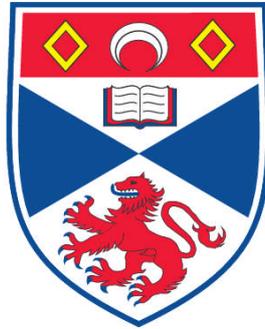


**EMPIRICAL INVESTIGATIONS INTO STOCK MARKET
INTEGRATION AND RISK MONITORING OF THE EMERGING
CHINESE STOCK MARKETS**

Xing Chen

**A Thesis Submitted for the Degree of PhD
at the
University of St. Andrews**



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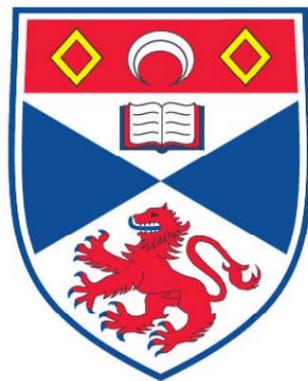
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STOCK MARKET INTEGRATION AND RISK MONITORING
OF THE EMERGING CHINESE STOCK MARKETS**

Xing Chen



**This thesis is submitted in partial fulfilment for the degree of PhD
at the University of St Andrews**

September 2011

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Abstract

The degree of stock market integration has important implication for cross-border portfolio diversification, for which the Mainland China has become an attractive destination, particularly following the gradual open-up of its A-share market to foreign institutional investors. The first part of this thesis explores the various aspects of stock market integration taking place in Mainland China, in an attempt to resolve the ambiguity between extant empirical and anecdotal evidence on the issue. The evidence drawn from different statistical perspectives collectively establishes that the Mainland Chinese stock market is in a process of further integrating with a selection of world's developed stock markets. Nevertheless, such increased integration should not preclude foreign institutional investors from diversifying into the Chinese A-share market, as the current integration is far from being complete.

Adopting appropriate risk monitoring technique for venturing into the volatile Chinese A-share market is another imperative issue faced by foreign institutional investors, whose risk practices and economic capital are largely regulated by the Basel Accord. The second leg of this thesis addresses this problem through an evaluation of various volatility forecasting models for Value-at-Risk (VaR) reporting. Our results highlight the importance of adopting heterogeneous risk monitoring models in different investment environments for the purpose of regulatory compliance and optimal economic capital allocation.

Overall, the studies contained in this thesis should add knowledge to the burgeoning literature on international financial integration at large, while serving the interests of institutional investors, and financial regulatory authorities alike.

Acknowledgement

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Summary

The main element of this thesis consists of four self-contained empirical chapters, each of which has research contributions in its own right. The Shanghai and Shenzhen stock markets in Mainland China have experienced tremendous growth since their establishments and are still expanding at unprecedented pace. Historically, these two markets had been perceived as being largely isolated from the rest of the world. Anecdotal evidence in recent years has raised the prospect that they have not only become more dependent to other stock markets in the international scene, but have also developed the capacity to influence those markets. Justification of this belief is fundamentally an underlying question of stock market integration. While research on international stock market integration has become exhaustive for developed stock markets and most Asian emerging stock markets, the amount of relevant academic research concerning the Mainland Chinese stock markets is relatively scarce. Although past evidence is largely in favour of the segmentation of the Mainland Chinese stock markets, whether this finding is still valid for the markets in their present forms is doubtful. At minimum, research in this area has not entirely kept pace with some of their recent developments.

Motivated by such need, we devote the first three empirical chapters to explore the various aspects of stock market integration taking place in Mainland China, if any, in an attempt to answer the question itemised above. The first empirical chapter looks specifically into the long-term price convergence between the stock market index of Shanghai and those of New York, London, Tokyo and Hong Kong, as evidence of integration; the second empirical chapter examines the return and volatility spillover effects among the same group of stock markets plus the Shenzhen stock market; the third empirical chapter pays attention to time-varying nature of the return correlations between the two Chinese A-share markets themselves and with each of the four developed stock markets. The combination of these indicators provides information on different dimensions of integration

and will thus give the reader a more balanced picture.

Given the recent developments of the Mainland China's stock market and its growing importance in the world capital market, we would expect the level of stock market integration to be higher than it was before. Although the findings obtained from these chapters are not directly comparable, they collectively establish that the Chinese A-share stock market is in a process of further integration with the four developed stock markets in question. While these findings do not contradict the perceptions of increased integration, the true extent to which these markets are integrated is found to be exaggerated by anecdotal evidence. Such knowledge will help international investors to objectively evaluate the Mainland Chinese stock market as a destination for cross-border portfolio diversification. It also has far-reaching implications for domestic investors who are equally eager to learn how their local stock markets react to world's major stock markets, and local financial regulatory authorities whose interests are to ensure the healthy development of its capital market.

The Chinese A-share market has experienced tremendous volatility since the bull market rally that began in early 2006. The market went up five-fold until its peak in October 2007, followed by an equally sharp correction – losing 70% of its value a year later. Although stock markets around the world bore a resemblance during this period, the one witnessed in Mainland China was certainly the most extreme. Such dramatic trajectory is not only detrimental to foreign investors who had substantial equity investment in Mainland China, but also raises the question about the market risk monitoring model that should be adopted given the special investment environment of the Chinese A-share stock markets. Against this background, the last empirical chapter evaluates a wide range of volatility forecasting models in order to ascertain which model delivers the most accurate market risk forecasts. The evaluation is validated through the calculation of Value-at-Risk (VaR) estimates in the context of Basel Accord. Our results suggest the superiority of traditional

RiskMetrics in providing improved VaR estimates for trading positions in the Shanghai A-share Index, whereas asymmetric and long-memory models appeal trading positions in the Shenzhen A-share Index. This exercise should draw the attention of financial institutions about the importance of adopting heterogeneous risk monitoring models when venturing new stock markets or asset classes.

Table of Contents

Chapter 1 – Introduction	12
1.1 Stock Market Integration.....	12
1.2 Development of the Chinese Stock Markets	14
1.3 Research Background and Motivations.....	16
1.4 Research Questions	20
1.5 Research Contributions	21
1.6 Data Description.....	24
1.7 Thesis Structure.....	26
References	28
Chapter 2 – Literature Review	31
2.1 Introduction	31
2.2 Methodology Review	31
2.2.1 Asset Pricing Models.....	33
2.2.2 Cointegration Analysis	35
2.2.3 Correlation and Covariance Analysis.....	37
2.2.4 Spillover Effects	38
2.2.5 Time-Varying Measures.....	40
2.2.6 Other Methods	40
2.2.7 Concluding Remarks	42
2.3 Sources of Stock Market Integration.....	43
2.3.1 Economic Integration	43
2.3.1.1 <i>Macroeconomic Variables</i>	44
2.3.1.2 <i>Formation of Trade and Currency Blocs</i>	47

2.3.2 Financial Liberalisation	48
2.3.3 Financial Crises	50
2.3.4 Stock Market Characteristics.....	53
2.3.5 Other Causes.....	53
2.3.6 Concluding Remarks	54
2.4 Survey of Empirical Findings.....	55
2.4.1 Evidence from Developed Markets	56
2.4.2 Evidence from Emerging Markets.....	60
2.4.2.1 Evidence from Asian Stock Markets	61
2.4.2.2 Evidence from Latin American Stock Markets	64
2.4.2.3 Evidence from Central and Eastern European Stock Markets	65
2.4.3 Evidence from Cross-Listed Stocks	66
2.4.4 Evidence from Greater China Region	67
2.4.5 Concluding Remarks	70
2.5 Implications of Increased Stock Market Integration	70
References	74
Chapter 3 – Long-Run Comovement between the Mainland Chinese Stock Market and Four Developed Stock Markets.....	101
3.1 Introduction	101
3.2 Methodology	102
3.2.1 Cointegration Analysis	102
3.2.2 Cointegration and Market Efficiency	108
3.2.3 Variance Decomposition and Impulse Response Analysis	109
3.3 Literature Review	110
3.4 Data	113

3.5 Empirical Analysis	117
3.5.1 Preliminary Analysis	117
3.5.2 Residual-Based Cointegration Test	118
3.5.3 Johansen Cointegration Test.....	124
3.6 Conclusion.....	141
References	143
Appendices	149
Chapter 4 – Return and Volatility Spillovers between Chinese Stock Markets and Developed Stock Markets.....	157
4.1 Introduction	157
4.2 Literature Review	159
4.2.1 Logic of Return and Volatility Spillovers	159
4.2.2 Empirical Evidence	161
4.3 Data	163
4.4 Methodology	167
4.5 Empirical Results	175
4.6 Conclusion.....	194
References	196
Appendices	202
Chapter 5 – Dynamic Return Correlation Structure between the Two Mainland Chinese Stock Markets and Four Developed Stock Markets	205
5.1 Introduction	205
5.2 Literature Review	207

5.3 Methodology	212
5.3.1 Unconditional Correlation	213
5.3.2 Realised Variance and Correlation	213
5.3.3 Multiple Structural Breaks Test.....	215
5.3.4 Smooth Transition Regression (STR) Model	216
5.3.5 Bivariate GARCH Models	219
5.4 Data	223
5.5 Empirical Results	225
5.5.1 Unconditional Correlations	225
5.5.2 Results from Smooth Transition Models.....	229
5.5.3 Realised Correlations.....	232
5.5.4 Conditional Correlations	234
5.6 Conclusion.....	237
References	238
Chapter 6 – Market Risk Monitoring in the Mainland Chinese Stock Markets: Comparative Evidence from Symmetric, Asymmetric, and Long-memory GARCH Models in Value-at-Risk Estimation	245
6.1 Introduction	245
6.2 Value-at-Risk.....	246
6.3 Volatility Models.....	248
6.4 Evaluation of VaR Models	255
6.5 Literature Review	261
6.6 Data	265
6.7 Model Specification and Estimation	267

6.8 Empirical Results	269
6.9 Conclusion.....	289
6.9.1 Summary of Results	289
6.9.2 Connections with Other Empirical Chapters	290
References	291
Chapter 7 – Conclusion	298
7.1 Summary of Results	298
7.2 Relationship with Extant Literature.....	302
7.3 Practical Implications	302
7.4 Methodological Contributions.....	304
7.5 Limitations and Directions for Future Research.....	306
References	308

List of Tables

Table 1.1 Summary of the Six Stock Exchanges	25
Table 3.1 Unit Root Tests.....	117
Table 3.2 Locations of Break Point in Cointegrating Relation	119
Table 3.3 Engle-Granger Cointegration Test (Full Sample in Local Currencies)	120
Table 3.4 Engle-Granger Cointegration Test (Full Sample in Common Currency).....	121
Table 3.5 Johansen Cointegration Test.....	125
Table 3.6 Estimation of VAR	135
Table 3.7 Variance Decompositions	136
Table 4.1 Trading Hours of the Six Stock Exchanges in Local and Greenwich Times.....	165
Table 4.2 Summary Statistics of the Daytime and Overnight Index Returns.....	166

Table 4.3 Contemporaneous Correlation between Domestic Overnight and Daytime Returns	167
Table 4.4 Formations of Exogenous Variables in the Mean Equation.....	171
Table 4.5 Day-of-the-Week Effect and Asian Financial Crisis Adjustments (Full Sample).....	175
Table 4.6 Autocorrelation Adjustments (Full Sample).....	176
Table 4.7 Mean and Volatility Spillovers for the Overnight Returns (Full Sample)	177
Table 4.8 Mean and Volatility Spillover for the Daytime Returns (Full Sample).....	178
Table 4.9 Mean and Volatility Spillover for the Overnight Returns (in USD).....	182
Table 4.10 Mean and Volatility Spillover for the Daytime Returns (in USD)	183
Table 4.11 Mean and Volatility Spillover for the Overnight Returns (First Subsample)	186
Table 4.12 Mean and Volatility Spillover for the Daytime Returns (First Subsample).....	187
Table 4.13 Mean and Volatility Spillover for the Overnight Returns (Second Subsample).....	189
Table 4.14 Mean and Volatility Spillover for the Daytime Returns (Second Subsample)	190
Table 5.1 Summary Statistics of Monthly Stock Index Returns	223
Table 5.2 Summary Statistics for Monthly Stock Index Returns (Continued).....	224
Table 5.3 Optimal Breakpoints for the Monthly Unconditional Correlations.....	225
Table 5.4 Summary Statistics for Monthly Unconditional Correlations	226
Table 5.5 Results from LSTR Model	230
Table 5.6 Results from ESTR Model	230
Table 5.7 Results from Second-Order LSTR Model.....	230
Table 6.1 Summary Statistics of Daily Stock Index Returns	266
Table 6.2 ARMA (m, n) Orders.....	267
Table 6.3 First-Stage Backtesting Results for SH	270
Table 6.4 First-Stage Backtesting Results for SZ	271
Table 6.5 First-Stage Backtesting Results for HK	273
Table 6.6 First-Stage Backtesting Results for US.....	274
Table 6.7 First-Stage Backtesting Results for UK	276

Table 6.8 First-Stage Backtesting Results for JP	277
Table 6.9 Second-Stage Backtesting Results for SH.....	281
Table 6.10 Second-Stage Backtesting Results for SZ	282
Table 6.11 Second-Stage Backtesting Results for HK	283
Table 6.12 Second-Stage Backtesting Results for US.....	284
Table 6.13 Second-Stage Backtesting Results for UK.....	284
Table 6.14. Second-Stage Backtesting Results for JP	285
Table 6.15 Summary of the Best Performing Models	287
Table 6.16 SPA Test Results.....	287

List of Figures

Figure 1.1 Rebased Nominal Prices of Shanghai and Shenzhen A-share Indices.....	14
Figure 3.1 Stock Index Prices (Local Currencies)	115
Figure 3.2 Stock Index Prices (Common Currency).....	116
Figure 3.4 5-year Recursive Cointegration Test Statistics for $r = 0$ (Common Currency).....	128
Figure 3.5 5-year Rolling Cointegration Test Statistics for $r = 0$ (Local Currencies).....	129
Figure 3.6 5-year Rolling Cointegration Test Statistics for $r = 0$ (Common Currency).....	130
Figure 3.7 Trends for the Coefficients of the ECTs	133
Figure 3.8 Generalised Impulse Responses from One-Standard Deviation Shock to SH.....	138
Figure 3.9 Generalised Impulse Responses from One-Standard Deviation Shock to US.....	139
Figure 3.10 Generalised Impulse Responses from One-Standard Deviation Shock to UK	139
Figure 3.11 Generalised Impulse Responses from One-Standard Deviation Shock to JP	140
Figure 3.12 Generalised Impulse Responses from One-Standard Deviation Shock to HK	140
Figure 4.1 Sequence of Opening and Closing Times of the Six Stock Exchanges	166
Figure 5.1 Plots of Monthly Unconditional Correlations and Breakpoints.....	227
Figure 5.2 Plots of Monthly Realised Correlations and Breakpoints.....	233

Figure 5.3 Plots of GARCH Estimated Monthly Correlations.....	235
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List of Appendices

Appendix 3.1 Critical Values for the Engle-Granger Cointegration Test on Residual Terms	149
Appendix 3.2a 3-year Dynamic Cointegration Test Statistics for $r = 0$ (Local Currencies)	150
Appendix 3.2b 3-year Dynamic Cointegration Test Statistics for $r = 0$ (Common Currency).....	150
Appendix 3.3a 4-year Dynamic Cointegration Test Statistics for $r = 0$ (Local Currencies)	151
Appendix 3.3b 4-year Dynamic Cointegration Test Statistics for $r = 0$ (Common Currency).....	151
Appendix 3.4a 6-year Dynamic Cointegration Test Statistics for $r = 0$ (Local Currencies)	152
Appendix 3.4b 6-year Dynamic Cointegration Test Statistics for $r = 0$ (Common Currency).....	152
Appendix 3.5a 7-year Dynamic Cointegration Test Statistics for $r = 0$ (Local Currencies)	153
Appendix 3.5b 7-year Dynamic Cointegration Test Statistics for $r = 0$ (Common Currency).....	153
Appendix 3.6a 8-year Dynamic Cointegration Test Statistics for $r = 0$ (Local Currencies)	154
Appendix 3.6b 8-year Dynamic Cointegration Test Statistics for $r = 0$ (Common Currency).....	154
Appendix 3.7a 9-year Dynamic Cointegration Test Statistics for $r = 0$ (Local Currencies)	155
Appendix 3.7b 9-year Dynamic Cointegration Test Statistics for $r = 0$ (Common Currency).....	155
Appendix 3.8a 10-year Dynamic Cointegration Test Statistics for $r = 0$ (Local Currencies)	156
Appendix 3.8b 10-year Dynamic Cointegration Test Statistics for $r = 0$ (Common Currency)....	156
Appendix 4.1a Day-of-the-Week Effect and Asian Financial Crisis Adjustments (in USD)	202
Appendix 4.1b Autocorrelation Adjustments (in USD)	203
Appendix 4.2a Day-of-the-Week Effect and Asian Financial Crisis Adjustments (Second Subsample).....	203
Appendix 4.2b Autocorrelation Adjustments (Second Subsample)	204

Chapter 1 – Introduction

1.1 Stock Market Integration

International financial integration has been a topical area for many financial economists. It is now widely contended that the degree of financial market integration around the world has increased significantly since the 1980s. A key factor underlying this process was the increased globalisation of investments as investors become increasingly aware of the benefits of international portfolio diversification. However, during the 1980s, cross-border diversification was largely confined to developed capital markets. Only in the 1990s did international investors start to invest sizable amounts in some of the developing and transition economies located in East Asia, Latin America, Central and Eastern Europe, all of which had embarked on market-oriented reforms or deregulations to attract and absorb the excess foreign capital (Agénor, 2005).

Financial integration can be further branched into integration of stock, bond and money markets, as well as direct ownership of foreign capital or foreign direct investment (Kose *et al.*, 2009). This thesis concerns primarily with stock market integration,¹ which itself alone represents a broad area of research in financial economics. Stock market integration encompasses many different aspects of the interrelationships across national stock markets (Bracker *et al.*, 1999), which has been commonly defined based on either asset pricing or statistical perspectives. Similar to financial integration, stock market integration at international level is only a recent phenomenon as national stock markets were not strongly correlated thirty years ago. A fair amount of research suggests that, for the period before 1980s, international stock markets were segmented in nature with asset prices determined mainly by national factors (see for example, Stulz, 1981; Cho, *et al.*,

¹ The terms stock market integration and equity market integration are used interchangeably in the literature. For the rest of this thesis, the term ‘stock market integration’ is used.

1986; Wheatley, 1988; and Gultekin, *et al.*, 1989). Since then, international stock market integration has been the subject of considerable empirical investigation. In particular, this issue has been of heightened interest in the wake of the October 1987 international crash that saw large, correlated price movements across many stock markets. The experience of global scale market crashes has made people realise that various national stock markets had become so integrated that the developed markets, especially the US market, exerted a strong influence on other smaller national stock markets. Examination of international stock market movements suggests that there exists a substantial degree of interdependence among stock markets of developed economies. Recently, an increasing number of studies have shown that the emerging stock markets have become more, although not fully, integrated with world stock markets (see for example, Kim and Roger, 1995; Siklos and Ng, 2001; and Darrat and Benkato, 2003). These studies of developing countries took place against a background of increasing liberalisation of domestic financial markets and opening up of markets to foreign investors. For example, Kim and Roger (1995) report increased spillover effects from Japan and the US on the opening prices of the Korean stock market following the liberalisation of the Korea stock market; similar is the story on the Istanbul Stock Exchange, which has become significantly integrated with the global markets following its market liberalisation in late 1989, according to Darrat and Benkato (2003); Siklos and Ng (2001) also suggest that sufficient liberalisation of stock markets in the Asia-Pacific region has permitted some form of integration to emerge among themselves and with the US and Japan.

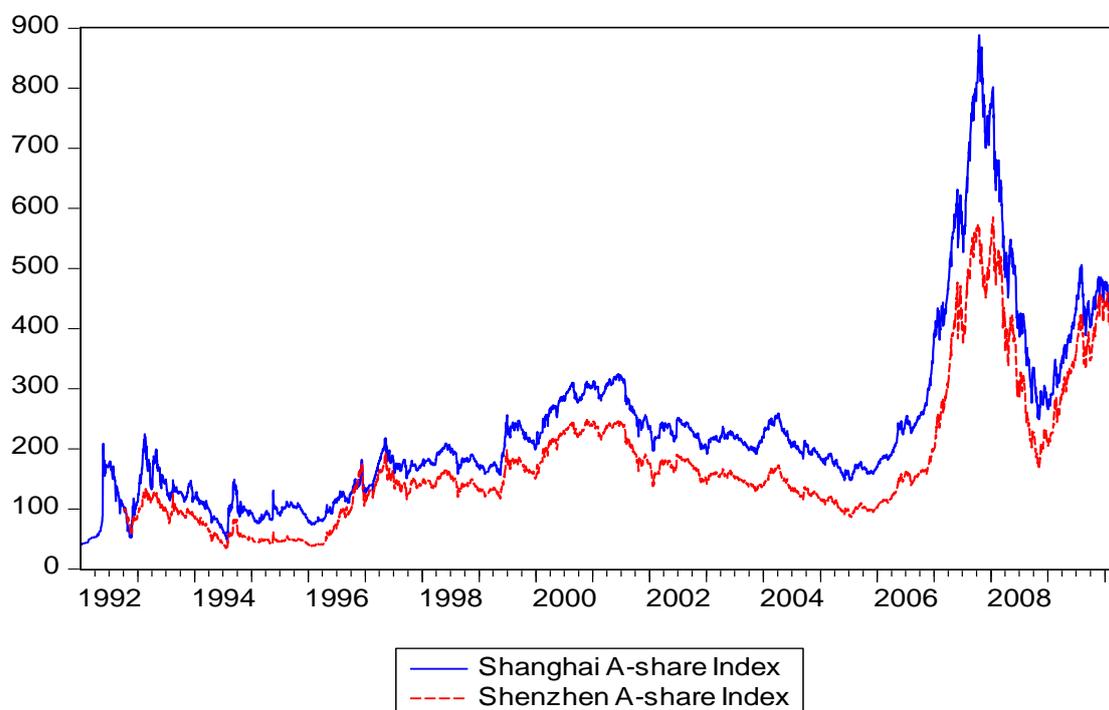
However, it is somehow striking that Mainland China's stock markets have received little coverage in the relevant literature, despite being the largest emerging stock market in the world by market capitalisation. The bulk of the empirical investigation in this thesis seeks to fill this gap by assessing the degree to which the Chinese A-share stock market is integrated with the world stock market, as an important part of its development. The next section chronicles the development of the two Mainland Chinese stock markets (i.e. the Shanghai and Shenzhen Stock Exchanges),

followed by another independent section outlining our research motivations.

1.2 Development of the Chinese Stock Markets

The Shanghai Stock Exchange was inaugurated on 19th December 1990. The Shenzhen Stock Exchange was formally established on 3rd July 1991 after seven months of ‘trial operation’. Over the past two decades, both markets have experienced a lot of ups and downs. Figure 1.1 plots the price movements of the Shanghai A-share Index and Shenzhen A-share Index over the period from 2nd Jan 1992 to 31st March 2010. The data for Shenzhen A-share Index commences on 5th October 1992 on which date the prices of both indices are rebased to 100.

Figure 1.1 Rebased Nominal Prices of Shanghai and Shenzhen A-share Indices



The prices of both indices have evolved in parallel throughout the sample period: trending strongly upward until early 1993, when expectations of state-owned shares becoming publicly

traded caused fear and led to an 80% drop in the Shanghai A-share Index in mid-1994. Government intervention caused the indices to recover sharply, followed by a year and half recession, which ended in 1995. Most of the year 1996 brought a steady rise in the indices, while 1997 saw them somewhat more stabilised and the isolation of the Chinese market prevented large immediate repercussions of the Asian financial crisis and the Russian financial crisis. Mid-1999 marked the start of a two-year speculative bubble, amid a general slowdown in the global economy. Mid-2001 saw the beginning of a 4-year slump, triggered by new rules on previously non-tradable state-owned shares, which led to a halving of the indices and finally came to an end in mid-2005. Both indices staged a fivefold surge since mid-2005. The Shanghai Index hit an intraday record high of 6,124 on 16th October 2007, marking the all-time peak for the market up to now. 2008 saw both indices go into freefall, losing two thirds of their values in response to the global financial crisis. After hitting their 25-month lows in October 2008, the markets began to revive, leaping 80% in 2009. The indices plunged more than 20% in the first half of the year in 2010 as the result of tighter bank lending and a government clampdown on sky-high property prices, though these measures were not directly aimed at the stock markets.

The relative size of these two markets has changed hand in their early years. The Shenzhen Stock Exchange, though initially larger and more active than the Shanghai Stock Exchange, was outsized by the Shanghai Stock Exchange by the end of 1994 due to government policy shift. In terms of the stock composition, companies listed on the Shanghai Stock Exchange are mainly state-owned corporations that are large in size; the Shenzhen Stock Exchange is more of a NASDAQ-style stock exchange and is filled with comparatively smaller, joint ventures, export-oriented and high-tech companies. In terms of their market structure, the Shenzhen market resembles a pyramid due to a relatively low degree of market concentration whereas the Shanghai market has become more funnel shaped due to the increasing domination of highly capitalised state-owned corporate giants.

1.3 Research Background and Motivations

For over a decade since their establishments, the Mainland Chinese stock markets had shown little inclination to follow other markets. Fluctuations in the regional and global markets seldom had any impact on China's A-share markets. One possible explanation of such segmentation was that Mainland China's stock markets had been associated with and steered by repeated government intervention. More importantly, Mainland China had previously been closed-off from world financial markets.

Since 2005, it appears that the Mainland China's stock markets have been moving increasingly in line with major international stock markets, though with greater swings in both directions. More evidently, the impact of the 2007-2009 global financial crisis was greatly felt in the Chinese stock markets, which was in sharp contrast to their previous experience during the Asian financial crisis. This has led market participants, the media, and financial regulatory authorities alike to conjecture that the Mainland Chinese stock markets have become more integrated with world major stock markets than they were before. There were also incidents in recent years when sudden slumps in the China's A-share markets triggered simultaneous falls in other international markets. For example, in late February 2007, after suffering its worst one-day slide for a decade, the Mainland markets plunged 9%. The New York market was severely affected, suffering its worst losses in point terms since the September 11th 2001 terrorist attacks. The leading European markets also tumbled, dropping an average of 3%. This dramatic movement was cited by the media as evidence of China's capability to spread global contagion. However, these beliefs are not without justification.

Over the past decade, the Chinese government has embarked on a financial liberalisation process by relaxing restrictions on foreign ownership of assets and taking other measures to develop its

capital market, though this financial liberalisation effort has understandably been a slow and deliberate process. Perhaps the most notable among these measures was the introduction of the Qualified Foreign Institutional Investor (QFII) scheme in November 2002 by the China Securities Regulatory Commission (CSRC) and the People's Bank of China as a provision for foreign investors to participate in the phenomenal growth of the Chinese economy. The parallel Qualified Domestic Institutional Investors (QDII) scheme was officially launch in April 2006, allowing Chinese institutions and residents to entrust Chinese commercial banks to invest in financial products overseas. Foreign investors cannot legally purchase Mainland China's A-shares outside the QFII schemes and formal channels of overseas portfolio investment by domestic residents are restricted to QDII schemes. The scope of these two schemes has been widened substantially since their inceptions. As of 29th April 2011, the investment quota for QFII stood at \$20.7 billion and that for QDII reached \$72 billion. It is also worth mentioning that foreign investors were only allowed to invest in class B-shares prior to the introduction of QFII program.² The QFII has certainly triggered increasing appetite of foreign institutional investors for A-shares over B-shares.

These open-up initiatives raise a number of intriguing questions. From the perspective of foreign investors, what are the diversification benefits of investing in the newly available emerging Mainland Chinese stock markets? While from the perspective of Mainland China itself, what are the effects of increased foreign capital on its interdependence to the world stock market?

