	t	0.20	0.31	4.93	0.20	0.13	0.13	-54.67
PHIL	t	0.18	0.29	4.05	0.19	0.15	0.15	-61.70
MALAY	t	0.18	0.28	8.24	0.18	0.05	0.05	-44.10
JAPAN	t	0.17	0.26	7.59	0.17	0.05	0.05	-34.00
THAI	t	0.15	0.24	6.95	0.15	0.06	0.06	-35.58
NZ	Survival Gumbel	0.14	1.19	0.00	0.16	0.21	-	-41.39
UK	t	0.10	0.16	6.18	0.10	0.06	0.06	-18.79
GER	Survival Gumbel	0.07	1.10	0.00	0.09	0.12	-	-14.09
US	t	0.05^	0.08	6.13	0.05	0.04	0.04	-10.13

Panel D: Post-crisis period: SHB versus other markets

	Copula name	Kendall's tau	Estimated copula parameter	Estimated second parameter	Tau	Lower tail dependence parameter	Upper tail dependence parameter	AIC
SZA	t	0.61	0.81	3.92	0.60	0.50	0.50	-969.95
SHA	t	0.59	0.80	4.33	0.59	0.47	0.47	-929.54
SZB	BB7	0.57	2.11	1.53	0.56	0.64	0.61	-928.65
HK	t	0.32	0.48	5.45	0.32	0.18	0.18	-266.82
HS	BB7	0.26	1.31	0.41	0.27	0.18	0.30	-200.23
JAPAN	t	0.12	0.18	14.50	0.11	0.00	0.00	-26.51
AU	t	0.11	0.18	9.40	0.12	0.02	0.02	-34.59
SING	Survival Gumbel	0.11	1.13	0.00	0.12	0.16	-	-38.20
INDO	Survival Gumbel	0.11	1.11	0.00	0.10	0.14	-	-26.60
THAI	t	0.11	0.17	6.08	0.11	0.06	0.06	-43.36
PHIL	t	0.11	0.17	4.98	0.11	0.09	0.09	-51.10
MALAY	t	0.11	0.17	5.88	0.11	0.06	0.06	-42.49
UK	t	0.09	0.14	9.24	0.09	0.02	0.02	-21.69
NZ	t	0.06	0.10	9.53	0.06	0.01	0.01	-12.05
GER	t	0.05	0.08	6.97	0.05	0.03	0.03	-15.51
US	BB7	0.04^	1.04	0.06	0.05	1.92	0.05	-4.61

Note: In each panel, ^ represents the p-value of the independence test as higher than 0.05, which indicates that the null hypothesis of independence cannot be rejected at the 5% significance level. This implies that the pair is not dependent. The rest have p-values less than 0.05, which indicates that the null hypothesis of independence is rejected at the 5% significance level, suggesting the pair is dependent.

Appendix E. Summary of results of the best-fitting copula for a bivariate distribution between SZA market and other markets in the four sub-periods

Panel A: Pre-GFC period: SZA versus other markets

	Copula name	Kendall's tau	Estimated copula parameter	Estimated second parameter	Tau	Lower tail dependence parameter	Upper tail dependence parameter	AIC
SHA	t	0.81	0.95	2.59	0.81	0.79	0.79	-2125.19
SHB	t	0.63	0.83	4.63	0.62	0.49	0.49	-991.92
SZB	BB1	0.59	0.18	2.23	0.59	0.18	0.63	-896.04
HK	Gaussian	0.15	0.24	0.00	0.15	-	-	-47.14
HS	t	0.10	0.15	13.64	0.10	0.01	0.01	-19.20
SING	BB7	0.08	1.08	0.11	0.09	0.00	0.10	-18.63
MALAY	Gumbel	0.07	1.08	0.00	0.08	-	0.11	-16.22
JAPAN	Gumbel	0.07	1.08	0.00	0.07	-	0.10	-14.34
NZ	t	0.06	0.10	10.22	0.07	0.01	0.01	-11.34
INDO	t	0.06	0.10	9.32	0.06	0.02	0.02	-14.01
AU	Gumbel	0.05	1.07	0.00	0.07	-	0.09	-12.65
THAI	t	0.04	0.07	8.69	0.05	0.02	0.02	-10.90
GER	t	0.04^	0.06	11.38	0.04	0.01	0.01	-5.84
US	t	0.02^	0.03	8.58	0.02	0.01	0.01	-5.59
UK	Gumbel	0.01^	1.04	0.00	0.04	-	0.05	-3.82
PHIL	t	-0.02^	-0.02	7.02	-0.01	0.02	0.02	-12.05