As part of this ongoing liberalisation process, the CSRC has also approved numerous high-profile IPOs of gigantic stated-owned companies, many of which have already been listed on the Hong

² B-shares are previously foreign invested shares issued domestically by Mainland Chinese companies. They are issued in the form of registered shares and carry a face value denominated in RMB, but they are subscribed and traded in USD if listed in Shanghai Stock Exchange, or in HKD if listed in Shenzhen Stock Exchange. Mainland Chinese citizens have been allowed to trade in the B-share market since March 2001.

Kong Stock Exchange as H-shares.³ The potential impact of this move on the degree of stock market integration is believed to be multiple.

First, the return of H-shares or ‘Red-chips’ to the Mainland stock exchanges is expected to strengthen the linkage between the markets involved since these dual-listed stocks are presumably driven by the same fundamentals.⁴ As of 31st March 2010, 53 out of 120 H-shares were also dually-listed on either the Shanghai or Shenzhen Stock Exchange and about one-fifth of these companies are the current constituents of the Hang Seng Index – the benchmark index of the Hong Kong Stock Exchange. As a result, the movement of the Hang Seng Index may bear more resemblance to those of Mainland China’s stock indices, leading to convergence in the long-run between these markets.

Second, the size of the stock market is another factor contributing to the degree of integration. Intuitively, the larger the stock market is, the less stock price manipulation will occur. The listings of those large-cap stocks effectively diversify ownership and absorb excess liquidity. This vision was shared by the CSRC in an effort to make its stock market less speculative and more reflective of economic fundamentals. Furthermore, the bigger a stock market in size, the greater its influence will be on the movements of other markets. Should the scale of the Chinese stock market continues to expand at its current pace, we may well see the market exerting influences over others.

Last but not least, the listings of those large state-owned corporations are believed to alter the

³ H-shares are shares issued by Chinese companies under Chinese law but are listed on the Hong Kong Stock Exchange and subject to its stringent listing and disclosure requirements. The H-shares are denominated in HKD and trade like any other shares listed on the Hong Kong Stock Exchange.

⁴ Red-chips refer to stocks of Chinese companies registered overseas and listed in Hong Kong.

composition and characteristics of the Mainland stock market. Previously, the listed companies mainly consisted of manufacturing, IT and property based businesses, which are usually characterised by low- to mid-market capitalisations. Since 2005, the major backbone industries, such as financials, material and energy have dominated the listings. Due to the nature and scale of their operation, companies in these industries tend to be more sensitive to worldwide macroeconomic factors. Mid- and small-cap companies, on the other hand, have relatively greater exposure to country-specific risks as many of which only conduct their business operations domestically. The impact of global shocks would be more substantive as the composition of the Chinese stock market has been altered.

On the surface, the three impacts outlined above would contribute to a higher degree of stock market integration in Mainland China. The aim of this thesis is to find empirical support, if any, for these claims.

Another motivation for studying the case of Mainland China arises from its uniqueness that distinguishes itself from the other emerging markets. The most distinct feature of the Mainland Chinese stock market is that it was created to serve a socialist market economy. Like its creation, its future, to some extent, depends upon the judgements made by the country's political leadership.⁵ This political uncertainty adds a layer of complexity to foreign investors who are less familiar with the investment environment and political system, which may act as a barrier to greater integration with the world stock market. The political intervention may also explain the lack of connection between the Chinese economy and its stock market performance. The stock market of Mainland China assumes the role of 'government signalling tool', besides its primary economic function of efficient capital allocation. Therefore, the integration experience documented by studies on typical emerging markets cannot be automatically extrapolated to

⁵ See Allen and Shen (2010) for a more detail discussion of China's top-down securities markets.

Mainland China.

Owing to its remarkable economic progress and growing importance to the global economy, there has been a growing amount of research on financial issues regarding China.⁶ However, the issue of stock market integration in Mainland China has received inadequate attention from academic researchers. While research relating to other Asian stock markets has been fruitful, the two Mainland Chinese stock markets are often neglected in the literature.⁷ This lack of coverage is not surprising because studies undertaken back then would have little practical relevance to international portfolio diversification given the Chinese A-share markets were virtually inaccessible by foreign nationals. The gradual removal of impediments to foreign investment has certainly made Mainland Chinese A-shares valuable additions to the optimisation of global portfolios since then. The natural question to be asked is how well they serve this purpose.

In sum, recent stock market liberalisation, unique nature, and less exposure in the extant literature are the main motivations that prompt us to focus on the integration of Mainland China's stock markets with the rest of the world. The findings emerged from this thesis will shed light on the ongoing debate of emerging stock market integration at large.

1.4 Research Questions

Building on the previous discussion, this thesis aims to advance the discussion of international stock market integration and market risk monitoring by addressing the following questions in particular:

⁶ Chan *et al.* (2007) provides an excellent survey.

⁷ See *Chapter Two* for more discussion.

With regard to stock market integration, to what extent are the emerging Mainland Chinese stock markets integrated with the world's developed stock markets? What is the evolution and current level of integration between the Chinese stock markets and the world's developed stock markets? Is integration progressing, at a standstill or even regressing?

To answer these questions, it is worth noting that stock market integration has different dimensions, with which the focus and scope of the empirical inquiries will vary. In response to such variation, we take different perspective by employing a wider range of methodological approaches, and the results from which will be consolidated and reconciled in an effort to present the reader a more complete picture of the state of stock market integration in Mainland China.

With regard to market risk monitoring, which volatility forecasting model produces the most accurate VaR estimates for equity index positions in the above-considered Chinese stock markets and the world's developed stock markets?

This question is largely underexplored in the context of the Chinese stock markets. Since VaR reporting was not statutorily imposed by the Chinese financial regulators to domestic financial institutions until 2010, the effectiveness of various VaR approaches in China has been subject to less scrutiny by market participants and academics alike. However, for foreign institutional investors (i.e. QFII participants), VaR is compulsory for computing regulatory capital under the Basel Accord. This itemised research question is believed to be of special value to foreign institutional investors.

1.5 Research Contributions

On a substantive level, to our best knowledge, this thesis is the first to systematically examine the

integration of Mainland Chinese stock markets with the world's stock markets. The issue of stock market integration in China is important and timely for several reasons. First, the extent to which the local market is integrated with foreign stock markets is of crucial importance to international investors, in that it informs them about the effectiveness of cross-country portfolio diversification. One of the most fundamental questions to portfolio managers, risk analysts and financial researchers, among others, has been to what extent the Mainland Chinese stock markets are in fact, now integrated with the world's major stock markets – a question with which this thesis attempts to answer.

Second, insights into the interrelationship between local and foreign stock markets will assist financial regulators to pursue market efficiency and control undesirable side effects associated with the increasing integration. This is of enormous practical relevance to the regulators and policy makers of the Chinese stock markets, since China is still very much in its early stage of financial liberalisation and is facing numerous ongoing decisions about the timing and pace of further integration of its stock markets.

Despite the growing research interest in emerging Chinese stock markets, research into the integration between China and those in the rest of the world is still in its infancy. As China's burgeoning stock markets continue to expand and undergo sweeping changes, several important issues remain under-addressed or deserve a re-examination. Particularly, practitioners and researchers alike are keen to discern the likely effects of the liberalisation initiatives by the Chinese government on the degree of stock market integration. Outbreak of the 2007-2009 global financial crisis and subsequent worldwide recession has made the issue of stock market integration even more imperative.

With most up-to-date data, we are able to reflect on all these issues and enrich the extant literature

on the integration concerning emerging stock markets. This thesis is therefore to serve the interests of both practitioners and academics.

On the methodological level, our contribution is multifold. Measuring integration is not an easy task. In the literature, measurement of the degree of stock market integration can proceed from a number of points which are detailed in *Chapter Two*. In this thesis, we employ three primary measures to examine the evolution of Chinese stock market integration: long-run comovement, short-run spillover effect, and return correlation. These measures are derived from two well-known and widely applied econometric models – cointegration and Generalised Autoregressive Conditional Heteroskedasticity (GARCH) model.

For the former, the belief is that stock markets that are integrated or in the process of integration should exhibit cointegration so that any gains from diversification across these markets will be confined to short-run horizons when markets temporarily diverge from their long-run path. Furthermore, cointegration results only impart economic significance when examined over sufficiently long time frames. On the contrary, because of events like episodes of financial crisis, global macroeconomic shocks, or policy changes, traditional cointegration technique that looks for commonality among series may perform poorly over such an eventful sample period. We suspect this problem may be more pronounced in the case of Mainland China. Our first solution to this problem involves considering a cointegration test with structural break. While imposing a structural break allows us to capture sudden shift in cointegrating relation, it is not entirely useful if the change is a gradual process. To accommodate this specific property of the data, we propose dynamic cointegration with continuous parameter changes, which is able to capture the fluid nature of stock market integration.

Regarding the GARCH models, we implement the Baba-Engle-Kraft-Kroner (BEKK) and

Dynamic Conditional Correlation (DCC) multivariate GARCH models to compute the conditional correlations between returns of different stock market indices. We extend the same line of argument used for cointegration analysis to correlation analysis by investigating the time-varying patterns in return correlations. This is aided by the break point test due to Bai and Perron (1998, 2003a, b).

Clearly, our approaches overcome the static nature inherited in many previous studies by accounting for potential time-variation in monitoring the evolution of stock market integration. We regard this as the main novelty of our research.

For the fourth empirical chapter, we consider an array of (G)ARCH models in the estimation of VaRs for equity investments in the markets considered in previous chapters. We contribute to the scarce literature in this area concerning Mainland China by broadening the class of (G)ARCH models to include asymmetric models and long-memory models. We expect the implementation of these alternative models will uncover some important features about the risk forecasting practices in the volatile Chinese A-share markets.

1.6 Data Description

As for any research, the choice of data is of great importance. This section briefly comments on our choices over the stock markets under investigation as well as the sample period used in the study. Full details of data sets used in each empirical chapter will be delineated in the respective chapter.

The stock markets considered in this thesis include the three largest markets in the world, New York, London and Tokyo, as well as those of Hong Kong, Shanghai and Shenzhen. The latter three

stock markets of China are closely tied economically and politically, but the two Mainland markets (i.e. Shanghai and Shenzhen) and Hong Kong market differ in terms of degree of openness to other markets (i.e. restriction on foreign investment), transparency, maturity, and capital/currency control. The Shanghai and Shenzhen stock markets combined form the largest emerging stock market in the world, which has market capitalisation far in excess of the size of some of the stock markets in developed countries. Hong Kong is regarded as a domestic neighbouring market of Shanghai and Shenzhen as well as a highly influential market in Asia; Tokyo, London and New York are the largest stock markets in Asia, Europe and North America respectively. Therefore, the stock markets of New York, London, Tokyo and Hong Kong are collectively a good representation of the world developed stock markets. The summary of the six stock exchanges is presented in Table 1.1.

Table 1.1 Summary of the Six Stock Exchanges

Stock Exchange	World Ranking	Market Cap as of Dec 2010	Index Used	Constituents
New York	1st	US\$13.39 trillion	NYSE Composite Index	All common stocks listed on the Exchange, including ADRs, REITs and tracking stocks
Tokyo	3rd	US\$3.8 trillion	Tokyo Stock Price Index	All domestic stocks listed on the Exchange's First Section
London	4th	US\$3.6 trillion	FTSE All-share Index	Around 600 constituent stocks representing at least 98% of UK market capitalisation
Shanghai	5th	US\$2.7 trillion	Shanghai A-share Index	All A-shares listed on the Exchange
Hong Kong	6th	US\$2.7 trillion	Hang Seng Index	45 constituent stocks representing about 60% of capitalisation of the Exchange
Shenzhen	13th	US\$1.3 trillion	Shanghai A-share Index	All A-shares listed on the Exchange

Source: World Federation of Exchanges

In each market, we choose the most comprehensive and diversified stock index. They are, namely, New York Stock Exchange Composite Index, Financial Times Stock Exchange All-Share Index,

Tokyo Stock Price Index, Shanghai Stock Exchange A-Share Index, Hang Seng Index, and Shenzhen Stock Exchange A-Share Index, all free-float adjusted. All data is taken from DataStream.

The sample period used in this thesis is from January 1st 1993 to March 31st 2010. Although the history of Shanghai and Shenzhen A-share Indices can be traced back to early 1992, we exclude the observations up to January 1st 1993 since both markets back then were characterised by low liquidity and a limited number of listed companies. We feel the inclusion of this portion of data will distort our analysis. Our modified sample encompasses different episodes of major internal and external market events took place in China. Daily data is used for most of our empirical analyses unless specified otherwise.

It is customary that all price data should be transformed into logarithmic scale prior to estimations. This particular transformation offers some convenience since logarithmic first-differences approximate stock returns. The stock index return (R_t) is calculated as: $R_t = 100 \times \ln (P_t / P_{t-1})$, where P_t is the value of the price index at time t . This transformation is used throughout this thesis.

1.7 Thesis Structure

Chapter Two starts by reviewing the methodological approaches that are prevalent in the literature for measuring stock market integration, followed by a survey of extant empirical evidence. This chapter is closed with a discussion on the implications of increasing stock market integration.

The subsequent main body of the thesis contains four separate studies, which are titled and structured as follows:

Chapter Three constitutes the first of four studies in this thesis and is titled ‘Long-Run Comovement between the Mainland Chinese Stock Market and Four Developed Stock Markets’. This chapter explores the long-run comovements between the Shanghai stock market and the stock markets of New York, London, Tokyo, and Hong Kong, through a series of cointegration tests that explicitly taking into account of structural break or time-variation in the long-run cointegrating relation(s). The empirical analysis is further supplemented by the Variance Decomposition (VDC) and Impulse Response Function (IRF) analyses.

Chapter Four presents the second of four studies in this thesis and is titled ‘Return and Volatility Spillovers between the Two Mainland Chinese Stock Markets and Four Developed Stock Markets’. This chapter attempts to model the patterns of short-run information transmission across these stock markets in their first-and second-moments (i.e. return and volatility spillover effects).

Chapter Five, titled ‘Dynamic Return Correlation Structure between the Two Mainland Chinese Stock Markets and Four Developed Stock Markets’, pays attention to return correlations between index pairs as evidence of stock market integration. Of special interest is the time-varying nature of the return correlation structure among these index pairs. To quantify correlations, we calculate three types of correlation coefficients – unconditional, realised, and conditional correlations. Next, we attempt to model the movement of correlation as a function of time in a nonlinear framework. This is done by fitting the bivariate return correlation into smooth transition models.

Chapter Six, titled ‘Market Risk Monitoring in the Mainland Chinese Stock Markets: Comparative Evidence from Symmetric, Asymmetric, and Long-memory GARCH Models in Value-at-Risk Estimation’, evaluates an extensive collection of univariate GARCH family models in terms of their ability to produce accurate Value-at-Risk (VaR) forecasts.

Finally, *Chapter Seven* provides a closing summary of main findings, contributions and implications of this thesis. We end our discussion by offering several unexplored opportunities for future research.

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Chapter 2 – Literature Review

2.1 Introduction

In connection to the first chapter, the present chapter provides a comprehensive review of the relevant literature on the issue of stock market integration. The first section examines various methodologies of measuring the degree of stock market integration. Specific attention is given to the developments of two parallel econometric modelling techniques in recent years, namely, cointegration analysis and Autoregressive Conditional Heteroskedasticity (ARCH) models, both of which have propelled the surge in the stock market integration literature and fundamentally changed way researchers enquire the issue. The second sections survey the causes of stock market integration suggested by financial theories or proposed in empirical literature. During the past two decades, the literature on international financial integration has literally exploded. The third section seeks to categorise these findings according to the stages of the stock market development (i.e. developed or emerging markets) and the geographical region where the stock markets reside. In the light of the burgeoning empirical evidence of increased stock market integration, the final section discusses the practical implications associated with these phenomena.

2.2 Methodology Review

Measuring stock market integration is not an easy task, owing to the fair amount of ambiguity about the definition of stock market integration. Despite voluminous papers written on the subject, there is yet no universally accepted definition of stock market integration among financial economists. As a consequence, studies usually differ in their identification of the markers of increased integration, and in their economic interpretation of the evidence.

Since stock market integration is an integral part of financial market integration, we open the discussion with the latter. In financially integrated markets, there is no barrier of any kind to cross-border transactions so that domestic investors are able to freely invest in foreign assets and foreign investors in domestic assets. Perfect financial integration invokes the law of one price and the absence of cross-market arbitrage opportunities. Given this definition, a direct measure of financial market integration is couched in terms of the extent to which returns on financial assets with identical payoffs are equalised across countries or political jurisdictions. For example, the test for financial integration of money markets utilises different interest parity conditions, such as the covered interest parity (CIP), the uncovered interest parity (UIP), and the real interest rate parity (RIP). Using the CIP condition implies that unrestricted international capital flows tend to equalise nominal interest rates across countries when they are contracted in a common currency. Using the UIP condition implies that unrestricted international capital flows tend to equalise nominal interest rates across countries despite exposure to foreign exchange risk. Using the RIP condition implies that free capital mobility tends to equalise real interest rates across countries. The difficulty in operationalizing these measures is that of finding financial assets that are sufficiently homogenous in terms of their risk profiles to facilitate meaningful comparisons (Adam *et al.*, 2002; and Kearney and Lucey, 2004).

In contrast, the extent of stock market integration has been tested in the literature through a wide spectrum of methodologies and empirical frameworks. Adam *et al.* (2002) divide these empirical methodologies into two groups: those of quantity-based and price-based. The quantity-based measures test whether the portfolio composition of domestic investors deviates from portfolio on the efficient frontier under full integration. The home-country bias, which refers to the phenomenon whereby investors overweight domestic securities in their portfolio, is viewed as evidence against financial integration. Indirect studies of quantity-based measures are exemplified by Bekaert *et al.* (2002), who search for the steps of world equity market integration by

identifying structural breaks in the size of international capital flows, and by Portes and Rey (2005) who analyse the timing and geographical pattern of cross-border equity flows. These quantity-based measures lack robust justification since they do not yield much information about either the dynamics of the integration process, or about the drivers of integration. Consequently, the literature of this type has shifted from testing the law of one price to alternative tests that are indirectly related to the degree of integration. The price-based measures, on the other hand, are more in keeping with the concept of evaluating returns and volatilities, as opposed to quantities, and thus will be the main focus in the remainder of this section.

The extant price-based literature has conducted the investigation of stock market integration largely along four broad lines of enquiries – each explores the issue from different theoretical and statistical viewpoints.

2.2.1 Asset Pricing Models

The first line of enquiry employs a joint test of stock market integration and validity of a particular asset pricing model. Studies of this type can be classified into three broad categories according to their assumed state of market integration. One set of models typically assumes that world capital markets are perfectly integrated, and the basic intuition is that the source of asset risk can be associated purely with the covariance of the local returns with the world portfolio and that diversifiable country-specific risk does not command any ex-ante returns in the presence of fully integrated stock markets. This set includes studies of an international CAPM (see Grauer, *et al.*, 1976; and Jorion and Schwartz, 1986), a world CAPM (see Harvey, 1991), a world CAPM with exchange risk (see Dumas and Solnik, 1995; and Dumas, 1994), a world consumption-based model (see Wheatley, 1988), a world arbitrage pricing theory (see Solnik, 1983; and Cho, *et al.*, 1986), a world multibeta model (see Ferson and Harvey, 1994), and world latent factor models

(see Bekaert and Hodrick, 1992; and Campbell and Hamao, 1992).

The difficulty with this strand of literature, however, lies in the interpretation of the joint hypotheses since rejection of these models can be viewed as a rejection of the underlying asset pricing model, inefficiency in the market, or rejection of market integration. The other extreme is a model where the standard CAPM of Sharpe (1964), Lintner (1965) and Black (1972), is applied to the returns of a single country. In such a case, the model implicitly assumes that the market is either perfectly segmented from the world market or it represents an adequate proxy to the world market. Many early seminal asset pricing studies assume that the US is a completely segmented market or that the market proxy represents a broader world market return. Bekaert and Harvey (1995) argue this might no longer be a reasonable working assumption from the 1980s onwards as the US equity capitalisation represented less than half of the world market capitalisation. Since neither of these extreme approaches is based on inherently plausible assumptions, a more realistic approach is to derive asset pricing model in which segmentation can be other than either of the extreme cases. This gives rise to the so-called mild segmentation model (see Errunza and Losq, 1985; and Errunza, *et al.*, 1992). The disadvantage of this approach is that the degree of segmentation is assumed to remain constant over time. This runs counter to the intuition (as do the polar cases) that some markets may have become more integrated through time.

A key weakness of the asset pricing methodology is that the results seem to depend heavily on the specification of the asset pricing model. Chen and Knez (1995) propose a way of testing stock market integration that does not depend on any particular asset pricing model. In this sense, they counter the critique that tests for integration are often joint tests of integration and assumed asset pricing model. Building upon the condition of absence of arbitrage opportunities, they attempt to measure integration by calculating the distance between the estimated stochastic discount factors implied in observed returns and the theoretical discount factor under full integration. Due to the

divergence from the law of one price, the method used by Chen and Knez (1995) suffers the same criticism.

2.2.2 Cointegration Analysis

Another line of price-based enquiry into stock market integration emerges following the development of the notion of cointegration. Studies of this kind examine whether there is any evidence of cointegration amongst international stock indices; for references, see for example, Taylor and Tonks, 1989; Kasa, 1992; Corhay *et al.*, 1995; Kanas, 1998; Ghosh *et al.*, 1999; and Fraser and Oyefeso, 2005. Such evidence is often cited as an important indication of the degree to which long-run diversification is available to international investors, the belief being that should stock markets exhibit cointegration and therefore follow the same long-run time path or stochastic trend then any gains from diversification across an international portfolio will be confined to short-run horizons when markets temporarily diverge from their long-run equilibrium (Evans and McMillan, 2009).

Prior to the development of cointegration, attempts to test for international linkages of stock markets have had focused on atheoretical vector autoregressive (VAR) models. The VAR model estimates a dynamic simultaneous equation system with uniform sets of lagged dependent variables as regressors, and is thus free of a priori restrictions on the structure of relationships. However, VAR models estimated with non-stationary data may be potentially spurious. Early papers, such as the one by Eun and Shim (1989), violate the assumption of stationarity when specifying their models. Stationarity can be achieved by taking difference(s) of the series, but such econometric practice filters out potentially important information regarding long-run common trends among non-stationary stock prices. Recognition of such deficiency has led researchers to explore possible long-run relations among national stock markets, using the notion of

cointegration, as formally defined in Engle and Granger (1987).

According to Engle and Granger (1987), cointegration implies that non-stationary time series (e.g. stock prices) move stochastically together towards some long-run stable relationship. Kasa (1992) points out that a necessary condition for complete integration is that there be $n - 1$ cointegrating vectors in a system of n indices. In this respect, the analytical tool of cointegration lends itself quite conveniently to investigate how integrated stock markets have become.

Two primary methods exist to examine the degree of cointegration among indices. The first is the Engle-Granger technique (see Engle and Granger, 1987) which is bivariate in nature, testing for cointegration between pairs of stock indices. The second is the Johansen-Juselius technique (see Johansen, 1988; and Johansen and Juselius, 1990) which is a multivariate extension and allows for more than one cointegrating vector or common stochastic trend to be present in the data. The advantage of the latter technique allows testing for the number as well as the existence of these common stochastic trends. In essence, the Johansen-Juselius approach involves determination of the rank of a matrix of cointegrating vectors. A more detailed statistical description of these techniques is provided in *Chapter Three*.

Cointegration was initially introduced into the analysis of stock market integration by Taylor and Tonks (1989) who conduct the tests in a bivariate setting, while multivariate cointegration technique was pioneered by Kasa (1992). Since then, cointegration analysis has gained in popularity among empirical studies, which employ the more sophisticated Johansen multivariate approach and generally yield stronger evidence of integration (see for example, Chan *et al.*, 1997; Masih and Masih, 1997, 2001; Sheng and Tu, 2000; and Yang *et al.*, 2003).

Engle and Granger (1987) show that in the presence of cointegration, there always exists a

corresponding error-correction representation. The error-correction term (ECT) measures the proportion by which the long-run disequilibrium in the cointegrating relationship is being corrected in the short-run. The error-correction model (ECM) therefore describes the changes in the dependent variable as a function of not only changes in the other explanatory variable(s) but also the ECT. Examples of studies utilising the ECM or its vector extension (the VECM) can be found in Arshanapalli *et al.* (1995), Masih and Masih (1997a, 1997b, and 2001), Chelley-Steeley *et al.*, (1998), Ghosh *et al.* (1999), Yang *et al.* (2003), and Psillaki and Margaritis (2008). The combination of cointegration and ECM helps researchers to effectively discern the short-run and long-run components of dynamic linkages among stock markets.

2.2.3 Correlation and Covariance Analysis

The third line of enquiry evaluates the evolution of stock market return correlations and covariances. Relevant studies include Makridakis and Wheelwright (1974), Kaplanis (1988), Koch and Koch (1991), Cheung and Ho (1991), Erb *et al.* (1994), Karolyi and Stulz (1996), Ramchand and Susmel (1998), Longin and Solnik (1995, 2001), Chelley-Steeley (2004, 2005), Goetzmann *et al.* (2005), Kim *et al.* (2005), and Aslanidis *et al.* (2010), among others. The rationale behind this approach is that if correlation structure demonstrates instability over time, then, assuming that the trend is towards increased correlation, this indicates greater integration. One argument in favour of this approach over cointegration analysis is that cointegration analysis assumes a long-run stable equilibrium path and is not able to capture the fluid nature of market integration. Correlation analysis commonly involves the computation of unconditional correlations over different sample periods and/or conditional correlations through an array of multivariate GARCH models. The two most widely used models of conditional correlations are BEKK-GARCH due to Engle and Kroner (1995) and DCC-GARCH due to Engle (2002), both of which are capable of capturing potential

time-variation in conditional correlations.⁸ The statistical properties of these models will be discussed in greater detail in *Chapter Five*.

A sub-genre of correlation analysis concentrates exclusively on the correlation structure among stock markets during crisis periods. Studies which fall into this category infer increased correlation during and after extreme market events as evidence of the ‘contagion effect’, a term initially coined by King and Wadhvani (1990) in rationalising the uniformity of the fall in world stock markets during the October 1987 crash. Examples include King and Wadhvani (1990), Meric and Meric (1997), Baig and Goldfajn (1999), Forbes and Rigobon (2002), Kleimeier *et al.* (2003), Caporale *et al.* (2005), Chiang *et al.* (2007), and Yoshida (2009), with the majority of these studies confirming the existence of contagion effect for the crisis under investigation. Given that contagion is usually defined as correlation between markets in excess of that implied by economic fundamentals, the test of contagion hypothesis can also be conducted from an asset pricing perspective (see for example, Corsetti *et al.*, 2002; and Bekaert *et al.*, 2005).⁹

Despite its widespread application, correlation analysis is not free from criticism. Opponents of correlation analysis argue that a market could be perfectly integrated into world markets but still exhibit a low or negative correlation with other markets. For example, Roll (1992) suggests that the disconnection between correlation and integration could be due to the difference in industry mix of the country relative to that of the world average.

2.2.4 Spillover Effects

The fourth line of enquiry attempts to examine the international integration of stock markets from the perspective of strengthened spillover effects in their returns and volatilities. From a risk

⁸ The relative merits of the BEKK- and DCC-GARCH models are examined by Caporin and McAleer (2009).

⁹ See Dungey *et al.* (2005) for a review of methodologies on modelling contagion effect.

management view point, price and volatility spillovers across markets deserve attention, because when spillover is substantial the motivation for holding a diversified international investment portfolio will be curtailed. 'This effect becomes even stronger, when the speed of the international shock transmission increases, further shortening the time interval over which international diversification benefits can be secured' (Elyasiani and Kocagil, 2001: p.1165). In addition, spillover asymmetry among national stock markets may have significant implications on portfolio decisions. For instance, if market A is unaffected by market B but market B is predominantly determined by market A, diversification benefits would be limited for portfolio managers investing in market A, while not for investors in market B. This is so because under these conditions the shocks in market B will have no repercussions on market A (Elyasiani and Kocagil, 2001).

One of the most prominent analytic tools for spillover effects is the variants of GARCH model. The combined formulation of mean and variance in the GARCH specification allows researchers to explore stock market interactions in terms of both first- and second-moment interdependence (i.e. price/return and volatility spillover effects). The analysis of spillover effects can be conducted in a univariate GARCH or a multivariate GARCH framework. The model estimation usually encompasses two stages: the first stage involves the extraction of unpredictable part of return; the estimated unexpected returns and its squared values are then inserted into the mean and variance equations of another market in the second stage estimation. The presence and the strength of spillover effects are determined by the statistical significance and magnitude of the inserted exogenous variables respectively. Studies based on the univariate GARCH approach include the widely cited work of Hamao *et al.* (1990) and Lin *et al.* (1994), while early ventures with the multivariate GARCH technique were made by Theodossiou and Lee (1993) and Koutmos and Booth (1995). The initial success of the GARCH models in these studies has provoked a large number of studies in the international return and volatility transmission literature. More recent

contributions include Ng (2000), Connolly and Wang (2003), Kim (2003) and Cotter (2004).

2.2.5 Time-Varying Measures

A very important but often ignored issue is that stock market integration may exhibit strong variations over time. Most research testing for stock market integration has either ignored this issue entirely or has looked at various sub-periods to obtain information about the dynamics of integration (for example Longin and Solnik, 1995; and Bodart and Reding, 1999). Although comparing different sub-periods may yield a first proxy for long-term changes, it masks much of the time variation and may still lead to partial results. Recognising the essentially static nature of the asset pricing and cointegration approaches outlined above, more recent studies have derived measures to accommodate the time-varying nature of stock market integration. For example, Bekaert and Harvey (1995) develop an asset pricing model that allows for the degree of integration to change over time. With their approach, the risk premium on a market depends on its volatility if the market is completely segmented and depends on its world market beta if it is completely integrated. The degree of segmentation of a market decreases when the market's world beta becomes a more important determinant of the market's expected return. Parallel to this contribution is the use of dynamic cointegration methodologies in monitoring the process of stock market integration (see for example, Rangvid, 2001; Pascual, 2003; Aggaral *et al.*, 2004; and Awokuse *et al.*, 2009).

2.2.6 Other Methods

Besides the mainstream methodologies outlined above, a few other techniques also deserve mentioning. Granger causality test allows researchers to analyse the predictive ability of one time series on another – variable X causes another variable Y in the Granger sense if present Y can be predicted better by using past values of X than by not doing so. For example, Malliaris and Urrutia

(1992) use Granger causality tests to study the lead-lag relationships during the October 1987 market crash. However, this method has lost its appeal to researchers since Granger causality is not enough to ascertain true causality, thus the use of which is rarely seen in the more recent literature.

The Vector Autoregressive (VAR) model was the predecessor of the cointegration technique. The VAR model was developed by Sims (1980) with the purpose of estimating unrestricted reduced-form equations that have uniform sets of lagged dependent variables as regressors. Free of a priori restrictions on the structure of relationships, the VAR system can be viewed as a flexible approximation to an unknown model of the actual economic structure. For example, early studies by Eun and Shim (1989), von Furstenberg and Jeon (1989) and King and Wadhvani (1990) use the VAR models to examine the daily transmission of international stock returns. However, VAR models estimated using non-stationary data may be spurious and misleading. Finding of cointegration among non-stationary variables leads to the consideration of (V)ECM instead of VAR. The use of VAR model in differences is thus only recommended in the absence of cointegrating relationship.

The VAR model is frequently supplemented by the use of variance decomposition (VDC) and impulse response function (IRF) in the literature; see for example, Masih and Masih (1997a, 1997b, and 1999), Sheng and Tu (2000), Soydemir (2000), Yang *et al.* (2003), and Darrat and Zhong (2005). VDC measures the relative strength of causality amongst the variables in the system by partitioning the variance of the forecast error of a certain variable into proportions attributable to shocks in each variable in the system including its own, while IRF traces the dynamic response path of one variable due to an innovation to another variable, thus enabling us to characterise the dynamic integration among stock markets, and to observe the speed of adjustment of these markets in the system. Both simulations are obtained from the moving average

representation of the original VAR model.

2.2.7 Concluding Remarks

The degree of stock market integration has been investigated through a rich set of empirical methodologies. The vast diversity in empirical methodologies is partially driven by the advances in statistical and econometrical modelling techniques (e.g. cointegration and GARCH models), which have continued to bring new perspectives on the issue of stock market integration. These approaches are developed to accommodate the differing perceptions and interpretations of stock market integration by researchers, the asset pricing model approach explicitly tests the validity of the law of one price while none of the cointegration, correlation, and spillover effect analyses is based on an explicit theoretical model of asset prices. The technique of cointegration is used to pinpoint whether there exists long-run benefits from international diversification, especially, equity investment with longer horizons. Correlation and spillover effect analyses primarily deal with short-run interdependence between stock markets. Hence, these approaches should be viewed as complementary to each other rather than being mutually exclusive.

In the following chapters of this thesis, we employ dynamic cointegration analysis, spillover effect analysis, and time-varying correlation analysis in *Chapter Three, Four* and *Five* respectively to investigate the extent to which the Mainland Chinese stock markets are integrated with the four world's major developed stock markets. We believe that the combined use of these indicators would provide information on the different dimensions of integration and thus give the readers a more balanced picture of the general trend of stock market integration in Mainland China.

2.3 Sources of Stock Market Integration

National stock markets may have been more integrated with each other and with the world for various reasons. For example, Jeon and Chiang (1991) cite deregulation and market liberalisation measures, rapid developments in communication technology and computerised trading systems, and increasing activities by multinational corporations as factors contributing to stock market integration; Koch and Koch (1991) attribute the trend towards greater integration of global capital markets to advances in communication technology and capital mobility, the cross-listings of stocks on different national exchanges, and the growth in financial innovations; Longin and Solnik (1995) posit the increase in correlation of international financial markets as the results of progressive removal of impediments to international investment, growing political, economic and financial integration. A better comprehension of the sources of stock market integration enables us to provide economic content to the observed changes in the nature and degree of stock market integration. According to the extant literature, there are several branches of explanation as to why stock markets are integrated: economic integration, financial liberalisation, financial crisis, and stock market characteristics.

2.3.1 Economic Integration

Stock market integration is one facet of capital market integration, itself a subset of economic integration. Intuitively, the more the economies of two countries are integrated, the more interdependent or integrated their stock markets will be. Eun and Shim (1989) argue that greater stock market integration is the natural consequence of greater economic integration that has been taking place over time. Studies have shown that the degree of real economic integration, measured by the correlation of business cycles, has a strong effect on financial integration (Fama and French, 1989; Ferson and Harvey, 1991; Jagannathan and Wang, 1996). Moreover, the degree of financial integration tends to be highest during periods when countries or the dominant country are in

recession (Erb *et al.*, 1994; Ragunathan *et al.*, 1999). Studies have also demonstrated that the stability of the correlation structure over time is determined primarily by real economic linkages between countries (Campbell and Hamao, 1992; Roll, 1992; Arshanapalli and Doukas, 1993; Bracker and Koch, 1999). Phylaktis and Ravazzolo (2002) find overwhelming evidence that stock market integration is accompanied by economic integration in a group of Pacific-Basin countries. All these studies seem to support the view that economic provides a channel for stock market integration.

Since economic integration may take many forms, we further summarise it into two main headings – macroeconomic variables, and formation of trade and currency blocs, to analyse their impacts on the progress of stock market integration.

2.3.1.1 Macroeconomic Variables

Bracker *et al.* (1999) hypothesise that the extent of stock market integration may depend upon certain macroeconomic factors that characterise and influence the degree of economic integration across countries. Campbell and Hamao (1992) similarly emphasise potential macroeconomic sources of covariation across markets. A number of empirical works has corroborated the role of macroeconomic fundamentals in explaining stock market interdependence. For example, Bracker and Koch (1999) investigate how and why the matrix of correlation across international stock markets changes over time and conclude that divergent behaviour across nations in several macroeconomic variables tends to be associated with divergent behaviour across national stock markets, resulting in lower correlations. Cheung and Lai (1999) find a weak contribution from macroeconomic fundamentals in explaining long-run cointegration of stock returns. Dickinson (2000) shows that a cointegrating relationship among the major European stock markets exists after the 1987 stock market crash and it may be partly driven by the long-run relationships of

macroeconomic fundamentals among these countries. The role of economic fundamentals in determining international transmission patterns of stock market movements is also confirmed by Soydemir (2000).

From a macroeconomic perspective, there are two broad categories of economic variables that influence the degree of stock market integration. First, the extent to which two economies depend on each other, as measured by the degree of bilateral trade ties between the two countries, will influence the extent to which their stock markets are integrated. Second, according to the cash flow model, several macroeconomic variables influence stock market performance. To the extent that these macroeconomic variables in two countries are convergent, their stock market performances should converge, thus a higher degree of integration.

Bilateral trade is a measure of the degree of economic integration of one country with another. One would expect the extent and nature of bilateral trade relationship between two countries to have a bearing on the degree of stock market integration. According to Bracker *et al.* (1999), the relative export dependence of country A on country B should be positively related to the degree of integration between the two stock markets; on the other hand, the degree of relative import dependence may have either a positive or negative influence on the extent of stock market integration. This influence of relative import depends on the substitutability of other import markets and the economic conditions that influence the terms of trade between countries (Bracker *et al.*, 1999: p.19). Studies on bilateral trade as a potential source of stock market integration has been rather fruitful and generally support the view that a relatively high degree of reliance on trade would further enhance the integration among stock markets across borders (Chen and Zhang, 1997; Bracker *et al.*, 1999; Chen *et al.*, 2002; Pretorius, 2002; Lin and Cheng, 2007; and Karim and Majid, 2010). For example, Forbes and Chinn (2004) find direct trade with large economies (i.e. top five global markets) appear to be the only important factor in explaining cross-section market

linkages.

Recall that stock price, P , can be written as the expected discounted stream of dividends:

$$P = \frac{(1 + g)D_0}{k - g} \quad \text{Eq. (2.1)}$$

where D_0 is the last dividend paid, g is the constant growth rate in dividends and k is the discount rate. Any factor that influences the stream of cash flows or the discount rate will systematically influence stock prices. Since the seminal article by Chen *et al.* (1986), the influence of interest rates and inflation on the discount rate, and of the industrial production growth on the expected cash flows, and hence on stock prices, has been well established. The empirical evidence on the importance of these three macroeconomic factors in explaining stock market interdependence is mixed. For example, Bracker *et al.* (1999) and Lin and Cheng (2007) find that the degree of stock market interdependence is a negative function of real interest rate differentials. Pretorius (2002) also provides positive evidence on the significance of industrial production growth differential in explaining stock market interdependence. On the other hand, King *et al.* (1994) specifically report that only a small proportion of the short-term market covariations can be explained by observable economic variables. In similar vein, Cheung and Lai (1999) explore whether long-term market comovements can be linked to similar comovements in macroeconomic variables, including the money supply, dividends, and industrial production, and suggest a limited role of these macroeconomic variables in accounting for the relative stock market movements among the three European Monetary System countries (i.e. France, Germany and Italy).

Since the interest rate and inflation differentials between countries will be settled through change in exchange rate eventually, as suggested by international parity conditions, the extent of stock

market integration may be also ascribed to exchange rate fluctuations. Volatility in exchange rate reflects not only the interest rate and inflation differentials between countries but also a source of uncertainty that imposes costs of trading equity across markets, which is expected to dampen the extent of integration across markets. This contention is empirically supported by Dumas and Solnik (1995), Bodart and Reding (1999), Hardouvelis *et al.* (2006), and Ling and Cheng (2007). In particular, Fratzscher (2002) shows that the reduction and elimination of exchange rate volatility plays a central role in explaining the increased financial integration among EMU member countries.

2.3.1.2 Formation of Trade and Currency Blocs

It is widely accepted that the formation of trade and/or currency blocs facilitates economic integration among the constituent countries on many levels, ranging from the macroeconomic policy coordination, harmonisation of regulatory and market structures, to the introduction of a common currency, thus one would expect greater stock market integration as a consequence.

Much of the focus in this branch of literature is placed on the European Monetary Union (EMU), since it represents the highest level of regional economic integration that has ever been reached. Studies have compiled overwhelming evidence that the establishment of the EMU has fostered greater stock market integration among its member countries. Relevant studies include Aggarwal, *et al.* (2004), Yang *et al.* (2003), Kim *et al.* (2005), Hardouvelis *et al.* (2006), Bartram *et al.* (2007), and Lafuente and Ordóñez (2009), to name a few. The vast majority of these studies provide supporting evidence on the hypothesis that the prospect of EMU was the causal driver behind the observed stock market integration among Eurozone countries through the identification of a clear regime shift. Hardouvelis *et al.* (2006) further prove that the increased integration appears to be a phenomenon specific to the Eurozone, independent of possible simultaneous world-market

integration. The formation of EMU along with the introduction of Euro has enhanced integration among Eurozone countries mainly through the elimination of exchange rate risk (Fratzscher, 2002), the unification of interest rates and macroeconomic convergence (Morana and Beltratti, 2002; Lafuente and Ordóñez, 2009).

Although there is substantially less literature on the impact of other trade blocs on stock market interdependence, most of the empirical results do point toward the increasing integration within the member countries involved: for example, Aggarwal and Kyaw (2005), Darrat and Zhong (2005), and Canarella *et al.* (2009) all document stronger stock market linkage among the three stock markets of the US, Canada and Mexico in the post-NAFTA period; Click and Plummer (2005) present evidence of integration, albeit far from complete, among the ASEAN stock markets.¹⁰

2.3.2 Financial Liberalisation

Countries embark on a set of wide-ranging reforms are likely to move towards market integration. Since the US took a big step in stock market deregulation by passing the US Securities Act Amendments of 1975, which deregulated stock brokerage commission rates, the world financial market has experienced a series of deregulation and financial innovation events. In Europe, the UK abolished its exchange controls on capital outflows in 1979. At the same time Germany opened its capital market to non-residents. Similar step was taken by Japan in the early 1980s, which effectively removed exchange controls on capital outflows. All these major market liberalisation initiatives are expected to have profound effects on world financial market integration, particularly on the world equity markets. Indeed, there has been ample evidence that financial liberalisation events bring about substantial stock market integration, not only in the

¹⁰ NAFTA is short for the North American Free Trade Agreement Region and ASEAN is short for the Association of Southeast Asian Nations.

developed stock markets but also in a number of emerging markets in recent years.

The abolition of exchange controls has been proposed as possible causal factor for structural change in the process of stock market integration. Using multifactor asset pricing models, Gultekin *et al.* (1989) provide evidence of segmentation and integration between the US and Japan before and after the elimination of capital controls in Japan at the end of 1980, and conclude liberalisation of capital flow is a source of capital market integration. Taylor and Tonks (1989) assess the impact of the relaxation of exchange control on the degree of integration of UK with other leading stock markets, and claim that there appears to be a marked increase in the degree to which these markets move together in the long-run. Byers and Peel (1993) find no convincing evidence that international stock markets were cointegrated in the period following the abolition of exchange controls in the UK, with the exception of the UK and Japan. Using the same cointegration framework, Chelley-Steeley *et al.* (1998) expand the work of Taylor and Tonks (1989) by examining the effect of the removal of exchange controls in several major European countries on the comovement of their stock market indices. On the contrary, their results show that four out of five countries experienced a reduction in the degree of cointegration following the removal of exchange controls.

Studies concerning the emerging markets have concentrated on examining whether the existence of foreign ownership restriction curbs stock market integration. Bekaert and Harvey (1995) report large shifts in the degree of integration in a handful of emerging markets following the relaxation of foreign ownership restrictions. Phylaktis and Ravazzolo (2005) find the relaxation of foreign ownership restrictions had strengthened stock market integration amongst a group of Pacific-Basin stock markets, Japan and the US in 1990s. Positive impact of investment restriction liberalisation on the integration of Pacific-Basin stock markets is also noted by Ng (2000). Using correlation analysis, Ng (2002) reports that the ASEAN stock markets have become more closely linked

following a period that encompasses substantial opening up of the financial markets to foreign investors by the ASEAN economies.

Segmentation of stock markets produces incentives for domestic companies to adopt countermeasures, one of which is to cross-list its stocks on foreign stock exchanges.¹¹ The widespread cross-listing of stocks has been a strong stimulus to further integration of the stock exchanges concerned. Cross-listed financial securities, which are presumably driven by the same long-term fundamental values, should have identical prices regardless of their trading locations and any price discrepancy will induce arbitrage activities that help integrate markets where securities are cross-listed. This hypothesis is empirically supported by the works of Alexander, *et al.* (1988), Pagano and Roell (1990), Mittoo (1992), Lee and Varela (1993), Bekaert (1995), Ng (2000), Karolyi (2004), Hansda and Ray (2003), and Cotter (2004), though from different methodological perspectives.

2.3.3 Financial Crises

Some have also suggested the effects of past episodes of financial crisis as potential catalyst for instability in the pattern of stock market interdependence, which would conceivably stimulate stronger linkages among national stock markets. This phenomenon, that the world stock markets become more integrated following some turbulence in the markets, is best known as the ‘contagion effect’ and was formally investigated by Roll (1989) and King and Wadhvani (1990), among others. Although many studies do not explicitly test for contagion, papers which do test for its existence generally conclude that contagion occurred during the crisis under investigation. Others who deny the contagion effect nevertheless find increased interdependence (see for example, Forbes and Rigobon, 2002).

¹¹ For example, cross-listing in the US usually takes the form of American Depositary Receipts (ADRs).

Stock market crashes, such as the 1987 stock market crash, have been widely argued to strengthen major international as well as Asian stock market linkages. Arshanapalli and Doukas (1993) suggest that the three major European stock markets (i.e. UK, France and Germany) have become more connected with the US stock market in the post-crash period while the Japanese stock market has drifted far away from the other four markets since the 1987 crash. In a later study, Arshanapalli *et al.* (1995) shift their focus by examining the possible links and dynamic interactions between the US and six major Asian stock markets before and after October 1987. The results are also in favour of a strengthened linkage amongst these markets in the post-crash period and further indicate that the Asian stock markets are less integrated with Japan than they are with the US market. Similar evidence is found by Hung and Cheung (1995) who investigate market integration in Hong Kong, Malaysia, South Korea, Singapore, and Taiwan and find no cointegrating vector among these Asian markets before the 1987 market crash, but find at least three after the crash. The finding from Masih and Masih (1997a, b) also lends support to the view that the 1987 crash has brought about a greater interaction amongst major stock markets.

Subsequent studies have shifted their focus to the 1997 Asian financial crisis. Jochum *et al.* (1999) show that the long-run equilibrium among the Eastern European stock markets had been replaced by a strong tendency of the markets to generate volatility spillovers and the resulting increase in short-term correlations after the 1997-1998 crises in the emerging markets (i.e. the 1997 Asian financial crisis and the 1998 Russian financial crisis). Sheng and Tu (2000) report no cointegration in the year before the Asian financial crisis but one cointegrating vector during the crisis between the US and many Asian stock markets. In a similar vein, Yang *et al.* (2003) show that the outbreak of the 1997 Asian financial crisis has altered market integration among Asian countries – the degree of integration has increased during and after the crisis than before the crisis. Yang *et al.* (2004) apply recursive cointegration analysis on the US and 13 relatively well-established

emerging markets from Latin America, Asia, Europe and Africa. They find no long-run relationship exists between emerging stock markets and the US throughout most of the sample period until 1997; the linkages between the US and these markets are intensified following the 1997-1998 global emerging market crisis, in which one cointegrating vector is consistently found. Choudhry *et al.* (2007) find highest number of significant cointegrating vectors and highest level of correlations among the eight Far East stock markets and larger markets of Japan and the US during the Asian financial crisis period. A recent study by Huyghebaert and Wang (2010) also provides evidence that the 1997 Asian financial crisis has strengthened the stock market integration in East Asia, though the outcome turns out to be only a temporary phenomenon.

Despite the numerous studies confirming the role played by stock market crashes in strengthening the international stock market linkages, there is still no consensus on whether a crisis-induced strengthening of international market linkages is transitory or permanent, whilst a handful of studies have provided evidence against the contagion effect. For example, Malliaris and Urrutia (1992) document a dramatic increase in contemporaneous causality during the month of 1987 stock market crash, but no significant lead-lag relationships are detected for the periods before and after the market crash. Chan *et al.* (1997) find that the number of significant cointegrating vectors increases before the October 1987 stock market crash but the crash itself had little enduring impact on the long-run relationship among the 18 countries in their sample. By showing a substantial proportion of the interdependence among emerging stock markets could be explained fundamentals, Pretorius (2002) argues that the proportion of stock market interdependence that is due to 'contagion' has been proved to be smaller than is widely perceived. The recursive cointegration analysis by Phylaktis and Ravazzolo (2005) indicates that the Asian financial crisis did not have a substantial effect on the integration of several Pacific-Basin stock markets.

2.3.4 Stock Market Characteristics

The size of a national stock market may reflect its stage of development, and may indicate the degree of market liquidity, information costs, and transaction costs associated with trading in that market. With this perspective, a large disparity in stock market sizes may result in less comovement among national stock markets. Bekaert (1995) suggests the limited size of stock market is among the most important de facto barriers to global stock market integration. By contrast, the greater the importance of a country's stock market in global capital markets, the more leading that market is expected to be in the information context, and thus greater integration will result.

Pairs of national stock indices with greater similarities in industry composition tend to experience more substantive comovement. Roll (1992) argues that the industrial structure and concentration of different national stock indices is a major potential source of comovement international equity market linkage, and that sets of countries with more similar industrial compositions tend to have more highly correlated stock market returns – a view that is further reinforced by Longin and Solnik (1995). Conflicting evidence is found in Heston and Rouwenhorst (1994), and Griffin and Karolyi (1998) – both suggest that industrial composition explains rather a small proportion of variation in country index returns.

Bekaert (1995) also suggests that the segmentation of emerging stock markets can be explained by poor credit rating, the lack of a high-quality regulatory and accounting framework of the respective countries.

2.3.5 Other Causes

Apart from the sources of stock market integration discussed above, several other developments

have also contributed to increasing integration of national stock markets over the years. These developments include innovation in communications technology, unprecedented growth in financial innovations involving options, futures and other derivatives on stock indices, and recent consolidation and merger of stock exchanges (Koch and Koch, 1991; Yang *et al.*, 2003, Hasan and Schmiedel, 2004). In addition, Bracker *et al.* (1999) contend that national stock markets whose trading hours overlap demonstrate systematically greater comovement with each other than those markets whose trading hours do not overlap; and countries in proximate geographical areas tend to display greater comovement than countries further apart, so that countries such as Australia-New Zealand and Malaysia-Singapore should exhibit higher levels of market integration.

2.3.6 Concluding Remarks

Although there is a wealth of empirical works on measuring how integrated stock markets have become, relatively few studies touch upon the economic determinants of the observed changes in stock market integration. What emerges from these studies is that the question as to why stock markets become more integrated is still unsettled, partly due to the difficulties in controlling for other factors that might confound the impact of the factor(s) under investigation. Early attempt was made by Bachman *et al.* (1996) who try to discriminate technological change, financial deregulation, and trade liberalisation as potential sources of integration among the stock markets of the G-Seven countries, by conducting cointegration tests on different subsets and subsample periods.

To assess the relative importance of various macroeconomic variables in explaining the extent of stock market integration, the common approach is to regress a number of instrumental variables against the time-varying measure of stock market integration. This approach may be vulnerable to either multicollinearity if variables pick up effects of other included variables, or omitted variable

problem if a very small set of variables is used. In many cases, it becomes virtually impossible to distinguish true factors behind the time variation in stock market integration.

In examining the effect of financial liberalisation on stock market integration, the usual practice is to split the sample into pre- and post-liberalisation periods and compare the model parameters. A problem arises since in many cases, there are no clear cut off dates for financial market liberalisation so that the division of sample may be arbitrary. Even if there were, any policy action is likely to be a gradual process and requires time before the full effect can be absorbed into and felt by the stock market. As a result, the inclusion of observations immediately after implementation of these policies would bias the analysis. The same argument could be extended to the formation of trade and currency blocs on stock market integration. One remedial practice in recent literature is to allow smooth transition from one regime to another rather than assuming an instantaneous regime switch, see for example, Chelley-Steeley (2004, 2005) and Aslanidis *et al.* (2010).

2.4 Survey of Empirical Findings

Empirical evidence of international stock market integration is abundant. This survey attempts to give the reader a synthesis and some perspective on this rapidly evolving literature, including both early contributions and more recent work. The rest of the section is structured as follows: we start by examining the evidence from stock markets of developed countries, followed by evidence from the emerging stock markets across Asia, Latin America, Central and Eastern Europe; we then shift our focus to evidence of integration at company levels; finally, we identify the research gap through the compilation of extant literature exclusively written on the Chinese stock markets.

2.4.1 Evidence from Developed Markets

The study on stock market integration can be traced back to as early as Granger and Morgenstern (1970). Subsequent analyses by Levy and Sarnet (1970), Grubel and Fadner (1971), Agmon (1972), Ripley (1973), Lessard (1976) and Hilliard (1979) find little or no correlation among national stock market indices based on mostly and monthly data from the 1960s and 1970s. For example, Grubel (1968) show that between 1959 and 1966, US investors could have achieved better risk and return opportunities by investing part of their portfolio in foreign equity markets. Levy and Sarnat (1970) analyse international correlations in the 1951-67 period and report diversification benefits from investing in both developed and developing equity markets. Grubel and Fadner (1971) show that correlation is an increasing function of holding periods and correlation between country index returns was smaller than correlation between domestic assets. These studies marked the beginning of an extensive literature on capital market integration and international diversification. Relying on simple correlations and regression methodologies for their investigation, the general finding from these studies is that correlations between national stock markets are significant but small in magnitude so that holding an internationally diversified portfolio could be quite advantageous. This documented empirical regularity has become increasingly less visible following the globalisation of world financial markets as subsequent studies generally point to a high degree of integration among developed stock markets.

There are studies which examine stock market integration using data from a bundle of developed stock markets. For example, Eun and Shim (1989) investigate the international transmission mechanism of stock market movements by estimating a nine-market VAR system. Their findings indicate a substantial amount of interdependence among national stock markets investigated, with the US being the most influential market and Japan acting like a follower to the world stock market. Bessler and Yang (2003) study the same set of major stock markets as in Eun and Shim

(1989) by applying more modelling techniques in addition to the VAR model. They draw similar conclusion to Eun and Shim (1989) that the US market has a consistently strong impact other major stock markets, but also demonstrates the exogeneity of the Japanese market – a finding that is broadly consistent with few other studies (for example, Malliaris and Urrutia, 1992; and Francis and Leachman, 1998). The relative segmentation of the Japanese stock market is also demonstrated by Harvey (1991), who executes the conditional CAPM model on a sample of seventeen country-specific stock portfolios and shows that the variation in returns across these countries can be adequately described by a single source of risk with the exception of Japan.

Kaplanis (1988) compares the correlation and covariance matrices of monthly returns of ten major stock markets over the period from 1967 to 1982. She finds evidence of stable correlation but less stable covariance of real international equity returns. Meric and Meric (1989), analysing the inter-temporal stability of the correlation matrix among seventeen national stock markets, assert that the longer the time period the greater the degree of stability among international stock market relationships. On the other hand, using data from seven major stock markets, Longin and Solnik (1995) find an upward trend in international correlations over the period from 1960 to 1990, of which leads to a rejection of a time invariant correlation matrix.

Blackman *et al.* (1994) examine whether there existed any long-term statistical relationships between monthly prices of share on seventeen OECD markets. Using a split-sample approach, their evidence supports the case of long-term relationships during the post-globalisation period.

Another group of studies focuses on the integration among a smaller group of stock markets. Using monthly and quarterly real US dollar deflated data, Kasa (1992) computes common stochastic trends in the developed markets of the US, Japan, the UK, Germany and Canada. Presenting evidence of a single common trend underlying the equity markets of these countries,

point estimates of factor loadings suggest that this trend is most important in the Japanese market and the least important in the Canadian market. In the subsequent study, using the monthly stock return data from the US, Japan, and the UK for the period from 1980 to 1993, Kasa (1995) further suggests that the conclusion of market integration depends sensitively on the assumed variation of the (unobserved) common world discount rate in that markets are more likely to be integrated the more volatile is the discount rate. Arshanapalli and Doukas (1993) document a significant change in the degree of international co-movements in five stock price indices since the crash of October 1987 and further reinforce the view that Japanese stock market had drifted far away from the world's major stock markets.