Panel B: GFC period: SZA versus other markets

	Copula name	Kendall's tau	Estimated copula parameter	Estimated second parameter	Tau	Lower tail dependence parameter	Upper tail dependence parameter	AIC
SHB	t	0.68	0.88	3.15	0.68	0.63	0.63	-589.67
SHA	t	0.65	0.85	3.74	0.64	0.56	0.56	-510.68
SZB	t	0.63	0.83	3.91	0.62	0.53	0.53	-479.80
HS	BB1	0.51	0.66	1.53	0.51	0.50	0.42	-306.41
HK	t	0.30	0.45	4.52	0.29	0.20	0.20	-99.60
MALAY	t	0.20	0.32	6.61	0.20	0.08	0.08	-45.88
SING	t	0.20	0.30	6.21	0.20	0.09	0.09	-40.70
AU	t	0.17	0.27	4.87	0.17	0.12	0.12	-38.97
INDO	t	0.16	0.25	6.27	0.16	0.07	0.07	-29.66
PHIL	t	0.16	0.24	8.32	0.16	0.04	0.04	-26.25
JAPAN	Clayton	0.14	0.31	0.00	0.13	0.11	-	-22.90
THAI	t	0.12	0.19	3.61	0.12	0.14	0.14	-33.11
NZ	Gumbel	0.12	1.14	0.00	0.13	-	0.17	-18.19
UK	Gumbel	0.10	1.13	0.00	0.11	-	0.15	-15.86
GER	t	0.09	0.14	4.69	0.09	0.09	0.09	-17.26
US	Gumbel	0.03^	1.06	0.00	0.06	-	0.08	-4.59

Panel C: Extended-crisis period: SZA versus other markets

	Copula name	Kendall's tau	Estimated copula parameter	Estimated second parameter	Tau	Lower tail dependence parameter	Upper tail dependence parameter	AIC
SHA	Survival Gumbel	0.71	3.43	0.00	0.71	0.78	-	-889.08
SHB	t	0.67	0.86	4.09	0.66	0.56	0.56	-712.22
SZB	t	0.61	0.82	5.57	0.61	0.44	0.44	-584.41

HS	t	0.48	0.68	6.79	0.48	0.26	0.26	-338.38
HK	t	0.31	0.46	9.21	0.30	0.08	0.08	-123.87
AU	t	0.20	0.30	6.91	0.19	0.07	0.07	-49.42
INDO	t	0.20	0.29	14.53	0.19	0.01	0.01	-43.06
SING	t	0.19	0.29	9.14	0.19	0.04	0.04	-44.51
MALAY	t	0.18	0.27	8.89	0.17	0.04	0.04	-39.32
THAI	t	0.18	0.28	8.13	0.18	0.05	0.05	-42.40
PHIL	t	0.17	0.25	5.00	0.16	0.11	0.11	-44.65
JAPAN	t	0.15	0.23	5.72	0.15	0.08	0.08	-31.25
NZ	Survival Gumbel	0.13	1.17	0.00	0.15	0.19	-	-33.23
UK	t	0.11	0.18	8.13	0.12	0.03	0.03	-19.77
GER	Survival Gumbel	0.08	1.10	0.00	0.09	0.12	-	-13.26
US	t	0.07^	0.11	8.49	0.07	0.02	0.02	-8.54