Studies using variations of the GARCH approach to investigate the spillover effects, due to their methodological nature, are often limited to a smaller set of stock markets. For instance, Hamao *et al.* (1990), Theodossiou and Lee (1993), Lin and Ito (1994), Susmel and Engle (1994) and Koutmos and Booth (1995) all report compelling evidence of some price and volatility spillovers radiate across the world's most developed stock markets.

Other researchers study the segmentation or integration of a particular market by pairing it with the US market. In a study using an international CAPM framework, Jorion and Schwartz (1986) find strong evidence of segmentation in the pricing of Canadian stocks relative to a global North American market. The rejection of integration even holds for Canadian stocks that are dual-listed on the US stock market. The authors attribute legal and regulatory barriers as a major source of segmentation. Mittoo (1992) re-examines the issue employing both the CAPM and the APT frameworks in a period that is relatively free from capital controls. The evidence in both frameworks suggests a move from segmentation to integration over time.

Gultekin *et al.* (1989) focus the integration between Japan and the US. Using multifactor asset pricing models, they show that the price of risk in the US and Japanese stock markets was different before, but not after the liberalisation, which offers support to the view that governments are the source of segmentation. Similarly, Campbell and Hamao (1992) show evidence of common movement in expected excess return across the US and Japanese markets, and thereby argue that the two markets are highly integrated though not perfectly. In contrast, Becker *et al.* (1992) report that the Tokyo stock market has only a small impact on US stock returns. Karolyi and Stulz (1996) study the daily return co-movements between the Japanese and US stocks from 1988 to 1992 and find evidence that correlations are high when there are significant markets movements. ‘This suggests that international diversification does not provide as much diversification against large shocks to national indices as one might have thought’ (Karolyi and Stulz, 1986: p.984). On balance, the bulk of the evidence has suggested that the Japanese stock market is tenuously integrated with other world’s major developed markets.

Parallel to the studies on major international stock markets, there is also a growing literature with a focus on stock markets within Europe. Using both bivariate and multivariate cointegration analyses, Corhay *et al.* (1993) reveal the existence of some long-run stochastic trends among five Western European stock markets in the late 1970s and 1980s. With a more up-to-date sample, Chan *et al.* (1997) employ the Johansen cointegration method and find little evidence of cointegration among a number of European stock markets. Meric and Meric (1997) indicate that correlations among the twelve largest European stock markets and between these market and the US market had increased substantially after the 1987 stock market crash. Using cointegration technique, Kanas (1998) finds that the US equity market is not pairwise cointegrated with any of its major European counterparts, which is in contrast to previous evidence on the linkages between the US and European markets.

Subsequent studies are centred on the issue of how the establishment of the EMU affects stock market integration among the EMU markets and major non-EMU markets: studies by Yang *et al.* (2003), Aggarwal *et al.* (2004), Fraser and Oyefeso (2005), Kim *et al.* (2005) and Hardouvelis *et al.* (2006) all acknowledge that the formation of EMU has significantly strengthened stock market integration among its constituent countries; the non-member countries (the UK and the US) are less influenced by, and contribute to, the increased integration. Hardouvelis *et al.* (2006) further suggest the integration in Europe as a Eurozone-specific phenomenon, independent of possible simultaneous world market integration.

In light of the ample empirical evidence in favour of integration, it may be fair to conclude that stock market integration is commonplace among developed countries.

2.4.2 Evidence from Emerging Markets

It is well documented that there has been a decline in the potential benefits of international diversification in developed stock markets, due largely to the increased levels of synchronicity displayed by these markets. Against this background, investors have recently focused to a greater extent than previously on underutilised emerging markets. For example, Goetzmann and Jorion (1999) find that the returns of a sample of emerging markets are three times higher than for a sample of developed markets. Such shift of interest has provoked a sheer volume of empirical works on the integration of emerging stock markets, which have so far yielded mixed results. For example, based on the estimation of the extent of stock market integration for twelve emerging markets during 1969-1992, Bekaert and Harvey (1995) challenge the common perception that world capital markets have become more integrated by showing that some countries are becoming less integrated into the world market. Most of the studies on stock market integration or interdependence in emerging markets have been done on geographical groups of markets, such as

in the Asian, Latin American, Central and Eastern European countries, often in conjunction with developed markets.

2.4.2.1 Evidence from Asian Stock Markets

The issue of financial market integration in Asia, particularly stock market integration, has been examined extensively in the literature. Pioneering work by Bailey and Stultz (1990) shows that up to 50% of a US investor's portfolio risk could be reduced if the stocks of Asian companies were included in his portfolio. Cheung and Ho (1991) and Cheung (1993) examine the correlation structure among eleven emerging Asian stock markets and developed markets and conclude that the correlation between the emerging Asian stock markets group and the developed market group is smaller than among the developed markets. Divecha *et al.* (1992) investigate ten emerging Asian stock markets and find that they are less correlated with each other and with the developed markets. Chan, *et al.* (1992) use a simpler Engle-Granger specification to examine Asian markets and report results in favour of segmentation. Chan, *et al.* (1997) expand their previous study, both in terms of the time period covered and in terms of the number of countries. They document a decrease in integration in the 1980's. Corhay, *et al.* (1995) address the significance of the regional aspects of the common stochastic trend in the stock markets among Pacific-Basin countries. They find that, in the long-run, there exists a geographical separation between the Asian and the Pacific markets.

The Asian financial crisis seems to have fundamentally altered the landscape of stock market integration among the Asian economies. Studies that employ sample period during and after the crisis generally find stronger ties within the region and with the US, see for example, Sheng and Tu (2000), Leong and Felmingham (2003), Yang *et al.* (2003), Click and Plummer (2005), Choudhry *et al.* (2007), Royfaizal *et al.* (2009), and Huyghebaert and Wang (2010). Others

disagree with this assertion and suggest the increased integration was the result of financial liberalisation that most Asian countries embarked on in the early 1990s. Ng (2002) finds the ASEAN markets had been more closely linked prior to the 1997 Asian financial crisis and attributes the increased linkage to the substantial financial liberalisation in these markets that begins in 1988. More convincing evidence against the claim that Asian financial crisis leads to greater integration is found in the recent study by Awokuse *et al.* (2009). They indicate that the wave of financial liberalisation policies in the early 1990s had led to a significant increase in linkages between Asian emerging markets and three developed markets, which were later weakened during the 1997 Asian financial crisis.

The role of US and Japan in leading the integration among Asian stock markets has been a contentious issue and empirical studies generally point towards the dominant role of the US market rather than the Japanese stock market. For example, Arshanapalli *et al.* (1995) find that the Asian stock markets are less integrated with the Japanese market than with the US market. Masih and Masih (1999) argue that Japan does not play a pivotal role in the non-crisis periods. Ng (2000) constructs a volatility spillover model to determine whether Japanese or US market factors are more important for the Pacific-Basin markets return volatility. Her results suggest greater importance of the US market in accounting for the return variations in the six markets considered. Siklos and Ng (2001) arrive at similar conclusion that the US stock market is the driving force in the Asian-Pacific stock markets. Ghosh *et al.* (1999) and Darrat and Zhong (2002) provide more dedicated studies on the issue. The study by Ghosh *et al.* (1999) suggests some Asian-Pacific stock markets are dominated by the US while some are dominated by Japan. Darrat and Zhong (2002) suggest that the US is the main permanent driving force behind major movements in eleven emerging Asian-Pacific stock markets while the effect of the Japanese market is only transitory.

Beakert (1995) demonstrates that emerging markets exhibit differing degrees of market integration.

This finding constitutes an important feature of the integration among Asian stock markets. Differing paces of Asian stock markets towards integration is perhaps firstly noted by Cheung and Mak (1992), who also argue that the US market generally leads the markets of Asia-Pacific except where countries have statutory restrictions on equity ownership by foreign nationals. This claim also receives support from Chowdhury (1994) and Chung and Liu (1994), both of which examine the interrelationship between the US and five East Asian countries, including Japan, Taiwan, Hong Kong, Singapore and South Korea. The former study finds that markets with severe restrictions on cross-country investing (i.e. Korea and Taiwan) are not responsive to innovations from other markets while the latter only suggests the segmentation of the Taiwanese market. Chelley-Steeley (2004) uses the nonlinear smooth transition logistic trend model to test for equity market integration in a sample of four Asia-Pacific countries (i.e. Korea, Singapore, Taiwan, and Thailand) over the period from January 1990 to January 2000. She finds that these markets have become progressively less segmented, both locally and globally, with local integration occurring at a faster pace than global integration with the region. Masih and Masih (1999) indicate that the four South-East Asian stock markets (i.e. Hong Kong, Singapore, Thailand and Malaysia) are explained mostly by their regional counterparts rather than developed stock markets of the US, the UK, Germany and Japan.

Studies that focus on the same group of Asian markets have frequently produced slightly different results. For example, Palac-McMiken (1997) concludes that the ASEAN markets are linked together with the exception of Indonesia; Sharma and Wongbangpo (2002) observe that the Philippine market does not share a long-run relationship with the other ASEAN markets; Click and Plummer (2005) suggest the five ASEAN markets sharing one cointegrating vector. The discrepancies arise chiefly due to the different sample periods scrutinised given these studies all employ cointegration technique. The inconsistent results may also serve as the evidence of increasing integration over time.

There is a tendency that most Asian stock markets have becoming increasingly integrated with the developed market or between themselves, with a lot of progress took place during the 1990s. On the question of the relative importance of regional versus global factors, the balanced view is that both factors are important to the Asian stock markets as a whole. However, their relative impacts on each individual stock market vary from one to another. From the perspective of the international investors, the benefits of international diversification by investing in the Asian region are reduced though not eliminated completely.

2.4.2.2 Evidence from Latin American Stock Markets

Although there is substantially less literature on stock market interdependence of emerging Latin American markets, all the available results point toward the increasing regional integration among these markets. Christofi and Pericli (1999) explore the short-run dynamics among the stock markets of Argentina, Brazil, Chile, Columbia and Mexico from 1992 to 1997. They model the joint distribution of stock returns using a VAR with errors following a multivariate EGARCH process and find evidence of first- and second-moment interactions among these markets. Choudhry (1997) investigates the long-run relationship between six Latin American stock markets (i.e. Argentina, Brazil, Chile, Colombia, Mexico and Venezuela) and the US market, and finds evidence of cointegration and significant causality among the six Latin American indices with and without the US index. Likewise, Chen, *et al.* (2002) investigate the interdependence of the same set of markets and find one cointegrating vector among these markets which is robust to conversion of a common currency and to partitioning the sample into periods before and after the Asian and Russian financial crises of 1997 and 1998, respectively. Barari (2004) finds a pattern of increased regional, relative to global, integration for most Latin American markets during the late 1980s and the first half of the 1990s. However, the pace of global integration accelerated around

the mid-1990s, and has outpaced regional integration in recent years.

2.4.2.3 Evidence from Central and Eastern European Stock Markets

The emerging markets of Central and Eastern Europe (CE thereafter) have been investigated to a smaller extent. Linne (1998) reports evidence of cointegration between the CE markets, although no cointegration relations with mature markets are found. MacDonald (2001) analyses the stock market indices of CE countries, as a group, against each of three developed markets (the UK, Germany, and the US). He documents significant long-run relations for each of the groupings. Jochum *et al.* (1999) scrutinise the effect of the 1997–1998 Russian crises on the long-run relations between the Visegrád countries (i.e. the Czech Republic, Hungary, and Poland), Russia, and the US. Bivariate cointegration relations found in the pre-crisis period cease for all but two pairs of markets due to the predominance of short-run dynamics in the post-crisis period. In contrast to this, however, Gilmore and McManus (2002) find no long-run links between the three CE markets and the US. These authors focus exclusively on the interactions with the US market, leaving out any connections with the important European stock markets. Voronkova (2004) investigates the existence of long-run relations between emerging Central European stock markets and the mature stock markets of Europe and the US and obtain stronger evidence in favour of integration by allowing for a structural break in cointegrating relations. Scheicher (2001) studies the spillover effects between the stock indices of Hungary, Poland and Czech Republic and a world equity portfolio. He finds both regional and global return spillovers, whereas for volatilities regional influences tend to dominate. Gelos and Sahay (2001) report mild shock propagation across CE stock markets during the Czech and Asian crises, but higher frequency spillovers during the Russian crisis. The authors further stress that, with greater financial market integration in the region, the stock markets of CE countries will behave more like their Asian and Latin American counterparts.

2.4.3 Evidence from Cross-Listed Stocks

The aforementioned studies primarily conduct their analyses at broad market index level. The increasing popularity of international cross-listings has engendered another strand of literature that looks at the price convergence and interaction between cross-listed stocks, which provides a microscopic view of stock market integration. Since this branch of research does not form part of the thesis, here we briefly overview a small number of articles written on the topic.

Garbade and Silber (1979) provide one of the earliest studies on dual-listed stocks that are traded in the US. They analyze NYSE and regional exchange trading patterns as well as their contribution to the price discovery. They observe asymmetrical adjustment to equilibrium price between different trade centers such that NYSE acts like a ‘dominant’ market whilst regional exchanges are best characterised as ‘satellites’. Werner and Kleidon (1996) analyse British cross-listed stocks that were trading on the US and the UK exchanges and find the intraday pattern for these stocks closely resemble those of otherwise similar non-cross-listed stocks. Kim, *et al.* (2000) examine the transmission of stock price movements between the ADRs and their respective foreign underlying stocks and note that the price differentials are too small to be exploitable in the presence of transaction costs. Eun and Sabherwal (2003) find that a sample of Canadian stock listed on both the Toronto Stock Exchange and a US exchange are cointegrating and mutually adjusting. Agarwal *et al.* (2007), using a sample of Hong Kong-listed stocks that are also traded on the London Stock Exchange, find the stock returns from London trading are closely correlated with those of the Hong Kong market and the London market plays a limited role in price discovery. The evidence of dual-listed stocks in the developed markets generally is largely in favour of integration and is broadly consistent with the law of one price.

However, studies on the dual-listed Chinese A- and H-shares often arrive at the opposite

conclusions. Peng *et al.* (2007) observe large and persistent price differentials between A- and H-share prices. Chong and Su (2006) also find little evidence on the comovement of the dual-listed Chinese A- and H-shares. The results from these studies explicitly support the segmentation between the Mainland Chinese stock markets and the Hong Kong market.

2.4.4 Evidence from Greater China Region

While Hong Kong and Taiwan have been common targets for empirical research, Mainland China has received scant attention in the Asian stock market integration literature, partly because of the underutilisation of the Chinese stock market for international diversification as the result of the direct and strict impediments to foreign investment that were in place. In recent years, the success of the Mainland Chinese economy and its ongoing liberalisation process to open up its stock markets has motivated a number of studies on the integration of the Mainland Chinese stock markets, among which only a handful few have examined the trend with the world's major stock markets rather than regional integration within the Greater China region.

The isolation of the Mainland China's stock markets before and during the 1997 Asian financial crisis has been well documented. For example, Huang *et al.* (2000) examine the bivariate cointegration and causality among the stock markets of the Greater China region (i.e. Shanghai, Shenzhen, Hong Kong and Taiwan), Japan, and the US using daily data in local currencies from October 1992 to June 1997. They note a strong interaction between Shanghai and Shenzhen, but find these two Mainland markets hardly interact with the other markets in the sample. Huyghebaert and Wang (2010) report that the Asian financial crisis has strengthened the linkages among stock markets in East Asia, except for those in Mainland China.

While the lack of integration was commonly found in most Asian stock markets prior to the Asian

financial crisis, it is striking that the isolation of the Mainland Chinese stock market continues thereafter. Hsiao *et al.* (2003) confirm China's isolation in a multivariate VAR model using daily local currency data from China, Taiwan, South Korea, Japan and the US from September 2001 to December 2002. Similar conclusion is reached by Bahng and Shin (2003) with a much longer sample period that spans from 1991 to 2000. Groenewold *et al.* (2004) find a strong contemporaneous relationship between the two Mainland markets but the two Mainland markets are relatively isolated from the neighbouring markets of Hong Kong and Taiwan. Few exceptions are Wang and Firth (2004) who obtain evidence of bidirectional return spillovers between the Chinese stock markets and the three developed international markets after the 1997 Asian financial crisis, and Cheng and Glascock (2006) who suggest more harmonious market comovement between the Chinese and the US stock market after the Asian financial crisis. Similarly, Tian (2007) find that the Shanghai A-share market uni-directionally Granger-causes the other regional markets after the Asian financial crisis, while the A-share market and Hong Kong H-share market have had a significant feedback relationship since then.

Wang and Di Iorio (2007) test the segmentation versus integration of the three classes of shares in Mainland Chinese stock markets with the Hong Kong and the world stock markets, using the Jorion and Schwartz (1986) model. Brooks *et al.* (2007) test the segmentation versus integration of Chinese A-share market and the US market by extending the Jorion and Schwartz (1986) model to a Fama-French (1993) framework. The results from both studies support the segmentation hypothesis. The authors of both studies attribute the lack of integration to the government's tight grip on foreign investment into the Chinese stock markets.

Studies dealing with the return correlations between the stock markets of Mainland China and other countries are very scarce while previous research overwhelmingly focuses on the correlation structure between the two domestic stock markets – the Shanghai and Shenzhen Stock Exchanges

or between the two classes of shares available on these two markets – the A-share and B-share. Chiang *et al.* (2007) document the time-varying correlations between A-share and B-share stock returns, which are not only significantly related to the trend factor but also associated with excessive trading activity. The correlation between these two classes of shares has also increased since the relaxation of the restriction on B-share market investments by domestic investors. In the sample period covering 15-year history of Chinese markets up to December 2006, Lin *et al.* (2009) show that the Mainland Chinese A-share indices have never been correlated with world markets while the B-share indices exhibit a low degree of correlation with Western markets and a slightly higher degree of correlation with other Asian markets – a finding in contrast to their expectation of a general upward trending correlation.

Taken together, the general consensus from these studies is that the Mainland Chinese stock market remains to be segmented or weakly integrated with its global counterparts. The prolonged segmentation of the Mainland Chinese stock markets has made itself a peculiar case for researchers, given the spectacular economic growth and fast financial development of Mainland China.

The results emerge from studies that cover the period of 2007-2009 global financial crisis echo greater integration between Mainland China and Hong Kong, and between Mainland China and the US. Sun and Zhang (2009) document significant price and volatility spillovers from the US and Hong Kong to Mainland China during the course of the US subprime mortgage crisis, suggesting Mainland China is no longer immune to external financial turmoil. Yi *et al.* (2010) confirm fractional cointegration relations between Mainland China and Hong Kong, and between Mainland China and the US. They also suggest the Mainland Chinese stock market has been experiencing stronger ties with both the US and Hong Kong in recent years.

2.4.5 Concluding Remarks

While the literature has pointed out a high degree of stock market integration among developed stock markets, particularly after the 1987 stock market crash, the degree of stock market integration in emerging countries remains open and vigorously examined with studies generally provide mixed results. The disparity in results throughout the literature is presumably attributable to the wide range of sample periods, sampling frequencies and national stock markets scrutinised, as well as different methodologies employed. Since the Asian financial crisis, there has been mounting evidence that emerging stock markets, particularly those in Asia, have become increasingly integrated at regional and/or international level. The Mainland Chinese stock markets, on the other hand, have not received much attention from researchers until recently. Much of the research on the integration of Mainland China stock markets is carried out and largely confined to the Greater China region or pairing with the US market. The issue is further complicated by the large deviation in empirical results. As China's burgeoning stock markets continue to expand and undergo structural changes, there is an urgent need of using most up-to-date data to systematically study the extent and nature of stock market integration, if any, in Mainland China.

2.5 Implications of Increased Stock Market Integration

Despite the abundant evidence of increased stock market integration, the ramifications of such results have not been clearly spelt out and need to be acknowledged. The nature and extent of stock market integration has important implications for corporate managers as it influences the cost of capital, and for investors as it influences international asset allocation and diversification benefits. To wider extent, stock market integration also has broad implications for economic growth and financial stability.

Interest in stock market integration arises primarily because financial theory suggests that an integrated stock market is more efficient than a segmented one. With an integrated world or regional stock market, investors from all member countries will be able to allocate capital to the locations in the region where it is more productive. With more cross-border flows of funds, additional trading in individual securities will improve the liquidity of the stock markets, which will in turn lower the cost of capital from firms seeking capital and lower the transaction costs investors incur (Click and Plummer, 2005).

At company level, the extent of integration among stock markets will have important bearings on the formulation of financial policies of multinational corporations (Masih and Masih, 1999). Knowledge of stock market interdependence would help managers to assess the potential benefits and risks of raising capital in foreign markets, to infer and mitigate the risks of conducting business on foreign soil, and to allocate capital to its most productive use, all of which will consequently lead to a reduction in the cost of capital.

Market participants who trade financial securities in multiple capital markets should be cognizant of the implications of stock market integration. For portfolio managers, highly integrated national stock markets would imply reductions in the benefits of portfolio diversification, such that portfolio managers would need to actively adjust their portfolios in search of assets with lower correlations (Evans and McMillan, 2009); for active traders, investigation of stock market interdependence, particularly the short-run dynamics across national stock markets, inform them about the existence of potential arbitrage opportunities across markets.

The issue of stock market integration has strong implications for international portfolio diversification. On the one hand, closer integration facilitates greater capital mobility and investors would invest capital in countries which offer the highest returns. The lifting of policy on

cross-border capital controls and capital restrictions makes international diversification easier and accessible. Hence, in the world of perfect capital mobility, investors will have significant opportunities to diversify their portfolio to eliminate country-specific risks and achieve higher returns. On the other hand, with increasing integration, the diversification benefits diminish as correlations between national stock markets strengthen and become increasingly positive. Cross-border diversification would not be justified given the main motive of which is to take advantage of the low correlation between stocks in different national markets. From the view point of arbitrageurs, integration leads to return equalisation of assets with similar risk exposures and economic fundamentals (for example, cross-listed stocks), and thus significantly weakens the prospect of profitable arbitrage.

Intensified financial linkages in a world of high capital mobility may also increase the risk of cross-border financial contagion, in particular when the economies of these countries become more interdependent. Should this be the case, then international diversification would be of little use since it may fail to function at exactly the time when its risk-reducing benefits are most desired (Bookstaber, 1997). Goetzmann *et al.* (2005) collect information from 150 years of global equity market history and demonstrate that diversification benefits are non-constant and may be least available when they are most needed.

With regard to economic growth, some economists (Goldsmith, 1969; King and Levine, 1993a, 1993b; Levine and Zevros, 1998; Demirguc-Kunt and Levine, 2001; and Bekaert *et al.*, 2003) suggest enhanced stock market integration being a major cause of economic development. The main drivers of this increased development are typically seen to be the increased rigour of legal practices, the increased supply of capital to local economies, and the increased competitive forces acting on local financial intermediaries.

Stock market integration would benefit national markets involved through more efficient allocation of capital, greater opportunities for risk diversification, a lower probability of asymmetric shocks and a more robust market framework. These effects would help improve the capacity of the economies to absorb shocks and foster development, thus promote greater financial stability. However, as markets become more integrated, it becomes more difficult for regulatory authorities to pursue financial policy independently because the extent of the effectiveness of the monetary, fiscal, wages and exchange rate policies of each country in dealing with its imbalances, such as trade and fiscal, will depend crucially on the extent of that country's financial integration with the rest. Any shocks from other markets should be taken into consideration by the authorities to design policies pertaining to its stock market. In light of the closer market linkage, there is an imperative need for policy coordination among these countries to mitigate the impacts of financial fluctuations.

While the preponderance of the literature finds that stock market integration enhances financial stability, a number of studies contend that intensified linkage among international stock markets may also harbour the risk of cross-border financial contagion such that shocks that impact on one stock market may potentially spread to others more rapidly (Yu *et al.*, 2007). They forcefully point to the plethora of developing country financial crises that swept across Asia, Latin America and Central and Eastern Europe in the 1990s as clear evidence of the potentially disastrous consequences of capital market integration. The repeated occurrence of these large-scale financial crises has motivated a reappraisal of the common view that capital mobility and integration bring unalloyed benefits. If stock market integration is a policy-induced phenomenon and does contribute to the severity and duration of the crisis, then regulatory authorities may deliberately slow the pace of its financial liberalisation process or strengthen inter-country financial cooperation to avoid the likely pitfalls of such integration.

To sum up, the extent of stock market integration has important implications to market participants and financial regulators. On the one hand, stock market integration facilitates better risk-sharing and allocative efficiency, which further stimulate economic growth. It also enhances financial stability, at least in the long run. Nevertheless, such benefits may be counterbalanced by the reduced attractiveness of international portfolio diversification and the increasing complexity of policy coordination among different countries. Lastly, stock market integration may heighten a country's vulnerability to macroeconomic and financial crises. The merits of stock market integration remain a matter of vigorous debate.

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Chapter 3 – Long-Run Comovement between the Mainland Chinese Stock Market and Four Developed Stock Markets

3.1 Introduction

This chapter explores the long-run comovement between the Mainland Chinese stock market and four other developed stock markets, namely, New York, London, Tokyo and Hong Kong. The question is primarily addressed through the examination of whether there exists a long-run cointegrating relationship among these markets. How much of the variance of local stock market return is explained by innovations from other markets is another genuinely interesting question. We attempt to answer the second question using the techniques of Variance Decomposition (VDC) and Impulse Response Function (IRF).

At a substantive level, the present chapter aims to remedy some of shortcomings of the extant literature on the issue of stock market integration of Mainland China. In particular, we acknowledge that ignoring the possibility of structural change and time-variation can affect the power of conventional cointegration tests and the relevance of their conclusions about the presence/absence of cointegration. While previous research generally finds no cointegration between the emerging Chinese and other developed stock markets, by incorporating a structural break, we document a number of significant cointegrating relationships from the stock market pairs involving the Shanghai A-share market and one of the four developed markets. The dynamic cointegration tests conducted in a multivariate framework also reveal substantial periods of comovement among these markets. Our results illustrate how conventional cointegration techniques may be appropriately augmented in a compatible fashion to unearth previously unfounded long-run linkage inherent amongst a system of stock market index prices.

While there is evidence that the Mainland Chinese stock market is in a process of integrating further with several developed stock markets, there are still periods when foreign investors are able to exploit the benefits of portfolio diversification into the Chinese A-share market. This is believed to have great practical implication to the participants of the QFII scheme.

The remainder of this empirical chapter is organised as follows: Section 2 introduces the notion of cointegration, its testing procedures, and the supplementary analyses of cointegration test; Section 3 briefly reviews the extant literature; Section 4 describes the data as well as the necessary modifications of which; Section 5 presents and discusses the empirical results; and Section 6 concludes the issue.

3.2 Methodology

3.2.1 Cointegration Analysis

Cointegration has an intuitive appeal to researchers of stock market integration. The concept was originally introduced by Engle and Granger (1987), who posit that cointegration exists among non-stationary time series that move stochastically together towards some long-run stable relationship. Since its development, the notion of cointegration has been rapidly assimilated into applied work. One of the pioneers of introducing cointegration into the analysis of stock market integration is Taylor and Tonks (1989), who conduct the tests using the Engle-Granger two-step method in a bivariate setting. Under this simple approach, the cointegrating relationship is estimated as such:

$$Y_{1t} = \alpha + \beta Y_{2t} + \varepsilon_t \tag{Eq.(3.1)}$$

where Y_{1t} and Y_{2t} represent logged prices of two national stock indices at time t respectively, both series follow $I(1)$ processes (i.e. they are integrated of order one). Coefficients α and β are the estimated cointegrating parameters and the residual term ε_t must be stationary and integrated of order zero, $I(0)$, should Y_{1t} and Y_{2t} to be cointegrated.

Cointegration also provides a logical extension to the idea of error-correction modelling, which has now been applied widely throughout the literature. The Granger Representation Theorem (Engle and Granger, 1987) suggests if a set of variables are cointegrated then an error correction model (ECM) must also exist. An ECM derived from the cointegration equation above can be expressed as:

$$\Delta Y_{1t} = \gamma \hat{\varepsilon}_{t-1} + \sum_{i=1}^n \delta_i \Delta Y_{1,t-i} + \sum_{i=1}^n \theta_i \Delta Y_{2,t-i} + \mu_t \quad \text{Eq. (3.2)}$$

where the error correction term (ECT), $\hat{\varepsilon}_{t-1}$, captures deviations from the long-run cointegration relationship. The coefficient of the ECT, γ , measures the proportion by which the long-run disequilibrium in the cointegrating relationship is being corrected in the short-run. Intuitively, a negative (positive) and large coefficient indicates a great effort of the dependent variable ΔY_{1t} (ΔY_{2t}) in restoring the long-run equilibrium. The combination of cointegration and its descended ECM helps researchers to effectively discern the short- and long-run components of dynamic linkages among series.

Because of events like episodes of financial crisis, global macroeconomic shocks, abrupt policy changes, and so on, models with constant coefficients have been found to perform poorly, particularly over long periods. The solutions to this problem have been models with structural break(s). Gregory and Hansen (1996) show that the power of traditional cointegration tests

deteriorates in the presence of structural break and failure to account for such structural change may erroneously signal the absence of cointegration among series. The Gregory-Hansen cointegration test incorporates the possibility of a break in the cointegrating relation at an unknown point in time. The test encompasses three alternative model specifications accommodating changes in parameters of the cointegrating equation. A level shift model allows for a level break only in the intercept:

$$Y_{1t} = \alpha_1 + \alpha_2 D_t + \beta Y_{2t} + \varepsilon_t \quad \text{Eq.(3.3)}$$

The second specification includes a trend term while allowing for a level break in the intercept:

$$Y_{1t} = \alpha_1 + \alpha_2 D_t + \beta Y_{2t} + \gamma t + \varepsilon_t \quad \text{Eq.(3.4)}$$

The third specification allows for a structural break both in the intercept and in the slope of the explanatory variable, such that:

$$Y_{1t} = \alpha_1 + \alpha_2 D_t + \beta Y_{2t} + \beta Y_{2t} D_t + \gamma t + \varepsilon_t \quad \text{Eq.(3.5)}$$

The dummy variable D_t which captures the structural change is represented as:

$$D_t = \begin{cases} 0, & t < n \\ 1, & t \geq n \end{cases} \quad \text{Eq.(3.6)}$$

where t is the total number of observations, n is the n th observation where the structural change occurs.

While the implementation of the Gregory-Hansen methods may provide additional insight, they are still bivariate in nature and thus are not capable of detecting cointegration for more than two series. In a series of papers, Johansen (1988, 1991) and Johansen and Juselius (1990) remedy this problem by considering cointegration in a multivariate framework, which allows for a more thorough delineation of interactions amongst a multivariate set of stock markets. As summarised in Masih and Masih (1999: p.258-9), the Johansen procedure possesses several advantages over the residual-based Engle-Granger two-step approach in testing for cointegration: first, the Johansen method does not, a priori, assume the existence of at most a single cointegrating vector, rather it explicitly tests for the number of cointegrating relationships; second, it assumes all variables to be endogenous and is insensitive to the choice of dependent variable; third, it estimates and tests cointegrating relations within the formulation of the vector error-correction model (VECM); Johansen and Juselius (1990) provide the appropriate statistics and the point distributions to test hypothesis for the number of cointegrating vectors. The Johansen cointegration test is initially applied by Kasa (1992), who notes that in a system with k indices, a condition for complete integration is that there be $k - 1$ cointegrating vectors. Therefore, as the process of market integration deepens, there should be a reduced number of independent stochastic trends governing the stock markets behaviour and an increasing number of cointegrating vectors which would constitute evidence of increasing market integration.

Here we provide a brief discussion of Johansen's maximum likelihood approach to testing for cointegration.¹² If k variables are cointegrated of order r , we may impose this constraint upon a k -dimensional vector autoregressive process of p th order to enable a VECM formulation, which can be expressed as:

¹² Since discussion on the econometrical properties of Johansen cointegration test would take us too far afield, the reader is encouraged to consult Johansen (1990) for more detail.

$$\Delta Y_t = \mu + \sum_{i=1}^{p-1} \Gamma_i \Delta Y_{t-i} + \Pi Y_{t-k} + \varepsilon_t \quad \text{Eq. (3.7)}$$

where Δ is the first-difference operator, Y_t is a $(k \times 1)$ random vector of time series variable integrated of order one or less, μ is a $(k \times 1)$ vector of constants, Γ_i are $(k \times k)$ matrices of parameters, ε_t is a sequence of zero-mean p -dimensional white noise vectors, and Π is a $(k \times k)$ matrix of parameters the rank of which contains information about long-run relationships among the variables.

Granger's representation theorem asserts that if the coefficient matrix Π has reduced rank $r < k - 1$, then there exist $k \times r$ matrices α and β each with rank r and such that $\Pi = \alpha\beta'$, where the columns of the matrix α are adjustment (or loading) parameters in the VECM and the rows of the matrix β are the cointegrating vectors, with the property that $\beta'y_t$ is stationary even though Y_t may comprise of individually non-stationary processes. r is the number of cointegrating relations and each column of β is the cointegrating vector.

Johansen's procedure essentially boils down to determine the rank of the Π matrix from an unrestricted VAR and to test whether we can reject the restrictions implied by the reduced rank of Π . If we find that Π has rank r , we then conclude that there are r cointegrating relationships among the elements of Y_t , or equivalently, $k - r$ common stochastic trends. The test generates two statistics of primary interest: the first is the trace statistic (denoted λ_{trace}), which is a joint test where the null is that the number of cointegrating vectors is less than or equal to r against an unspecified alternative that there are more than r ; the alternative test statistic is the maximum-eigenvalue statistic (denoted λ_{max}), which allows testing of the precise number of cointegrating vectors, r , against an alternative of $r + 1$. The two test statistics are formulated as:

$$\lambda_{trace}(r) = -T \sum_{i=r+1}^k \ln(1 - \hat{\lambda}_i) \quad \text{Eq. (3.8)}$$

and

$$\lambda_{max}(r, r + 1) = -T \ln(1 - \hat{\lambda}_{r+1}) \quad \text{Eq. (3.9)}$$

The problem with traditional cointegration techniques (for example, the static Engle-Granger and Johansen cointegration tests) is that they fail to recognise the existence of a cointegrating relationship that is changing over time, particularly when stock market integration is going through a transitional phase. Applying dynamic cointegration methodology using rolling or recursive samples can overcome this problem by explicitly taking into account of such time variation: the rolling cointegration analysis acknowledges the possibility that series may be more cointegrated in certain subsample than in others and allows us to detect potential multiple structural break points in a data-determined manner; the recursive cointegration analysis – a procedure that is initially presented in Hansen and Johansen (1999), investigates whether stock indices have become increasingly integrated as time passes. Unlike rolling estimation which facilitates us to investigate the degree of convergence during different subsamples, recursive estimation assumes that the system is evolving to some final form and thus is used to study the dynamics of convergence for the full sample of observations. Hence, the results from dynamic cointegration analysis could be especially insightful when there are continuous changes in the cointegrating parameters.

Under the dynamic cointegration approach, both λ_{trace} and λ_{max} statistics can be plotted over time to examine how the nature of market integration is evolving over time. The output of this practice is twofold: first, the largest λ_{trace} or λ_{max} statistic which tests the general hypothesis of no

cointegration versus cointegration; second, the number of cointegrating vectors given by the test statistic. A set of series that are in the process of converging should be expected, as in Hansen and Johansen (1999) and Rangvid (2001), to show increasing numbers of cointegrating vectors. Alternatively, if we have a static number of cointegrating vectors then recursive estimation will simply lead to an upward trend in the test statistic (Aggarwal *et al.*, 2004).

3.2.2 Cointegration and Market Efficiency

Studies on stock market integration tend to make reference to market efficiency hypothesis based on the finding of cointegrating relationship (see for example, Palac-McMiken, 1997; and Chan *et al.*, 1997). Granger (1986) first suggests that cointegration among prices of different stock market indices implies an informationally inefficient market because the ECM would indicate that at least one of the price is predictable. This view is later shared by Taylor and Tonks (1989), who contend that the presence of a significant cointegrating relationship is sufficient to establish joint market inefficiency in the sense that international investors are able to explore arbitrage opportunities. This proposition has since opened a new venue for testing market efficiency with cointegration test serving as the standard tool.

The link between the presence of cointegrating relationship and market efficiency, however, has been subject to dispute. For example, Dwyer and Wallace (1992) effectively demonstrate that this claim is false. With market efficiency defined as the lack of arbitrage opportunities, they assert that there is no general equivalence between market inefficiency and cointegration. They also show that whether asset prices are cointegrated is a function of the relevant model. Their view is further reinforced by Engel (1996) who argues that cointegration or lack of cointegration has nothing to do with international capital market efficiency. Baillie and Bollerslev (1989) and Crowder (1996) show that the correspondence between cointegration and efficiency is weak and

that empirical finding of cointegration may stem from sources other than inefficiency. Specifically, Crowder (1996) identifies four sources for the existence of cointegration: markets are inefficient and traders are indeed wasting valuable information; markets are efficient but there exist some omitted factors, such as a risk premia or regime switches, that manifest themselves as cointegration; markets are inefficient but agents are ignoring the information from the ECM because it cannot engender significant profits; and finding of cointegration is due to questionable statistical properties of the tests. At very least, one must practice caution in concluding cointegration or the lack thereof, implies anything about market efficiency. Furthermore, Caporale and Pittis (1998) show that the role of cointegration test on asset prices lies primarily in the identification of price predictability and that this can be investigated without referring to the question of market efficiency. Hence, for the purpose of this study, cointegration that links different stock markets is interpreted as evidence of predictability, but we are refrained from making an inference with regard to market efficiency.

3.2.3 Variance Decomposition and Impulse Response Analysis

The VECM or VAR is frequently supplemented by impulse response function (IRF) and variance decomposition (VDC) in the literature.¹³ IRFs trace out the responsiveness of one variable to shocks to each of the other variables in the VAR; VDC measures the proportion of the movements in one variable that are due to its 'own' shocks, versus shocks to the other variables. VDCs determine how much of the s-step-ahead forecast error variance of a given variable is explained by innovations to each explanatory variable. Both IRFs and VDCs are obtained from the moving average (MA) representation of the original VAR model and often offer very similar information.

¹³ The VECM expressed in Eq.(3.3) reduces to an orthodox VAR model in first-differences if the rank of Π is zero (i.e. no cointegration among the set of variables). As for the discussion of IRF and VDC, VECM and VAR are used interchangeably.

The results based on standard VDCs and IRFs are generally found to be sensitive to the lag length used and the ordering of the variables since the errors of different equations in VAR are orthogonalised through Choleski decomposition. The generalised IRFs circumvent this problem as they do not assume that all other variables are switched off when one variable is shocked.

The IRFs and VDCs are useful additions to cointegration analysis and the collective use of these techniques will provide a more complete picture of the dynamic properties of a VAR or multivariate cointegrated system.

3.3 Literature Review

Johansen multivariate cointegration methodology was popularised by Kasa (1992) and had been the catalyst for the burgeoning literature on the long-run comovements between national stock markets in the 1990s. Other notable studies employing the Johansen method include: Chung and Liu (1994) and Corhay *et al.* (1995) on Pacific-Rim country stock markets, Blackman *et al.* (1994) on seventeen OECD markets, Chan *et al.* (1997) on eighteen international stock markets, Masih and Masih (1997a, b, 1999, and 2001) on a mix of Asian and established OECD stock markets, Sheng and Tu (2000) on twelve Asian-Pacific stock markets, Yang *et al.* (2003) on the US, Japan, and ten Asian emerging stock markets.

Investigations into the existence of long-run stock market relations have traditionally focused on the mature markets (i.e. markets of Western Europe, the US and Japan) and the emerging markets of Asia. While Hong Kong and Taiwan have been common targets for empirical research, Mainland China has much less exposure in the stock market integration literature. This is partly because of the underutilisation of the Chinese stock market for international diversification due to

the direct and strict impediments to foreign investment that were in place. In recent years, the success of the Mainland Chinese economy and its increasingly important role in the global financial market have motivated a number of studies on the linkage between the Mainland Chinese stock market and those of developed economies (for example, see Huang *et al.*, 2000; Cheng and Glascock, 2005; and Tian, 2007). Huang *et al.* (2000) conduct pair-wise cointegration among the stock markets of the US, Japan, and the Greater China region and find no cointegration except for that between Shanghai and Shenzhen. Restricting cointegration analysis to pairs precludes the possibility of finding more than one cointegrating relations. In a subsequent study, Cheng and Glascock (2005) examine the linkage of the same set of markets in the Johansen multivariate framework and conclude that the markets in the Greater China region are not cointegrated with either the US or Japan. With a more updated sample, Tian (2007) document the existence of a cointegration among the Chinese A-share, Hong Kong and Taiwanese stock markets and to less extent the US market in the post-Asian financial crisis period. A very recent study by Yi *et al.* (2010) makes a methodological advance by extending the VECM to the fractionally integrated VECM in examining the comovements of the China's A-share market with the US and Hong Kong markets. Their empirical results show that the China's A-share market is fractionally cointegrated with the aforementioned stock markets, and the tie with Hong Kong market is stronger than with the US market.

While studies have generally found no cointegration between the emerging Chinese and other developed stock markets, the experience in recent years has led market participants, the media and financial regulatory authorities alike to conjecture that the Mainland Chinese stock market has become increasingly integrated with world's major stock markets. However, this widely held view may stem from a biased impression of anecdotal evidence and thus would require a careful empirical investigation.

Despite a large body of literature written on the integration among emerging stock markets and between emerging and developed stock markets, the existing empirical evidence remains ambiguous and has yielded conflicting results, which leads naturally to the question of why there are differences in results. In order to reconcile the ambiguity in past studies, some researchers argue that the mixed results may be due to the time-varying nature of international stock market interrelationships. Any attempt to model the integration of stock markets without taking account of such time variation may yield confusing and partial results. Among the numerous studies that employ the notion of cointegration to investigate the long-run interdependence between international stock markets, relatively few papers have devoted their effort in exploring the stability of such long-run equilibrium. Following the work of Hansen and Johansen (1999) on recursive cointegration analysis, recursive and rolling cointegration techniques have gained their popularity and have been frequently applied to the literature of stock market integration, since they explicitly address the potential time-variation in the long-run relationship among national stock indices. Early work by Rangvid (2001) uses recursive approach to examine the convergence among the three major European stock markets and suggests these markets were being increasingly integrated throughout the 1980s and 1990s on the basis of an upward trending trace statistics. This finding, however, might be an artifact due to the continuous enlargement of the sample size rather than a genuine integration process. To this end, Pascual (2003) proposes to conduct rolling cointegration test with a constant sample size as the estimation rolls over to the next period. Under the rolling cointegration analysis, an upward trend in the test statistics can then be interpreted as evidence of increasing convergence. Based on the rolling estimation approach, Pascual (2003) finds no evidence of increasing cointegration among the same group of European stock markets in Rangvid (2001).

3.4 Data

This study uses daily closing prices for five stock market indices. They are Shanghai Stock Exchange A-Share Index (SH) for Mainland China,¹⁴ New York Stock Exchange Composite Index (US) for the US, Financial Times Stock Exchange All-Share Index (UK) for the UK, Tokyo Stock Price Index (JP) for Japan, and Hang Seng Index (HK) for Hong Kong. These stock market indices are chosen because each represents the largest possible proportion of its respective market, whether in terms of capitalisation or turnover. The stock markets of the US, UK, Japan and Hong Kong as a whole are thought as a good representation of the world's developed markets.¹⁵ Unlike some prior studies (for example, Arshanapalli and Doukas, 1993) which use Dow Jones Industrial Average and Nikkei 225, we choose NYSE Composite Index and TOPIX to represent the stock markets of the US and Japan respectively, so that all five stock indices in this study are capitalisation-weighted. Since it is generally agreed that cointegration tests pertain to the long-run and only impart economic significance when examined over sufficiently long time horizons, our data is taken over the period Jan 1st 1993 – March 31st 2010 from Datastream, covering almost the entire history of the Shanghai Stock Exchange.

A technical problem we encounter is the existence of nonsynchronous holidays among the stock markets being considered. If one market is closed due to national holidays, bank holidays or other special occasions, the data for other markets are eliminated to avoid nonsynchronous holiday bias. The holiday-adjusted sample contains 3845 observations. All data are presented in natural logarithms.

¹⁴ We choose Shanghai Stock Exchange to represent the Mainland China's stock market since the other stock exchange – Shenzhen Stock Exchange is relatively small and its price movement is almost perfectly correlated with that of Shanghai Stock Exchange. Substituting Shanghai Index with Shenzhen Index for cointegration analysis yields almost identical results.

¹⁵ Under the taxonomy of Morgan Stanley Capital International, Hong Kong is categorised as a developed market.

Daily data is chosen since lower frequency data may fail to capture the additional information content embedded in the data series. However, it has been argued that frequency of data (i.e. daily, weekly, and monthly) likely has only limited effects on the cointegration analysis, as Hakkio and Rush (1991) have shown that, given a fixed sample period, cointegration test would yield identical results regardless of the number of observations. However, they did not demonstrate the validity of this argument in a multivariate setup.

When working with stock prices denominated in several currencies, we encounter a practical question of whether these prices should be converted into a common currency. There are those that make the conversion such as Taylor and Tonks (1989), Kasa (1992), DeFusco *et al.* (1996), Masih and Masih (1999), there are others who use stock prices in local currencies, for example, Chung and Liu (1994) and Ghosh *et al.* (1999), as well as those conduct their analyses in both settings, for example, Hassan and Naka (1996) and Manning (2002). According to Fratzscher (2002), the underlying assumption of using prices in local currencies is that investors are able to hedge at least some of their foreign exchange exposure. Using prices denominated in a common currency would assume that investors are not able to hedge any of their exposure. This may also introduce a bias in that a high degree of integration may simply be due to a similarity in exchange rate changes rather than direct stock market integration.

Tsutsui and Hirayama (2004) suggest that if the dominant cause of the stock price comovements were real shocks common to many countries, exchange rates would not play a leading role in stock price linkage; if active portfolio adjustments by international investors are the chief cause of the linkage, exchange rates must be a contributing factor in stock market interdependence, since investors compute stock returns in their local currency. For example, Hassan and Naka (1996) conduct cointegration tests both in local currency and in common currency (the US dollar) and find that cointegration is detected only in the case of local currency. This might be an indication

that portfolio adjustments are not an important factor in stock price comovements. Following Hassan and Naka (1996), Manning (2002) and others, we conduct our analysis in both local currencies and common currency. In the common currency case, we assume the viewpoint of the US investors and thus convert all index prices into US dollar. The nominal stock index prices in local and common currencies (rebased to 100) are plotted in Figure 3.1 and 3.2.

Figure 3.1 Stock Index Prices (Local Currencies)

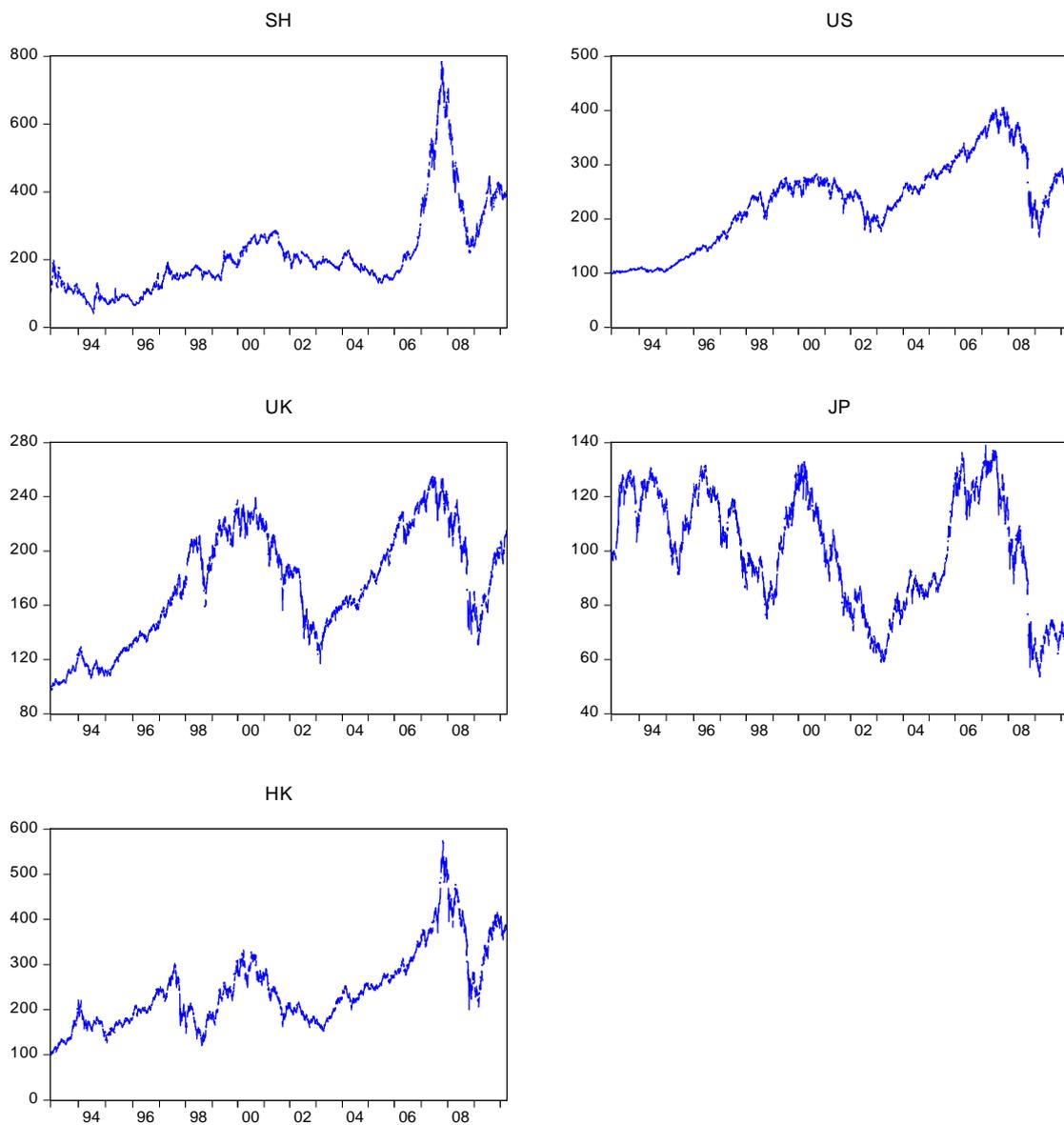
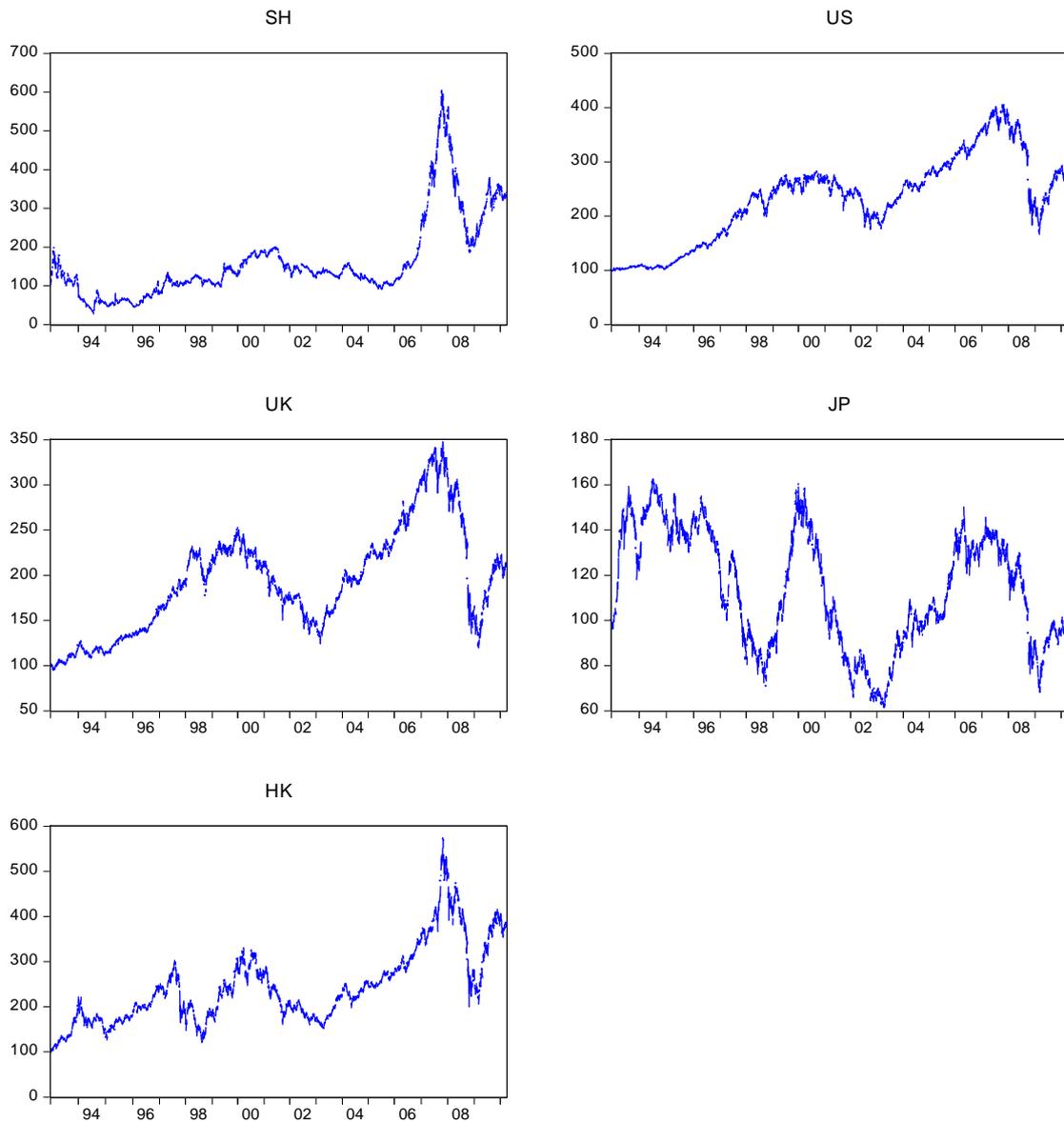


Figure 3.2 Stock Index Prices (Common Currency)



The visual inspection of the stock index prices given in Figure 3.1 and 3.2 reveals that the all five index prices plummeted during the 2007-2009 global financial crisis. The dot-com boom and burst in 2000 was evident in US, UK, HK and JP, but less apparent in SH. The prices of JP and HK also dipped temporarily as the result of 1997 Asian financial crisis whereas SH was largely immune from this dramatic event. The conversion into common currency has subtle changes on the trends of index prices. While experiencing at least one downturn over the sample period, index prices of US, UK, HK and SH have either doubled or tripled over this time horizon. The only exception was

JP, whose price remains a standstill over the 17-year period. The sluggish performance of the Japanese stock market mirrors the ‘Lost Decades’ of its economy.

3.5 Empirical Analysis

3.5.1 Preliminary Analysis

In application of cointegration test, we first consider whether each series is integrated of the same order. To ensure robustness, we consider three widely implemented unit root testing procedures: the Augmented Dickey-Fuller (ADF), the Phillips-Perron (PP), and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) unit root tests. Unit root test results are presented in Table 3.1.