Panel D: Post-crisis period: SZA versus other markets

	Copula name	Kendall's tau	Estimated copula parameter	Estimated second parameter	Tau	Lower tail dependence parameter	Upper tail dependence parameter	AIC
SHA	t	0.65	0.85	3.93	0.65	0.56	0.56	-1188.72
SHB	t	0.61	0.81	3.92	0.60	0.50	0.50	-969.95
SZB	t	0.55	0.76	3.86	0.55	0.46	0.46	-810.62
HK	t	0.29	0.45	5.41	0.30	0.17	0.17	-224.12
HS	t	0.25	0.39	6.38	0.25	0.11	0.11	-161.94
THAI	t	0.12	0.18	5.10	0.12	0.09	0.09	-53.11
JAPAN	t	0.12	0.19	9.11	0.12	0.02	0.02	-35.09
AU	Survival Gumbel	0.11	1.13	0.00	0.11	0.15	-	-38.46
SING	Survival Gumbel	0.11	1.14	0.00	0.12	0.16	-	-42.88
PHIL	t	0.10	0.16	6.95	0.10	0.04	0.04	-33.67
INDO	t	0.10	0.15	8.81	0.10	0.02	0.02	-23.49
MALAY	t	0.09	0.15	7.47	0.09	0.03	0.03	-30.31
UK	t	0.08	0.14	6.26	0.09	0.05	0.05	-32.49
GER	t	0.06	0.09	6.72	0.06	0.04	0.04	-20.13
NZ	t	0.05	0.09	10.21	0.06	0.01	0.01	-11.97
US	Survival Gumbel	0.02^	1.04	0.00	0.03	0.05	-	-3.64

Note: In each panel, ^ represents the p-value of the independence test as higher than 0.05, which indicates that the null hypothesis of independence cannot be rejected at the 5% significance level. This implies that the pair is not dependent. The rest have p-values less than 0.05, which indicates that the null hypothesis of independence is rejected at the 5% significance level, suggesting the pair is dependent.

Appendix F. Summary of results of the best-fitting copula for a bivariate distribution between SZB and other markets in the four sub-periods

Panel A: Pre-GFC period: SZB versus other markets

	Copula name	Kendall's tau	Estimated copula parameter	Estimated second parameter	Tau	Lower tail dependence parameter	Upper tail dependence parameter	AIC
SHB	BB1	0.61	0.27	2.28	0.61	0.33	0.65	-1001.36
SZA	BB1	0.59	0.18	2.23	0.59	0.18	0.63	-896.04
SHA	BB1	0.57	0.17	2.11	0.56	0.15	0.61	-802.72
HK	t	0.18	0.28	11.42	0.18	0.02	0.02	-76.16
HS	t	0.15	0.23	6.91	0.15	0.06	0.06	-56.81
SING	t	0.12	0.19	6.67	0.12	0.05	0.05	-42.74
INDO	Gumbel	0.10	1.11	0.00	0.10	-	0.14	-29.48
MALAY	t	0.10	0.16	6.26	0.10	0.05	0.05	-39.03
JAPAN	Gumbel	0.10	1.10	0.00	0.09	-	0.12	-23.16
THAI	t	0.09	0.14	6.50	0.09	0.05	0.05	-28.32
AU	Gumbel	0.09	1.11	0.00	0.10	-	0.13	-28.84
NZ	t	0.08	0.13	8.09	0.08	0.03	0.03	-20.43
GER	t	0.07	0.12	5.58	0.08	0.06	0.06	-31.42
US	t	0.07	0.10	5.82	0.07	0.05	0.05	-25.93
UK	t	0.05	0.09	5.51	0.06	0.06	0.06	-28.46
PHIL	t	0.03^	0.05	5.46	0.03	0.05	0.05	-24.77

Panel B: GFC period: SZB versus other markets

	Copula name	Kendall's tau	Estimated copula parameter	Estimated second parameter	Tau	Lower tail dependence parameter	Upper tail dependence parameter	AIC
SHB	BB1	0.69	0.67	2.40	0.69	0.65	0.67	-635.63
SZA	t	0.63	0.83	3.91	0.62	0.53	0.53	-479.80
SHA	t	0.62	0.83	2.92	0.62	0.57	0.57	-472.38
HS	t	0.48	0.68	5.55	0.48	0.31	0.31	-255.74
INDO	BB1	0.36	0.51	1.24	0.36	0.34	0.25	-143.70
MALAY	BB1	0.27	0.38	1.16	0.28	0.21	0.18	-79.49
PHIL	BB7	0.26	1.23	0.47	0.27	0.23	0.24	-79.94
THAI	Survival Gumbel	0.25	1.34	0.00	0.26	0.33	-	-77.06
HK	Survival Gumbel	0.24	1.32	0.00	0.24	0.31	-	-66.16
SING	BB7	0.22	1.20	0.33	0.22	0.12	0.22	-53.12
JAPAN	BB1	0.21	0.36	1.07	0.20	0.16	0.08	-45.18
AU	Clayton	0.19	0.43	0.00	0.18	0.20	-	-41.50
NZ	t	0.18	0.29	3.41	0.19	0.19	0.19	-52.49
UK	Gumbel	0.15	1.17	0.00	0.14	-	0.19	-22.16
GER	BB7	0.14	1.12	0.20	0.14	0.03	0.15	-20.87
US	Gumbel	0.07^	1.09	0.00	0.09	-	0.12	-9.22