Table 3.1 Unit Root Tests

Series in Levels (Local Currencies)						
Test	Equation	SH	US	UK	JP	HK
ADF	C	-1.33	-1.84	-2.09	-1.83	-2.36
	T/C	-2.39	-1.75	-2.12	-2.26	-3.10
PP	C	-1.38	-1.83	-2.04	-1.73	-2.33
	T/C	-2.51	-1.60	-2.02	-2.16	-3.04
KPSS	C	4.86*	5.52*	3.45*	1.58*	4.52*
	T/C	0.30*	0.96*	0.79*	0.35*	0.33*
Series in First Differences (Local Currencies)						
Test	Equation	SH	US	UK	JP	HK
ADF	N	-62.61*	-62.74*	-62.28*	-60.07*	-62.76*
	C	-62.62*	-62.77*	-62.29*	-60.06*	-62.78*
	T/C	-62.61*	-62.78*	-62.29*	-60.06*	-62.77*
PP	N	-62.61*	-62.99*	-62.42*	-60.12*	-62.79*
	C	-62.61*	-63.04*	-62.44*	-60.12*	-62.81*
	T/C	-62.61*	-63.07*	-62.45*	-60.12*	-62.80*
KPSS	C	0.04	0.20	0.14	0.08	0.07
	T/C	0.04	0.06	0.07	0.06	0.06

Series in Levels (Common Currency)						
Test	Equation	SH	US	UK	JP	HK
ADF	C	-1.08	-1.84	-2.03	-2.02	-2.37
	T/C	-2.69	-1.75	-1.89	-2.31	-3.10
PP	C	-1.07	-1.83	-1.99	-1.88	-2.33
	T/C	-2.41	-1.60	-1.75	-2.17	-3.05
KPSS	C	4.57*	5.52*	3.90*	1.49*	4.48*
	T/C	0.31*	0.96*	0.55*	0.60*	0.34*
Series in First Differences (Common Currency)						
Test	Equation	SH	US	UK	JP	HK
ADF	N	-22.63*	-62.74*	-61.41*	-62.40*	-62.84*
	C	-22.63*	-62.77*	-61.42*	-62.39*	-62.86*
	T/C	-22.65*	-62.78*	-61.42*	-62.39*	-62.85*
PP	N	-62.90*	-62.99*	-61.61*	-62.59*	-62.88*
	C	-62.90*	-63.04*	-61.63*	-62.58*	-62.89*
	T/C	-62.90*	-63.07*	-61.64*	-62.58*	-62.89*
KPSS	C	0.08	0.20	0.18	0.08	0.07
	T/C	0.05	0.06	0.07	0.08	0.06

Notes: For test equations N refers to none, C refers to constant, T refers to trend. * denotes the rejection of the null at the 5% significance level. The KPSS test has stationarity as the null as opposed to the other tests that have null of non-stationarity. The lag lengths are determined by the Schwarz Information Criterion (SIC) for the ADF tests, while the bandwidths in the PP and KPSS tests are determined by the method of Newey-West.

All three tests unanimously support the belief of a unit root in the levels and stationarity in the first differences for all series – a usual feature in global stock markets. The test results are indifferent to trend assumptions. Given that all logged price series follow unit root processes and are integrated of the first order, the potential for co-movement between series exists, this means that a linear combination of them is stationary.

3.5.2 Residual-Based Cointegration Test

We start by implementing the conventional Engle-Granger test in bivariate setting. In light of the potential existence of neglected break in the cointegrating relationship, the three models Eq.(3.3-5)

proposed by Gregory and Hansen (1996) are estimated sequentially. The locations of the break points along with their corresponding dates are reported in Table 3.2. Since stock market integration in Mainland China is the primary focus of this study, we restrict our analysis to the pairings between SH and one of the four developed stock market indices (i.e. US, UK, JP and HK). The dates of the structural break are estimated to be on February 1st 2007 for most of the pairings with both US and UK; the dates for the pairings with JP and HK vary depending on the model adopted, which span from as early as of December 7th 1996 to March 19th 2011.

Table 3.2 Locations of Break Point in Cointegrating Relation

Local Currencies			
Index Pair	Break in Intercept	Break in Intercept with Trend	Break in Intercept and Slope
SH – US	3143 (01/02/2007)	3143 (01/02/2007)	3143 (01/02/2007)
US – SH	3143 (01/02/2007)	3212 (01/06/2007)	2615 (15/09/2004)
SH – UK	3143 (01/02/2007)	3143 (01/02/2007)	3143 (01/02/2007)
UK – SH	3212 (01/06/2007)	3212 (01/06/2007)	1846 (26/03/2001)
SH – JP	2991 (08/06/2006)	3109 (07/12/2006)	3154 (26/02/2007)
JP – SH	1842 (19/03/2011)	2530 (30/04/2004)	3109 (07/12/2006)
SH – HK	1097 (30/10/1997)	2388 (09/09/2003)	910 (16/12/1996)
HK – SH	1097 (30/10/1997)	2414 (22/10/2003)	910 (16/12/1996)
Common Currency			
Index Pair	Break in Intercept	Break in Intercept with Trend	Break in Intercept and Slope
SH – US	3143 (01/02/2007)	3143 (01/02/2007)	3143 (01/02/2007)
US – SH	964 (01/04/1997)	3256 (07/08/2007)	907 (11/12/1996)
SH – UK	3143 (01/02/2007)	3143 (01/02/2007)	3143 (01/02/2007)
UK – SH	3252 (01/08/2007)	3268 (23/08/2007)	3233 (04/07/2007)
SH – JP	2991 (08/06/2006)	3109 (07/12/2006)	3154 (26/02/2007)
JP – SH	924 (14/01/1997)	2530 (30/04/2004)	924 (14/01/1997)
SH – HK	1097 (30/10/1997)	2388 (09/09/2003)	910 (16/12/1996)
HK – SH	2621 (27/09/2004)	1861 (19/04/2001)	2621 (27/09/2004)

Notes: Date corresponds to each break point is presented in brackets.

The results from Engle-Granger as well as Gregory-Hansen residual based cointegration tests are

presented in Table 3.3 and 3.4. We address the problem of cointegration vector normalisation that arises in the residual-based approach by testing cointegration in both directions: we set the price series of each index first as a dependent, and then as independent variable. The tests are conducted on series in local currencies as well as common currency. The ADF unit root test is performed on the residual term ε_t , obtained from the estimating equation, whose t-statistic is compared against the critical values supplied by Engle and Yoo (1987) rather than the ones by MacKinnon (1996).¹⁶ The existence of cointegration is verified by the rejection of the null hypothesis of non-stationarity. The last two columns of Table 3.3 and 3.4 present the ECT for each differenced series considered (i.e. index return), which serve as additional evidence supporting (or rejecting) the presence of cointegration.

Table 3.3 Engle-Granger Cointegration Test (Full Sample in Local Currencies)

Engle-Granger Cointegration Test without Structural Break (Eq.3.1)						
Index Pair	Cointegrating Parameters			CT	ECM	
	α	β	ε_t	$\varepsilon_{SH,t-1}$	$\varepsilon_{US/UK/JP/HK,t-1}$	
SH – US	-1.93**	1.07**	-2.52	–	–	
US – SH	4.38**	0.58**	-1.24	–	–	
SH – UK	-4.35**	1.51**	-2.37	–	–	
UK – SH	5.30**	0.33**	-1.96	–	–	
SH – JP	11.54**	-0.59**	-1.64	–	–	
JP – SH	7.93**	-0.10**	-1.69	–	–	
SH – HK	-4.14**	1.21**	-2.93	–	–	
HK – SH	5.94**	0.48**	-2.23	–	–	

Structural Break in Intercept (Eq.3.3)						
Index Pair	Cointegrating Parameters			CT	ECM	
	α	D_t	β	ε_t	$\varepsilon_{SH,t-1}$	$\varepsilon_{US/UK/JP/HK,t-1}$
SH – US	0.18†	0.64**	0.82**	-3.79*	-0.0058*	–
US – SH	3.26**	-0.31**	0.74**	-3.35†	0.0056*	–
SH – UK	-1.69**	0.73**	1.15**	-3.67*	-0.0056**	–
UK – SH	4.47**	-0.25**	0.45**	-3.41*	0.0078*	–
SH – JP	9.95**	0.87**	-0.39**	-2.68	–	–

¹⁶ The critical values by Engle and Yoo (1987) for the cointegration test are provided in Appendix 3.1.

JP – SH	7.06**	-0.23**	0.03**	-2.33	–	–
SH – HK	-1.25**	0.50**	0.87**	-3.37*	-0.0042*	–
HK – SH	5.74**	-0.05**	0.51**	-3.60*	0.0043†	-0.0035*

Structural Break in Intercept with Trend (Eq.3.4)

Index Pair	Cointegrating Parameters				CT	ECM	
	α	D_t	β	t	ε_t	$\varepsilon_{SH,t-1}$	$\varepsilon_{US/UK/JP/HK,t-1}$
SH – US	-0.51**	0.69**	0.90**	-0.000047**	-3.90*	-0.0059*	–
US – SH	5.35**	-0.46**	0.39**	0.000241**	-3.52*	0.0049†	-0.0033*
SH – UK	–	0.57**	0.90**	0.000114**	-3.59*	-0.0060**	–
UK – SH	5.13**	-0.30**	0.34**	0.000080**	-3.23†	0.0068*	-0.0024†
SH – JP	5.48**	0.44**	0.17**	0.000283**	-2.71	–	–
JP – SH	6.20**	0.41**	0.19**	-0.000300**	-3.23†	0.0052*	-0.0031*
SH – HK	0.59**	-0.45**	0.65**	0.000392**	-3.36†	-0.0042†	–
HK – SH	6.99**	0.21**	0.32**	0.000033**	-3.80*	–	-0.0053**

Structural Break in Intercept and Slope (Eq.3.5)

Index Pair	Cointegrating Parameters				CT	ECM	
	α	D_t	β	$D_t*\beta$	ε_t	$\varepsilon_{SH,t-1}$	$\varepsilon_{US/UK/JP/HK,t-1}$
SH – US	0.33**	-1.24**	0.80**	0.21**	-3.89*	-0.0057*	–
US – SH	3.28**	4.57**	0.73**	-0.59**	-3.63*	0.0064*	–
SH – UK	-1.52**	-0.92**	1.12**	0.21**	-3.74*	-0.0056*	–
UK – SH	3.85**	2.36**	0.54**	-0.33**	-3.47*	0.0087*	–
SH – JP	11.69**	-8.99**	-0.63**	1.40**	-3.32†	–	–
JP – SH	8.58**	-6.28**	-0.20**	0.78**	-2.60	–	–
SH – HK	10.34**	-12.59**	-0.40**	1.43**	-3.77*	-0.0043*	–
HK – SH	10.59**	-5.12**	-0.22**	0.76**	-3.71*	–	-0.0038*

Notes: CT stands for the cointegration test on the residual term, ε_t . $\varepsilon_{SH,t-1}$ is the ECT for SH, $\varepsilon_{US/UK/JP/HK,t-1}$ is the ECT for US, UK, JP and HK respectively. ** denotes significant at 1% level, * denotes significant at 5% level, † denotes significant at 10% level, and – indicates the variable is insignificant at 10% level.

Table 3.4 Engle-Granger Cointegration Test (Full Sample in Common Currency)

Engle-Granger Cointegration Test without Structural Break (Eq.3.1)					
Index Pair	Cointegrating Parameters		CT	ECM	
	α	β	ε_t	$\varepsilon_{SH,t-1}$	$\varepsilon_{US/UK/JP/HK,t-1}$
SH – US	-3.72**	1.04**	-2.41	–	–
US – SH	6.05**	0.49**	-2.62	–	–
SH – UK	-4.36**	1.17**	-1.82	–	–
UK – SH	6.43**	0.34**	-2.51	–	–

SH – JP	6.71**	-0.59**	-1.29	–	–
JP – SH	3.00**	-0.11**	-2.19	–	–
SH – HK	-3.86**	1.23**	-2.80	–	–
HK – SH	5.20**	0.42**	-3.60*	–	-0.0037**

Structural Break in Intercept (Eq.3.3)

Index Pair	Cointegrating Parameters			CT	ECM ε_{t-1}	
	α	D_t	β	ε_t	$\varepsilon_{SH,t-1}$	$\varepsilon_{US/UK/JP/HK, t-1}$
SH – US	-1.04**	0.81**	0.71**	-3.54*	-0.0048*	–
US – SH	7.19**	0.63**	0.18**	-3.21†	0.0062*	-0.0024†
SH – UK	-1.16**	0.87**	0.76**	-3.19†	-0.0038†	–
UK – SH	5.86**	-0.27**	0.46**	-2.95	–	–
SH – JP	6.52**	1.01**	-0.60**	-2.92	–	–
JP – SH	2.37**	-0.37**	0.07**	-2.93	–	–
SH – HK	-1.82**	0.47**	0.91**	-3.05†	–	–
HK – SH	5.91**	0.32**	0.27**	-4.03**	–	-0.0057**

Structural Break in Intercept with Trend (Eq.3.4)

Index Pair	Cointegrating Parameters				CT	ECM	
	α	D_t	β	t	ε_t	$\varepsilon_{SH,t-1}$	$\varepsilon_{US/UK/JP/HK, t-1}$
SH – US	-1.61**	0.85**	0.79**	-3.86E-05**	-3.60*	-0.0048*	–
US – SH	6.69**	-0.49**	0.28**	0.000281**	-3.17†	–	-0.0030*
SH – UK	0.46**	0.71**	0.54**	0.000119**	-3.15†	-0.0041†	–
UK – SH	6.68**	-0.38**	0.25**	0.000173**	-2.70	–	–
SH – JP	5.22**	0.69**	-0.20**	0.000205**	-2.86	–	–
JP – SH	2.43**	0.48**	0.07**	-0.000275**	-3.47*	–	-0.0041**
SH – HK	–	-0.35**	0.60**	0.000379**	-3.54*	–	–
HK – SH	6.32**	-0.41**	0.12**	0.000340**	-3.89*	–	-0.0065**

Structural Break in Intercept and Slope (Eq.3.5)

Index Pair	Cointegrating Parameters				CT	ECM	
	α	D_t	β	$D_t*\beta$	ε_t	$\varepsilon_{SH,t-1}$	$\varepsilon_{US/UK/JP/HK, t-1}$
SH – US	-0.93**	-0.62*	0.70**	0.16**	-3.59*	-0.0047*	–
US – SH	8.44**	-1.04**	-0.09**	0.35**	-3.45*	0.0054*	-0.0026†
SH – UK	-0.98**	–	0.71**	0.09**	-3.57*	-0.0049*	–
UK – SH	6.01**	-2.54**	0.43**	0.38**	3.00	–	–
SH – JP	6.70**	-2.93**	-0.66**	1.66**	-3.45*	-0.0035†	–
JP – SH	3.35**	-1.62**	-0.14**	0.26**	-2.91	–	–
SH – HK	11.55**	-14.90**	-0.98**	2.15**	-3.61*	-0.0040*	–
HK – SH	6.25**	-0.50**	0.20**	0.15**	-4.05**	–	-0.0059**

Notes: $\varepsilon_{SH,t-1}$ is the ECT for SH, $\varepsilon_{US/UK/JP/HK, t-1}$ is the ECT for US, UK, JP and HK respectively. ** denotes

significant at 1% level, * denotes significant at 5% level, † denotes significant at 10% level, and – indicates the variable is insignificant at 10% level.

The conventional Engle-Granger tests suggest that SH is not cointegrated with any of the four developed stock indices to varying degrees with only one exception – the pairing between HK (dependent variable) and SH (independent variable) in the common currency case. Given the lack of cointegration detected using the Engle-Granger method, the results of the Gregory-Hansen approach could be of special value. As shown in Table 3.3 and 3.4, the Gregory-Hansen approach does bring more insights by rejecting the null hypothesis of no cointegration for a number of index pairs. This indicates that structural change is indeed present in the pattern of long-run equilibrium of these index pairs. It also appears that SH is integrated with these markets to varying degrees in that SH is comparatively more integrated with US and HK, moderately integrated with UK, and less integrated with JP, on the basis of the statistical significance of the residual term. The lack of cointegration between SH and JP is not surprisingly, given there is little commonality in the movement of their prices as we observed in Figure 3.1. The lack of cointegration between SH and JP is reminiscent of the finding of Tian (2007), and lends support to Arshanapalli *et al.* (1995), among others, that the Asian stock markets are less integrated with the Japanese market than with the US market. Moreover, the evidence of cointegration between SH and UK is slightly stronger in local currency case than in US dollar case. Supposedly, currency factor would play a lesser role in the long-run relationship between SH and US and between SH and HK, since the Chinese currency RMB (currency code: CNY) has been pegged to the USD and HKD over the sample period investigated. In contrast to the stability of these exchange rates, the exchange rate between CNY and GBP has been subject to greater fluctuation over the same period, which may contribute to the weaker evidence of cointegration under the common currency setting.

Scrutinising the ECTs estimated from each cointegrating equation allows us to gauge the speed of

adjustment in the process of restoring the long-run equilibrium and relative exogeneity of each market in the pairing. Intuitively, a faster speed of adjustment can be interpreted as a higher degree of stock market integration. The ECTs for SH are generally found to be negative when SH index return is set as the dependent variable, which implies that SH actively responds to equilibrium errors in the cointegrating equation; and positive occasionally when the counterpart index return is set as dependent variable, which suggests SH is forceful in driving the cointegrating relationship out of equilibrium or does not bear the burden of short-run adjustment to the long-run equilibrium.¹⁷ As for the relative exogeneity, it is fair to conclude that US and UK are comparatively more exogenous than HK in driving the price movement of SH.

Although residual-based cointegration test can be conducted in a multivariate framework, it assumes the existence of at most a single cointegrating vector. Johansen cointegration test overcomes this difficulty and possesses several other advantages over the residual-based cointegration test as outlined earlier. To this end, it is worthwhile to examine the long-run comovement of these market indices altogether using the Johansen multivariate cointegration test.

3.5.3 Johansen Cointegration Test

Given the possible sensitivity of cointegration results to sample selection and the general potential for parameter instability in cointegrating relationships, two different windowing strategies of Johansen cointegration test are deployed in this study in addition to the estimation based on the full sample period. The first, a recursive approach, derives the statistic of interest over the chosen period t_0 to t_n . This period is then extended by j and the statistic is re-estimated from t_0 to t_{n+j} . The iteration continues until the estimation procedure reaches the end of the data. An upward trend

¹⁷ A negative ECT implies that: positive errors tend to cause the change in the variable to be negative in the next period, so that the variable in level will fall; negative errors tend to cause change in the variable to be positive in the next period, so that the variable in level will rise. Either way, the variable will respond the errors in the opposite way thus restore the long-run equilibrium. A positive ECT implies the deviation from the long-run equilibrium will be further exacerbated rather than being corrected in the next period.

indicates either increased integration and/or a move towards integration, a downward trend indicates decreased integration and/or a move away from integration.

The alternative, a rolling approach, estimates the statistic of interest over an n period window, from t_0 to t_n , and this is then moved j observations along the dataset and the statistic is re-estimated from t_0 to t_{n+j} . The statistic is thus estimated over a window of constant length. The rolling window approach focuses on changes in cointegration during the previous n -period and provides a more refined tool to investigate the impact of external shocks on the market integration process.

To test whether the application of the dynamic cointegration procedure reveals any additional cointegrating relations, we first conduct conventional Johansen (1988) multivariate test over the full sample period. One lag is specified for the Johansen test determined by the Schwarz Information Criterion (SIC). This particular lag length also ensures that the errors are uncorrelated. Cointegration tests are conducted assuming the presence of an intercept in the cointegrating equation but not in VAR.¹⁸

Table 3.5 Johansen Cointegration Test

Full Sample in Local Currencies				
Hypothesised rank (r)	Trace statistic	5% C.V.	Maxeigen statistic	5% C.V.
$r = 0$	51.38	76.97	22.34	34.81
$r \leq 1$	29.04	54.08	8.45	28.59
$r \leq 2$	20.59	35.19	7.90	22.30
$r \leq 3$	12.69	20.26	7.26	15.89
$r \leq 4$	5.43	9.16	5.43	9.16
Full Sample in Common Currency				
Hypothesised rank (r)	Trace statistic	5% C.V.	Maxeigen statistic	5% C.V.
$r = 0$	62.74	76.97	28.34	34.81

¹⁸ This specification is preferred over other four settings available in EViews on the basis of SIC.

$r \leq 1$	34.39	54.08	17.18	28.59
$r \leq 2$	17.22	35.19	7.36	22.30
$r \leq 3$	9.86	20.26	5.31	15.89
$r \leq 4$	4.55	9.16	4.55	9.16

The cointegration test results presented in Table 3.5 suggest no cointegrating relationship between SH and the four other developed stock market indices, supported by both the trace and the maximum eigenvalue statistics at 5% level of significance. The test results are robust and insensitive to trend assumption, lag specification and currency choice. Based on this particular, one may argue that these stock market indices share no long-term equilibrium relationship.

However, the finding of no cointegration, based on the data of the entire sample period, may be misleading. As suggested by Elyasiani and Kocagil (2001: p.1169-1170), it is possible that equilibrium relationships do exist among variables over some of the embedded sub-periods but these relationships are too dissimilar in nature to allow a cointegrating relationship to be exhibited over the entire period. The stock markets considered herein have collectively experienced several major episodes of financial market turmoil over the sample period, which include the 1997 Asian financial crisis, 1998 Russian financial crisis, 2000 dot-com bubble burst, 2001 September 11th terrorist attack, and 2007-2009 global financial crisis. The history suggests that finding empirical evidence to support one persistent long-run relationship amongst these markets may prove unlikely. Given the possible sensitivity of results to sample selection, the issue of temporal stability of the cointegration relationship warrants further examination. A series of recursive and rolling window cointegration tests are conducted in addition to the conventional cointegration test. The application of these dynamic cointegration techniques offers several advantages: first, it facilitates a check on the robustness of the results based on the entire sample period; second, it enables us to examine potential time variation in the nature of the relationship among national stock markets; and third, it allows us to identify possible structural changes that take place

gradually over time.

For the recursive estimations, we adopt a five-year window, starting from January 1st 1993 – December 31st 1997. The initial observation is kept fixed and the sample length is increased by adding an additional observation at each recursive estimate. The recursive cointegration tests are presented in Figures 3.3 and 3.4, which show the movements of the test statistics for $r = 0$ for local and common currency cases, respectively. The test statistic is reported on the last day of the recursive sample period from which it is derived. To aid the visual presentation, the test statistics are normalised such that the critical values for rejection of each null hypothesis are represented by the value zero. If the test statistic is greater than zero, then the null hypothesis that the chosen cointegration rank is maintained can be rejected at that data point. For example, if a test statistic for $r = 0$ is greater than zero for, say, December 31st 2005, it means that we can reject the hypothesis that the series in question are not cointegrated for a period of 1304 days (effectively 5 years) up to and including December 31st 2005.

Figure 3.3 5-year Recursive Cointegration Test Statistics for $r = 0$ (Local Currencies)

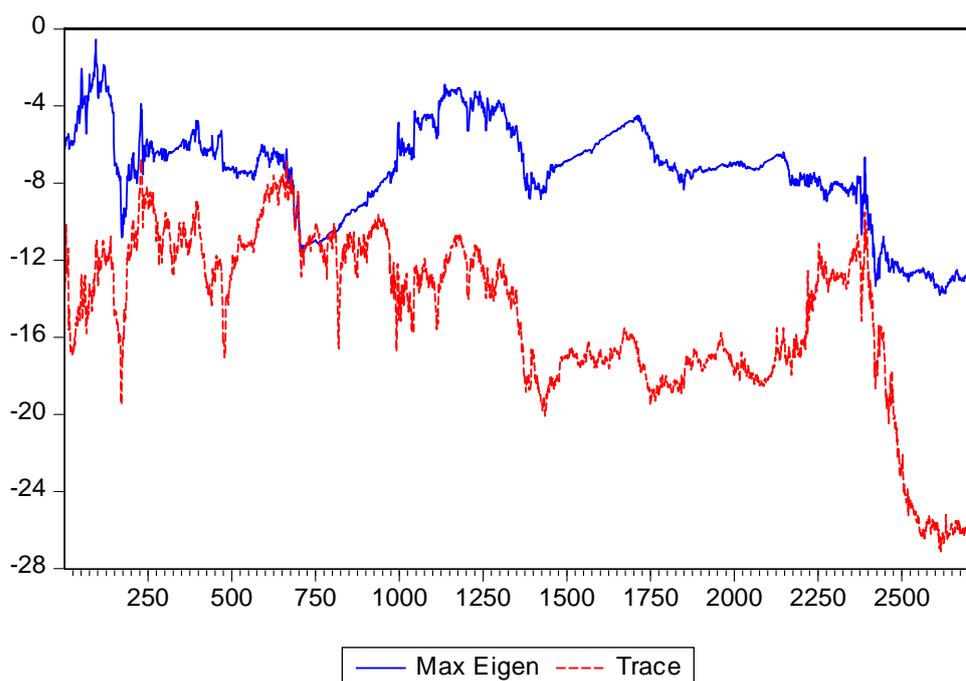
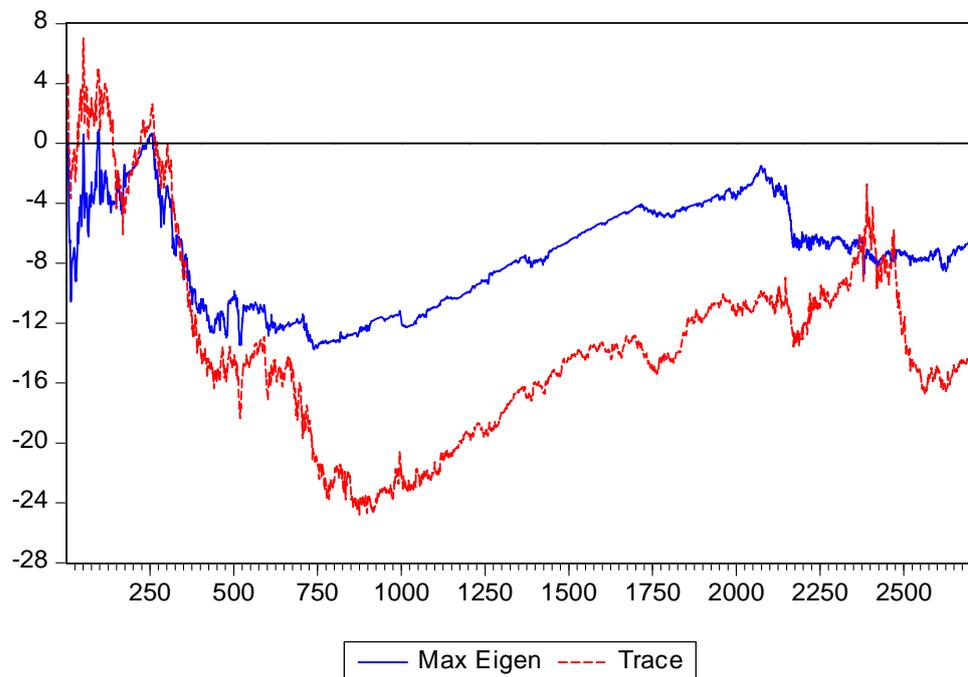


Figure 3.4 5-year Recursive Cointegration Test Statistics for $r = 0$ (Common Currency)

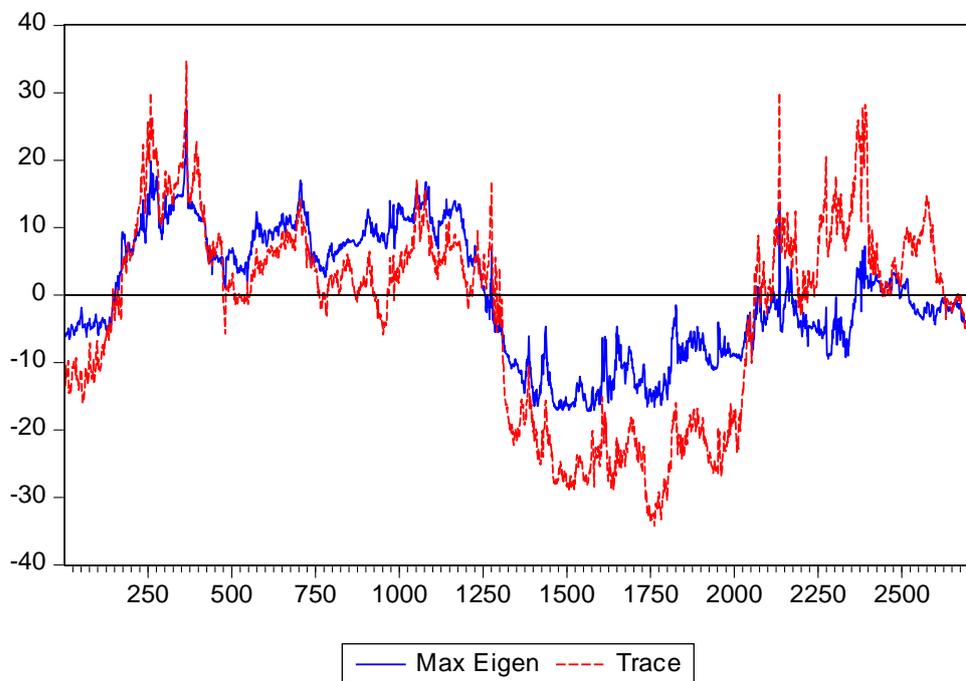


The recursive cointegration analyses indicate the absence of a persistent cointegrating vector over the recursive sample period, though it acknowledges a rather short-lived cointegration at the beginning in the common currency case. This finding reasserts the previously obtained results from the static Johansen cointegration test over the full sample. Nevertheless, in the common currency case, it is worth noting that the maximum eigenvalue and trace statistics reach a trough in December 2001 and start to climb up until reaching their peaks in June 2007 and November 2008 respectively. This has led us to believe that the cointegrating relationship among the markets is not stable and subject to structural changes over time. As a result, the cointegration analysis may be distorted by the inclusion of early observations should there be a structural change in the recursive sample.

The recursive cointegration analysis provides a strong case that the 17-year time horizon may be simply too long to allow an equilibrium relationship to sustain itself, given the occurrence of

regime shifts, regulatory changes, and financial crises during this period. It is possible, however, that once these factors are accounted for, a sequence of equilibria will manifest itself over different sub-periods (Elyasiani and Kocagil, 2001: p.1170). We now proceed to the rolling cointegration. Once again, we start with a 5-year period from January 1st 1993 to December 31st 1997 but move this window forward by one observation at a time. The 5-year rolling cointegration test statistics for local and common currency cases are depicted in Figures 3.5 and 3.6 respectively.

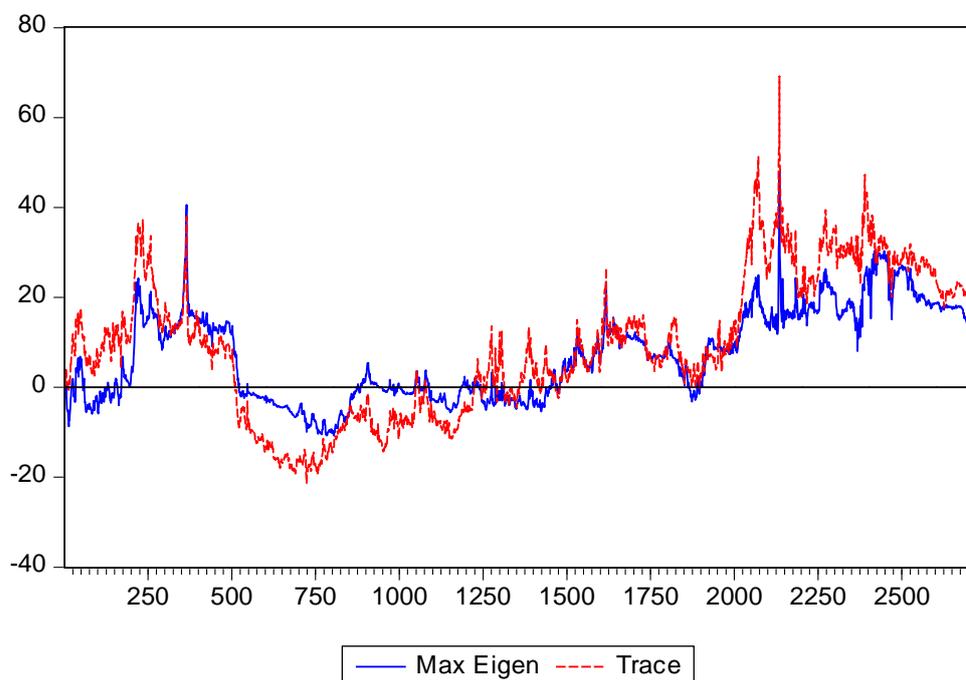
Figure 3.5 5-year Rolling Cointegration Test Statistics for $r = 0$ (Local Currencies)



The maximum eigenvalue and trace test statistics are far from being invariant in both Figures. In the local currencies case, the null hypothesis of no cointegration is rejected for the period between October 1993 and October 1998 rolling forward until late October 2003 (observations 172 – 1281), indicating the existence of a long run relationship binding SH with its four other peers. This cointegrating relationship breaks down for a substantial period between late November 2003 and early May 2007 (observations 1301 – 2059) until the trace statistic rises above critical value again for a relatively shorter period between late July and late November 2007 (observations 2114 –

2189) despite the sharp fall shortly after. The trace statistic then quickly reverts to a level that is sufficient to reject the null of no cointegration beginning in mid-January 2008 until the end of 2009 (observations 2220 – 2624). Though fluctuating less widely than the trace statistic, the maximum eigenvalue statistic reveals similar pattern except that it suggests a longer period of no cointegration commencing October 2003 (observation 1277) and the cointegrating relationship is re-formed only temporarily for samples ending between September 2008 and May 2009 (observations 2363 – 2520) thereafter. Based on the above observation, the variation in the long-run relationship can be characterised by four phases – the periods prior to October 1998, from October 1998 to October 2003, from November 2003 to May 2007, and from July 2007 onwards.

Figure 3.6 5-year Rolling Cointegration Test Statistics for $r = 0$ (Common Currency)



A slightly different picture emerges for the common currency case. A cointegrating vector exists from the beginning of the sample period till May 2000 (observation 511). It takes a little less than

4 years for this cointegrating relationship to re-establish itself (observations 512 – 1360). The strength of the newly established cointegrating relationship continues to cultivate in the subsequent years and gives rise to a prolonged period of comovement, which is supported by a rarely disrupted upward trend in the test statistics.

Since the different pattern observed in each case is solely due to the currency assumption, the finding of a prolonged period of cointegration commencing in 2004 in the common currency analysis is caused by the exchange rate dynamics among the countries these stock markets reside rather than the nominal index prices comovement among these markets. According to Tsutsui and Hirayama (2004), this result suggests that active portfolio adjustments by international investors must have given rise to a stronger stock price linkage.

The rolling cointegration analyses point to two periods of intensified cointegration where the test statistics reach their climax. The first one occurs shortly after the Asian financial crisis and the Russian financial crisis; the second one coincides with the outbreak of the US sub-prime mortgage crisis and the resultant worldwide economic downturn. This offers partial support to the finding of Yang *et al.* (2003) that long-run cointegrating relationship among US, Japan and other Asian emerging stock markets was strengthened during the Asian financial crisis and that these markets have generally been more integrated after the crisis than before the crisis. No cointegration is observed during the Asian financial crisis – this is probably due to the fact that China at the time was largely insulated from and unaffected by the crisis. The results lend support to the belief that significant regional and global financial events strengthen the long-run relationship between the stock market of Mainland China and those of developed countries and are largely consistent with the contagion hypothesis of stock market integration. Moreover, the periodic formation of cointegrating relationship can be also attributed to the synchronisation of cyclical patterns of the markets under investigation. Evidently, all five stock market indices had been subject to

exponential growth two or three years after the burst of the dot-com bubble in 2000. The increasing vulnerability of Mainland China's stock market to global downturn requires some explanations. We believe this may be caused by the gradual relaxation of foreign equity investment in Mainland China. The surge in QFII-led equity trading activities is expected to be the main driver behind the intensified linkage between SH and four other developed stock markets. Another plausible explanation to this phenomenon lies in the growing "psychological contagion" between markets, and a bursting of a strong rational speculative bubble over this period.

To avoid the arbitrary results specific to our window choice, we also experiment the dynamic cointegration with various time horizons, ranging from 3 to 10 years (see Appendices 3.2-8). Not surprisingly, the duration of cointegration changes as we narrow or stretch the estimation window – this suggests that a shorter time horizon may fail to recognise the existence of cointegration whilst a longer time horizon may prevent cointegrating relationship to endure and sustain its character.

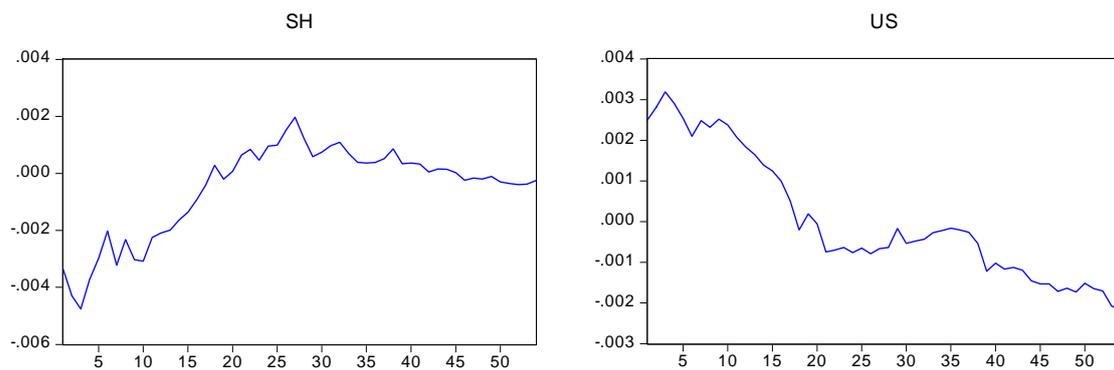
We observe the following from the dynamic cointegration analyses: first, our results highlight the time-varying nature of the cointegrating relationship, which supports Sephton and Larsen's (1991) view that absence of significant long-run relationship obtained by cointegration tests performed over an arbitrarily chosen horizon may be misleading; second, the time-varying character of the cointegrating relationship may be brought about by transitory world events or the synchronisation of economic cycle among countries; finally, the instability of long-run relationship helps reconcile the mixed results regarding stock market integration between Mainland China and other developed stock markets.

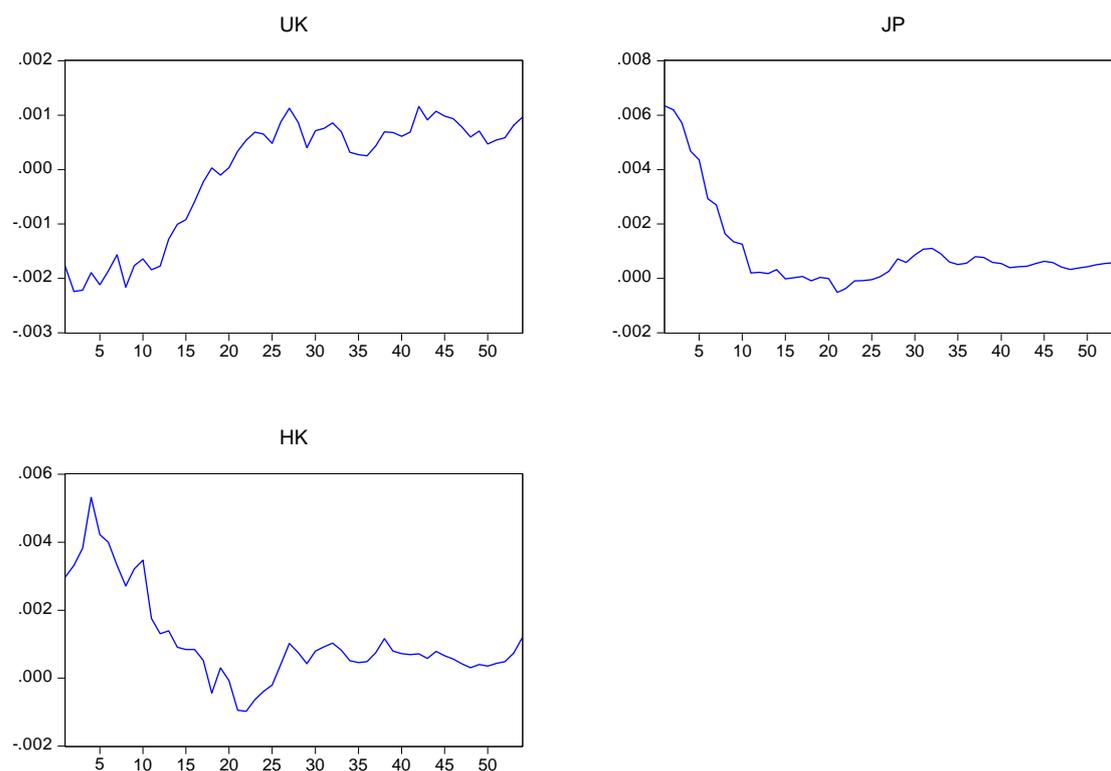
The absence of a persistent cointegration prevents us from examining the VECM over the full sample since the formulation of the VECM is conditional upon the presence of cointegration.

Nevertheless, given that the rolling cointegration analysis in the common currency case reveals a substantial period of persistent cointegration (from September 17th 2004 to March 31st 2010), a rolling VECM can be estimated to illustrate the time paths of ECTs. Similar practice can be found in Pascual (2003) who employs a rolling VECM to assess whether the degree of stock market integration has changed over time between the UK, France and Germany. The author argues that higher values of ECTs, as the sample rolls forward, can be interpreted as a higher degree of stock market integration.

Conventionally, rolling VECM are estimated under two VAR representations: first, in the unrestricted representation, all the parameters of the VECM are re-estimated during the sequence of rolling estimations; second, in the restricted representation, all the short-term parameters in the VECM are held fixed to their full sample values and only the long-run parameters (i.e. ECTs) are re-estimated. To ensure consistency with previous cointegration analysis, we adopt the unrestricted representation and roll forward 20 observations for each VECM estimate. Each VECM estimate would yield five ECTs, the trends of which are plotted in Figure 3.7.

Figure 3.7 Trends for the Coefficients of the ECTs





Graphically, the ECTs for SH and UK exhibit an upward trend while those for US, JP and HK are characterised by a downward trend. This finding suggests that the collective effort of SH and UK in maintaining the long-run equilibrium has deteriorated over time. The ECTs for JP and HK have seldom hit the negative zone even though they have declined over time, implying JP and HK have become insensitive to equilibrium errors and less forceful in driving the cointegrating equation out of equilibrium. The ECT for US has experienced the greatest change among all ECTs: it has switched its role from being exogenous to endogenous within the system. It has become the only market that characterised by a negative ECT towards the end of the sample, which may be purely caused by the fluctuation of USD exchange rate against other four currencies.

Since the examination of rolling ECTs only presents a partial picture of the dynamic response of each market to the long-run equilibrium, the short-term channels of causality also warrants a formal investigation. In the absence of cointegration, the short-term causality can be modelled in the VAR framework. We proceed to estimate a VAR model of the first differences of the five price

series over the full sample. The appropriate lag length again is set to one. The estimation of VAR is presented in Table 3.6.

Table 3.6 Estimation of VAR

Full Sample in Local Currencies					
	ΔSH	ΔUS	ΔUK	ΔJP	ΔHK
$\Delta SH(-1)$	-0.0112	-0.0064	-0.0048	-0.0113	-0.0229†
$\Delta US(-1)$	0.1071**	-0.0036	0.3875**	0.4126**	0.5259**
$\Delta UK(-1)$	0.0684	-0.0076	-0.2321**	0.1125**	0.1302**
$\Delta JP(-1)$	-0.0381	-0.0110	-0.0651**	-0.0548**	-0.1256**
$\Delta HK(-1)$	0.0085	-0.0029	0.0209*	-0.0433**	-0.0881**
Full Sample in Common Currency					
	ΔSH	ΔUS	ΔUK	ΔJP	ΔHK
$\Delta SH(-1)$	-0.0154	-0.0063	0.0040	-0.0124	-0.0116
$\Delta US(-1)$	0.1251**	-0.0090	0.4261**	0.3769**	0.5232**
$\Delta UK(-1)$	0.0337	0.0016	-0.2216**	0.0864**	0.0989**
$\Delta JP(-1)$	-0.0254	-0.0067	-0.0302*	-0.0511**	-0.0739**
$\Delta HK(-1)$	-0.0010	-0.0063	0.0182	-0.0320*	-0.1082**

Notes: ** denotes significant at 1% level, * denotes significant at 5% level, † denotes significant at 10% level. Nevertheless, the standard error inferred p-values should be treated with some degree of caution due to the potential multicollinearity problem among the lagged variables in the VAR system.

As illustrated in Table 3.6, US is unambiguously econometrically exogenous as it exerts influences to all other markets but not vice versa. HK is influenced by all markets, including itself, given that all of the short-term channels of Granger-causality are active in the system. SH is only led by changes in fluctuations of US return. JP is prone to short-term fluctuations from the developed markets, but from SH. Lastly, UK is influenced by significant short-run causal influences from the US, and Japan, apart from the lagged returns of its own.

Variance Decomposition (VDC) and Impulse Response Function (IRF) are natural extensions of the VAR model. The former measures the percentage of a market's forecast error variance that

occurs because of a shock from a market in the VAR system, while the latter traces the response of one market to change in one of the market's innovations.

VDC is essentially an out-of-sample causality test. It partitions the variance of the forecast error of a certain variable into proportions attributable to shocks in each variable in the system including its own. VDCs from one-standard deviation shocks to each market over 1 to 10 days are listed in Table 3.7.

Table 3.7 Variance Decompositions

Full Sample in Local Currencies					
	Percentage of forecast variance explained by innovations in				
Variance of Δ SH	Δ SH	Δ US	Δ UK	Δ JP	Δ HK
1	97.640	0.000	0.000	0.808	1.552
10	97.095	0.181	0.319	0.807	1.598
Variance of Δ US	Δ SH	Δ US	Δ UK	Δ JP	Δ HK
1	0.012	60.406	28.635	6.483	4.464
10	0.059	60.371	28.624	6.510	4.435
Variance of Δ UK	Δ SH	Δ US	Δ UK	Δ JP	Δ HK
1	0.098	0.000	81.700	11.301	6.900
10	0.101	11.337	72.070	10.036	6.455
Variance of Δ JP	Δ SH	Δ US	Δ UK	Δ JP	Δ HK
1	0.000	0.000	0.000	100.000	0.000
10	0.086	7.719	7.276	84.694	0.224
Variance of Δ HK	Δ SH	Δ US	Δ UK	Δ JP	Δ HK
1	0.000	0.000	0.000	18.633	81.367
10	0.151	7.240	6.577	16.050	69.982
Full Sample in Common Currency					
	Percentage of forecast variance explained by innovations in				
Variance of Δ SH	Δ SH	Δ US	Δ UK	Δ JP	Δ HK
1	97.677	0.000	0.000	0.488	1.835
10	97.200	0.226	0.229	0.486	1.858
Variance of Δ US	Δ SH	Δ US	Δ UK	Δ JP	Δ HK
1	0.038	61.790	29.048	2.179	6.945
10	0.054	61.760	29.035	2.194	6.957

Variance of ΔUK	ΔSH	ΔUS	ΔUK	ΔJP	ΔHK
1	0.001	0.000	84.928	5.866	9.204
10	0.027	10.548	75.545	5.241	8.639
Variance of ΔJP	ΔSH	ΔUS	ΔUK	ΔJP	ΔHK
1	0.000	0.000	0.000	100.000	0.000
10	0.068	5.696	5.226	88.598	0.412
Variance of ΔHK	ΔSH	ΔUS	ΔUK	ΔJP	ΔHK
1	0.000	0.000	0.000	12.728	87.272
10	0.048	7.271	6.096	11.083	75.501

Note: The ordering of variable in the VAR is $\Delta JP - \Delta HK - \Delta SH - \Delta UK - \Delta US$. Such order is based on the sequence of opening time for each stock exchange.

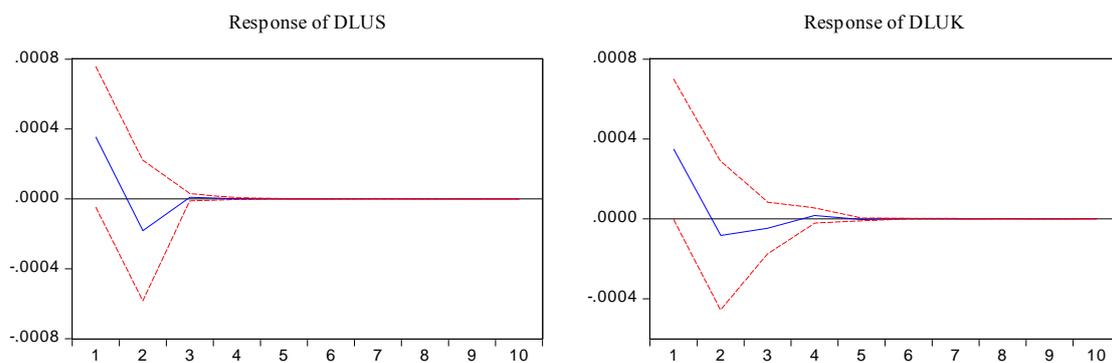
While a large proportion of a market's forecast variance is explained by its own shock, SH is least vulnerable to shocks from other markets but it has very little impact on other markets. The US is the least exogenous among the five markets, as almost 40% of its variance is explained by innovations from other markets, mainly UK (28.6%). After a 10-day horizon, innovations from US, JP and HK all have a fair share in explaining the variance of UK (10.3%, 10.0% and 6.5%). Similarly, moderate proportions of HK variance are attributable to shocks from US, UK and JP (7.2%, 6.6% and 16.0%). JP is the second most exogenous market in the system, about 10% of its variance is jointly explained by shocks from US and UK. The VDCs results from the common currency case are broadly in line with those from the local currencies case, thus will not be mentioned in further detail.

It is well acknowledged that the results based on VDCs and IRFs are generally sensitive to the ordering of the variables. By construction, the errors in any equation in a VAR are usually serially uncorrelated. However, there could be contemporaneous correlations across errors of different equations. VAR model relies on a Choleski factorisation to orthogonalise VAR innovations so that they are uncorrelated contemporaneously. However, innovation accounting results based on the Choleski factorisation are sensitive to the ordering of variables when the residual covariance

matrix is non-diagonal (Yang *et al.*, 2003). Alternative orderings of the trends may therefore affect the results of VDCs and IRFs. The results presented in Table 3.7 are indeed subject to changes should alternative orderings have been imposed in the VAR. However, results pertain to SH remain robust to these alternations.

In order to circumvent the above mentioned drawback, instead of using IRF, we employ generalised IRF analysis developed by Pesaran and Shin (1998), which is invariant to the ordering of the variables in the VAR model. This feature is particularly useful for studies on equity markets, which are generally characterized by quick price transmissions and adjustments (Ewing *et al.*, 2003). Generalised IRFs from one-standard deviation shock to each of the five markets are traced out for each individual market in Figures 3.8-12 (excluding the own shock to each market).¹⁹ In each graph, the horizontal axis represents days elapsed after shock; the vertical axis represents standard deviations; the dashed lines refer to 95% confidence bands.

Figure 3.8 Generalised Impulse Responses from One-Standard Deviation Shock to SH



¹⁹ Graphs of generalised IRFs based on series denominated in common currency look very similar to those shown in Figures 3.8-12, thus are not presented in order to conserve space.

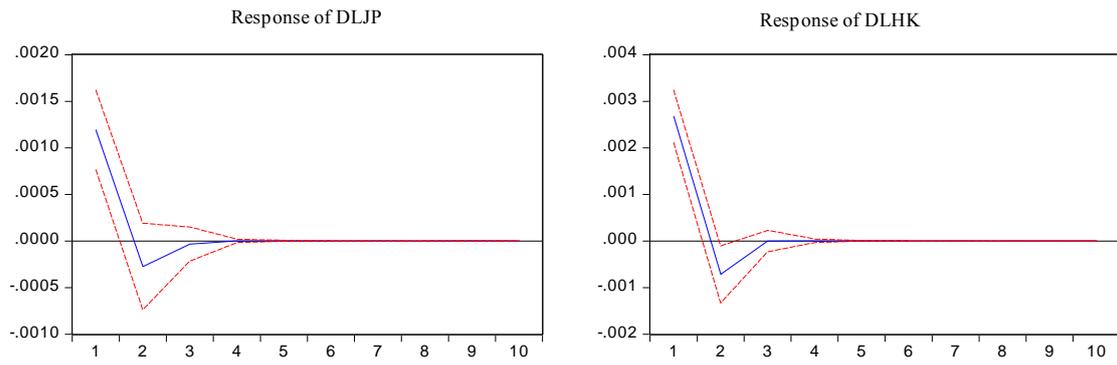


Figure 3.9 Generalised Impulse Responses from One-Standard Deviation Shock to US

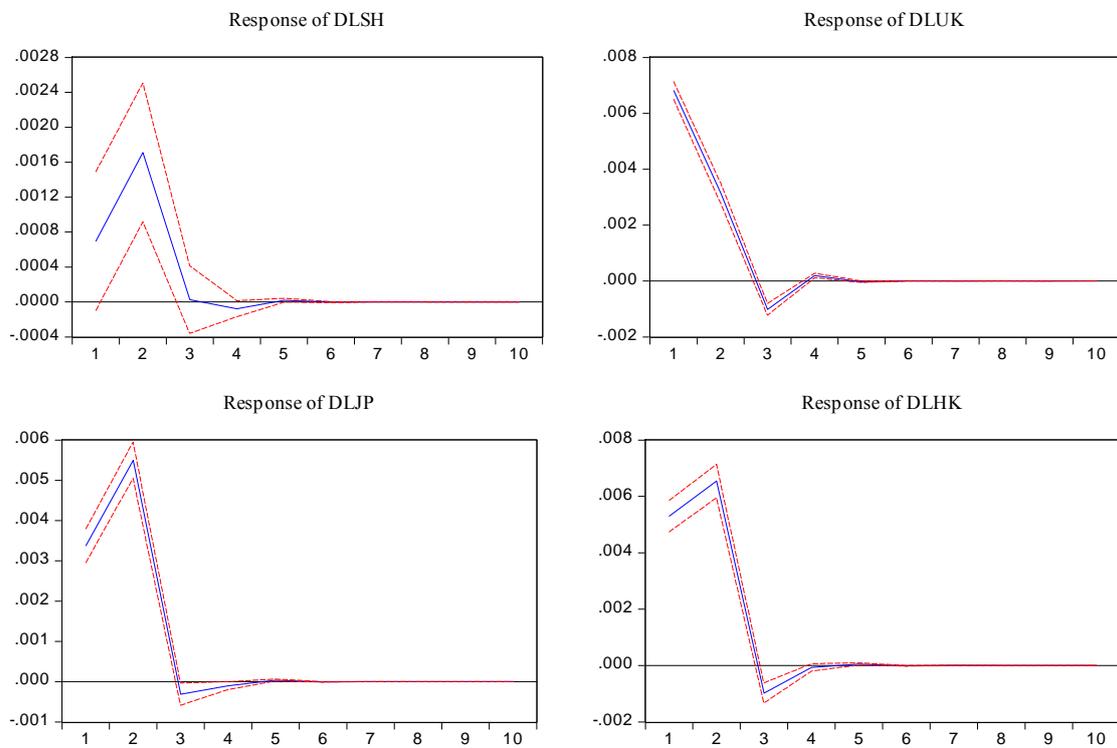
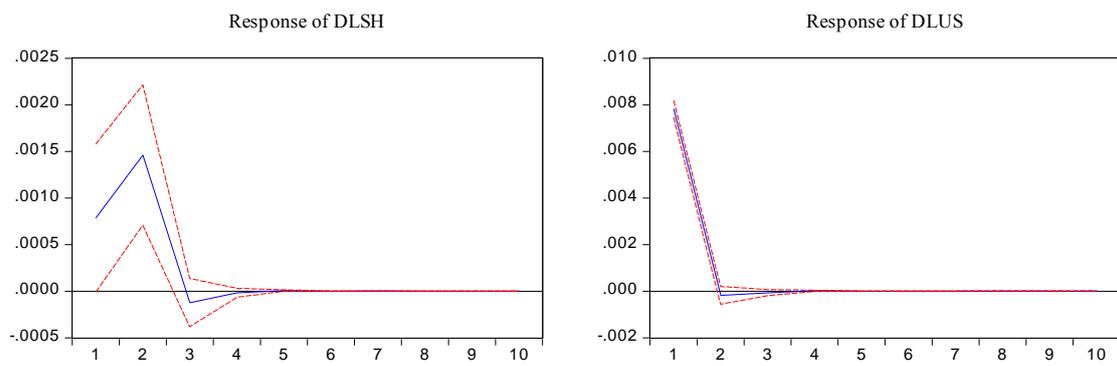