Panel C: Extended-crisis period: SZB versus other markets

	Copula name	Kendall's tau	Estimated copula parameter	Estimated second parameter	Tau	Lower tail dependence parameter	Upper tail dependence parameter	AIC
SHB	t	0.63	0.84	4.43	0.63	0.52	0.52	-658.25
SHA	BB1	0.62	0.90	1.79	0.61	0.65	0.53	-627.99

SZA	t	0.61	0.82	5.57	0.61	0.44	0.44	-584.41
HS	t	0.48	0.67	8.99	0.47	0.19	0.19	-309.68
HK	Gaussian	0.38	0.56	0.00	0.38	-	-	-195.25
INDO	Gaussian	0.26	0.40	0.00	0.26	-	-	-88.84
SING	BB1	0.26	0.32	1.15	0.25	0.15	0.18	-88.85
AU	t	0.25	0.38	6.05	0.25	0.12	0.12	-84.25
MALAY	Gaussian	0.25	0.37	0.00	0.24	-	-	-75.42
PHIL	t	0.24	0.37	5.13	0.24	0.14	0.14	-86.50
JAPAN	t	0.23	0.34	10.46	0.22	0.04	0.04	-57.71
THAI	t	0.20	0.31	11.72	0.20	0.02	0.02	-53.55
NZ	t	0.19	0.30	6.25	0.19	0.09	0.09	-57.86
UK	t	0.16	0.25	8.79	0.16	0.04	0.04	-36.35
GER	Gaussian	0.12	0.21	0.00	0.13	-	-	-20.32
US	BB7	0.07	1.08	0.12	0.10	0.00	0.10	-12.66

Panel D: Post-crisis period: SZB versus other markets

	Copula name	Kendall's tau	Estimated copula parameter	Estimated second parameter	Tau	Lower tail dependence parameter	Upper tail dependence parameter	AIC
SHB	BB7	0.57	2.11	1.53	0.56	0.64	0.61	-928.65
SHA	t	0.55	0.77	4.24	0.56	0.44	0.44	-824.78
SZA	t	0.55	0.76	3.86	0.55	0.46	0.46	-810.62
HK	t	0.35	0.53	5.67	0.35	0.20	0.20	-319.55
HS	BB7	0.31	1.38	0.50	0.31	0.25	0.35	-258.51
AU	t	0.17	0.26	8.38	0.17	0.04	0.04	-69.03
SING	Survival Gumbel	0.16	1.19	0.00	0.16	0.21	-	-74.19
THAI	t	0.15	0.24	6.62	0.15	0.06	0.06	-65.63
JAPAN	t	0.14	0.23	10.94	0.14	0.02	0.02	-47.76
INDO	Survival Gumbel	0.14	1.16	0.00	0.14	0.18	-	-49.60
PHIL	t	0.14	0.22	4.17	0.14	0.13	0.13	-78.70
MALAY	t	0.14	0.21	5.37	0.14	0.09	0.09	-70.06
NZ	t	0.11	0.17	10.05	0.11	0.02	0.02	-29.59
UK	t	0.10	0.15	7.17	0.10	0.04	0.04	-35.26
GER	t	0.07	0.11	7.73	0.07	0.03	0.03	-20.02
US	BB7	0.05	1.04	0.09	0.06	0.00	0.06	-10.34

Note: In panels A and B, ^ represents the p-value of the independence test as higher than 0.05, which indicates that the null hypothesis of independence cannot be rejected at the 5% significance level. This implies that the pair is not dependent. The rest have p-values less than 0.05, which indicate that the null hypothesis of independence is rejected at the 5% level, suggesting the pair is dependent.

Timeline

The timeline is not included in this version of the thesis.

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