Figure 3.10 Generalised Impulse Responses from One-Standard Deviation Shock to UK



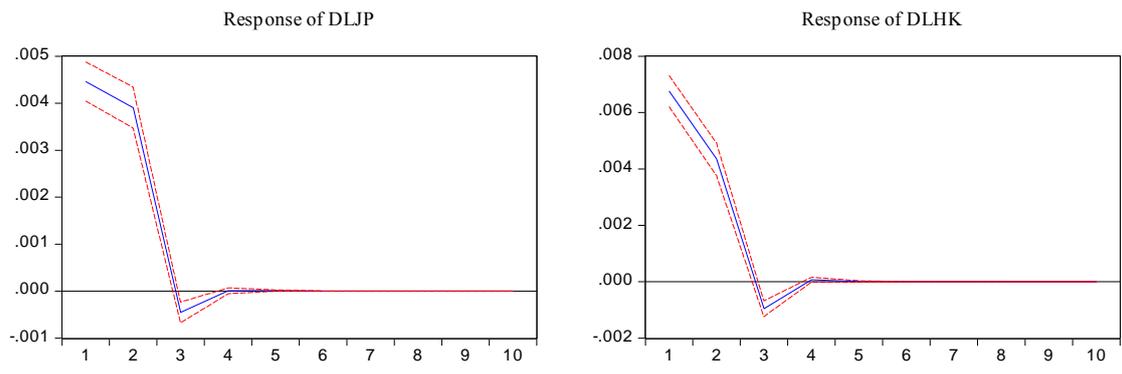


Figure 3.11 Generalised Impulse Responses from One-Standard Deviation Shock to JP

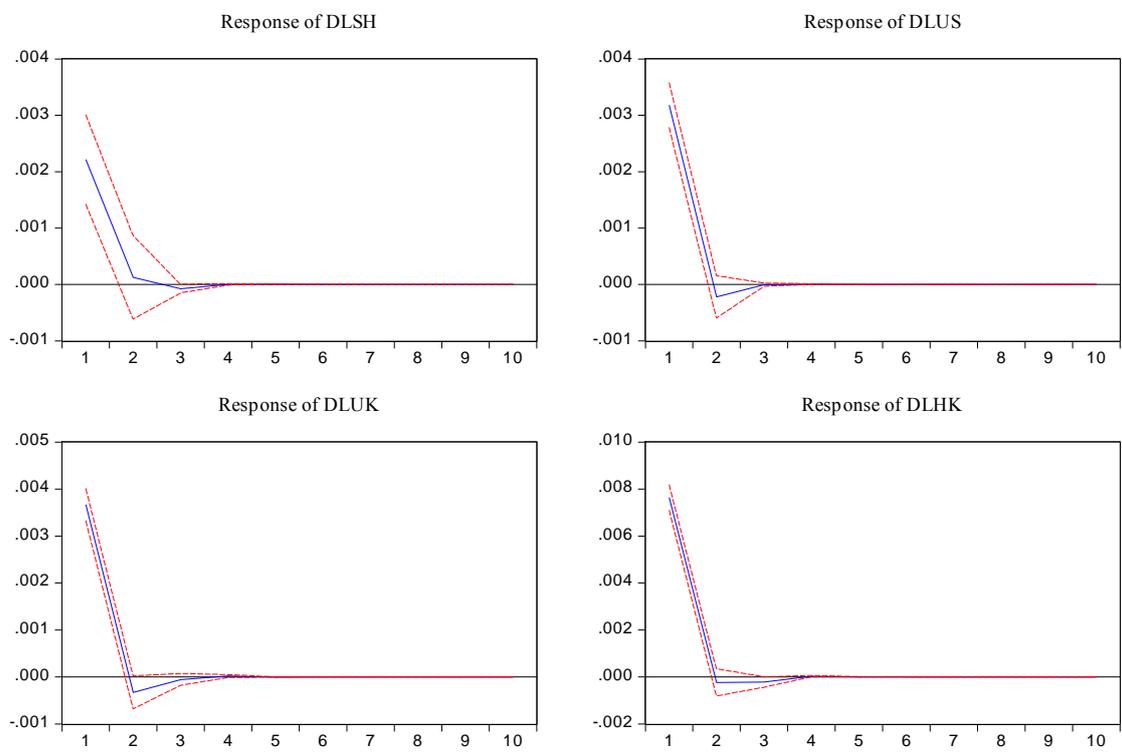
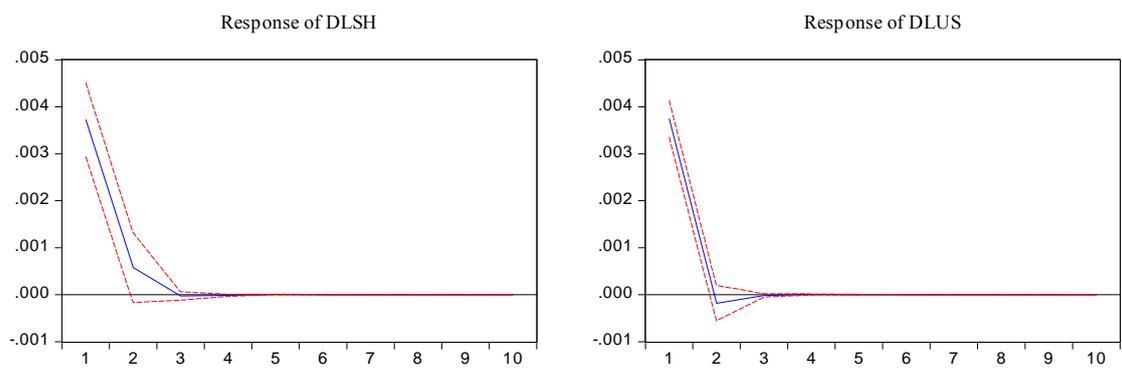
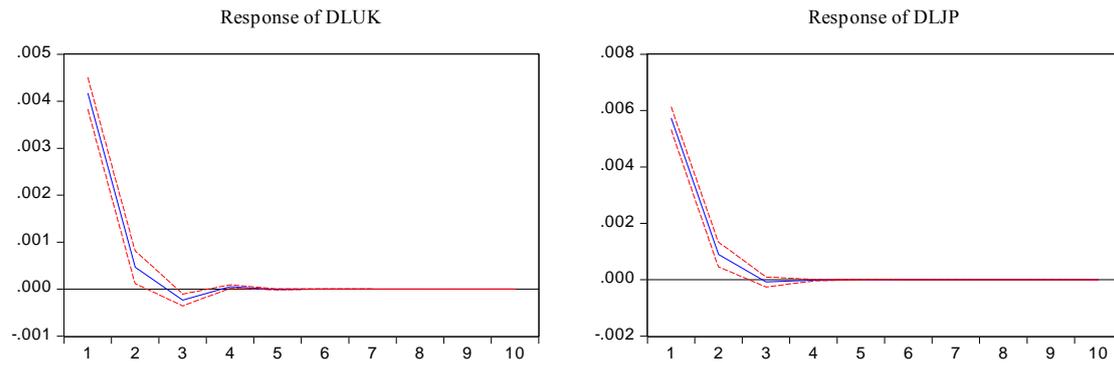


Figure 3.12 Generalised Impulse Responses from One-Standard Deviation Shock to HK





Graphs of IRF map out the dynamic response path of a variable due to one standard deviation shock to another variable. The initial responses are positive and markets generally settle back to its pre-shock level in no more than 6 trading days after a shock to a particular market. The results once again suggest the lack of mutual influence between SH and the two Western stock markets – US and UK. There is evidence that SH is relatively more responsive to shocks from its regional counterparts – JP and HK. In summary, the generalised IRFs are reminiscent of results obtained from VDCs.

3.6 Conclusion

This chapter examines the long-run comovement between the Mainland China’s stock market (SH) and four other developed stock markets (US, UK, JP and HK), through the implementation of alternative cointegration techniques as well as various extensions of VAR model. As noted in Evans and McMillan (2009), any cointegration test conducted over a fixed sample period does not necessarily produce meaningful results as it fails to capture the fluid nature of stock market integration. The use of Gregory-Hansen cointegration test as well as rolling and recursive cointegration tests in the present study effectively overcome this deficiency. The empirical results obtained from these cointegration analyses confirm our contention that the lack of proper accounting for structural break or time-variation in the cointegrating relationship among national

stock markets could have significant inferential implications and lead to spurious conclusions. It can be reasonably inferred that the cointegrating relationship between SH and the four other indices is subject to periodic breakdown and reformation. This observation provides some interesting evidence to compare with previous research undertaken in the similar context and helps to settle the dispute over to what extent the Mainland Chinese stock market is integrated with the world stock market. We have acquired marginal evidence that the five stock markets are in the process, generally speaking, of integrating further. Nevertheless, the integration in the sense of long-run comovements among these markets is far from complete. More substantially, the periodic breakdown of cointegrating relationship is believed to be advantageous to foreign investors who may still yield significant benefits by diversifying their equity investment into the emerging Mainland China's stock market, even though the downside protection for foreign investors may not be as strong during crisis periods.

Moreover, our results also demonstrate how currency treatments may give rise to different results regarding the long-run stock market interdependence. Hence, on a practical level, international investors may need to adequately assess the exchange rate fluctuation as a potential contributing factor to the overall effectiveness of their portfolio diversification strategies.

The supplementary results from VDC and IRF analyses based on the VAR model inform us about the immunisation of the Chinese stock market to shocks from other markets as well as its inability to exert influence over the propagation mechanism among these markets, which could be interpreted as evidence of market segmentation. This particular evidence should be assessed with caution since it is derived from the full sample period. This limitation leads to a full chapter dedicated to the issue of information propagation and spillover effect among these stock markets.

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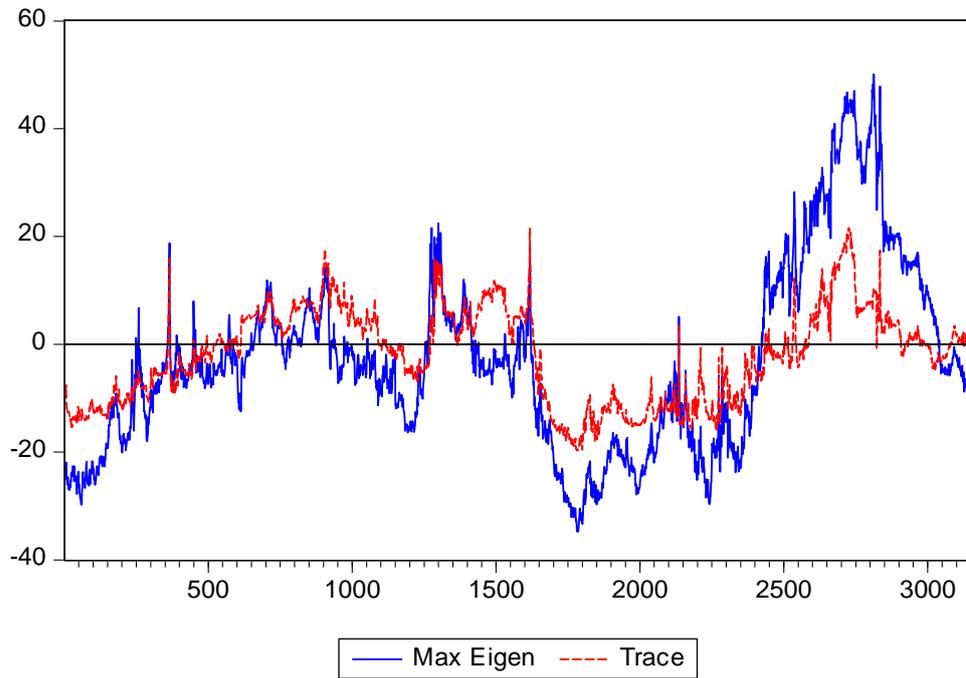
Appendices:

Appendix 3.1 Critical Values for the Engle-Granger Cointegration Test on Residual Terms

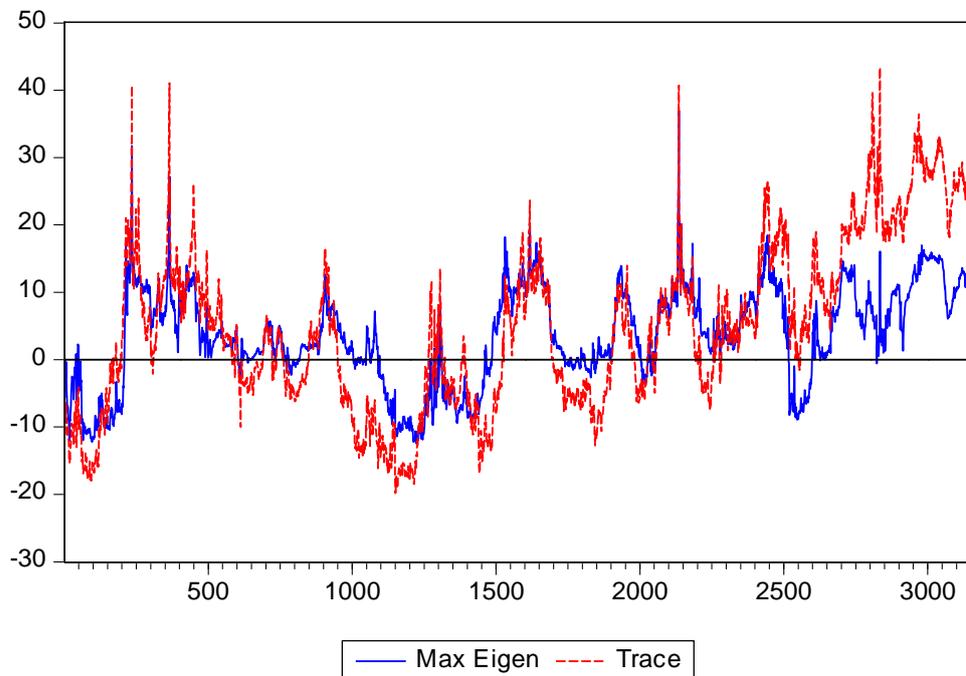
No. of Variables in the System	Sample Size	1%	5%	10%
2	> 200	-4.00	-3.37	-3.02
3	> 200	-4.35	-3.78	-3.47
4	> 200	-4.70	-4.18	-3.89
5	> 200	-5.02	-4.48	-4.18

Source: Engle and Yoo (1987)

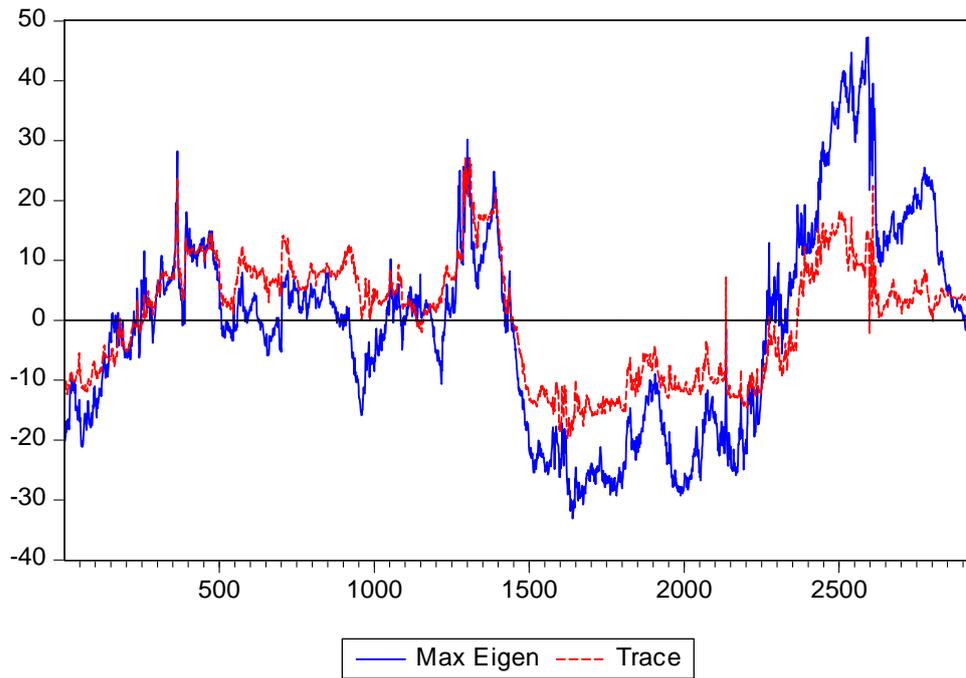
Appendix 3.2a 3-year Dynamic Cointegration Test Statistics for $r = 0$ (Local Currencies)



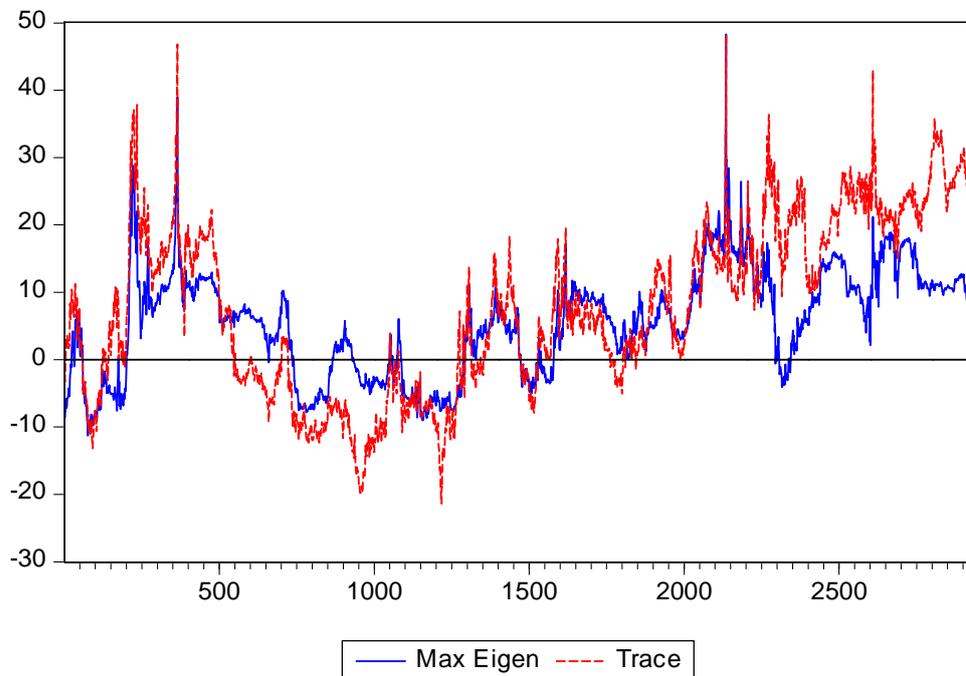
Appendix 3.2b 3-year Dynamic Cointegration Test Statistics for $r = 0$ (Common Currency)



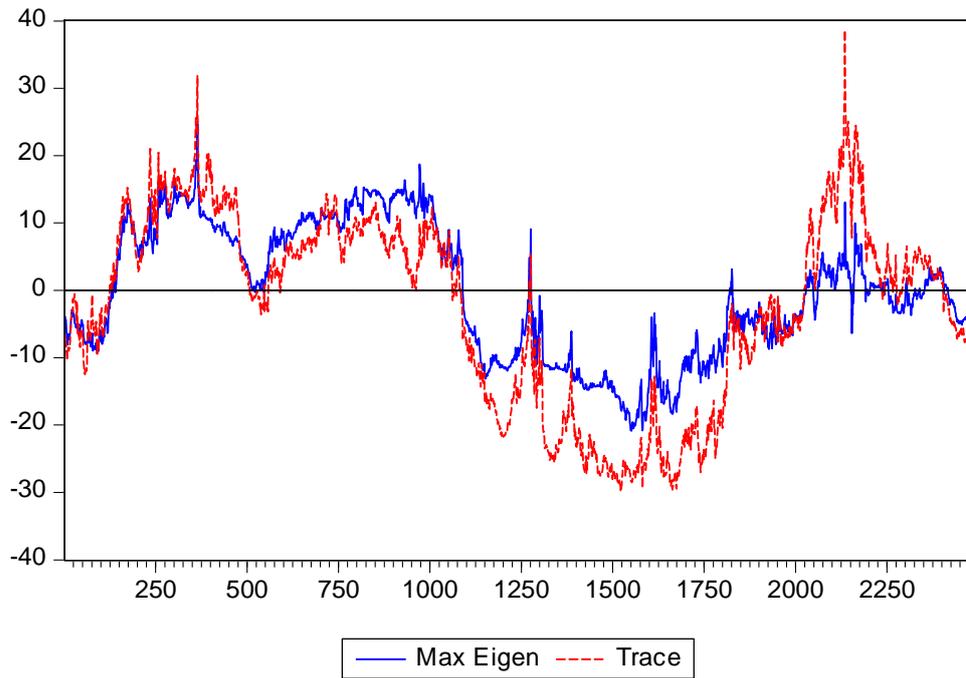
Appendix 3.3a 4-year Dynamic Cointegration Test Statistics for $r = 0$ (Local Currencies)



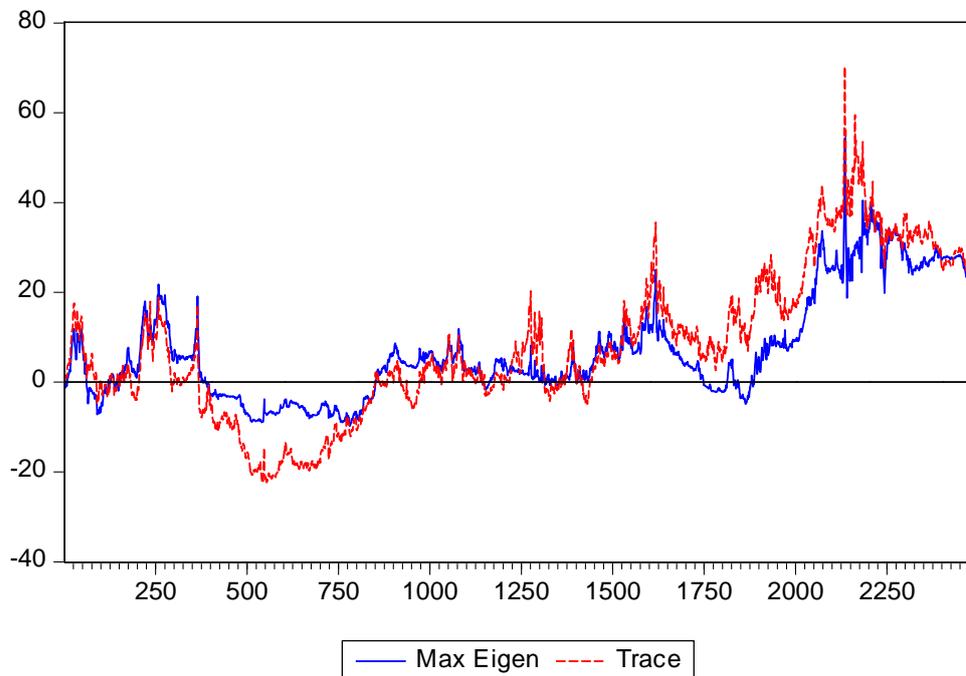
Appendix 3.3b 4-year Dynamic Cointegration Test Statistics for $r = 0$ (Common Currency)



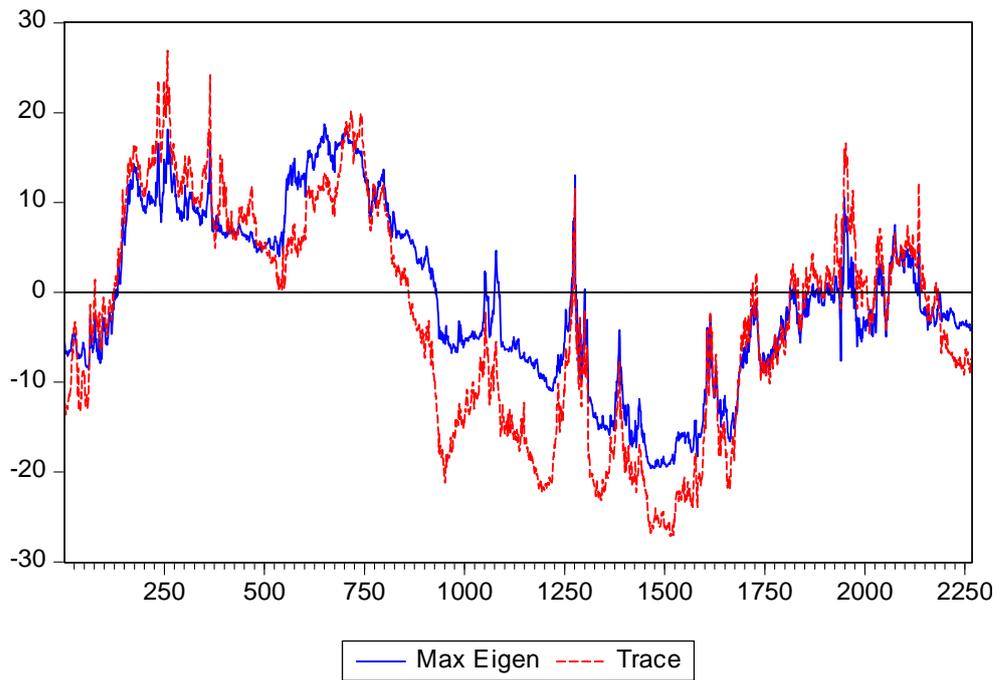
Appendix 3.4a 6-year Dynamic Cointegration Test Statistics for $r = 0$ (Local Currencies)



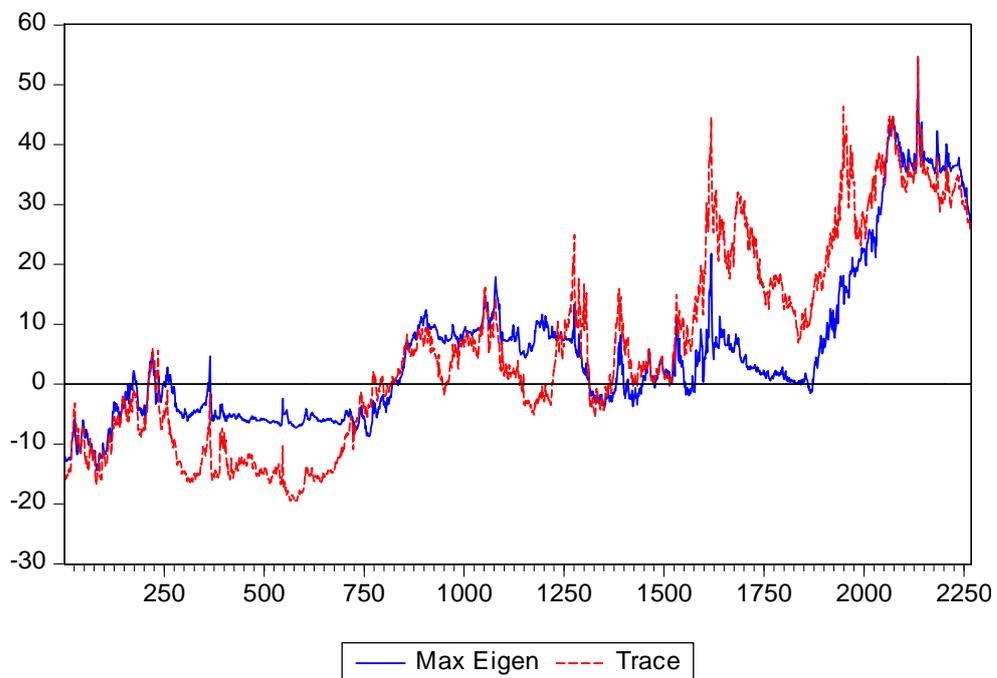
Appendix 3.4b 6-year Dynamic Cointegration Test Statistics for $r = 0$ (Common Currency)



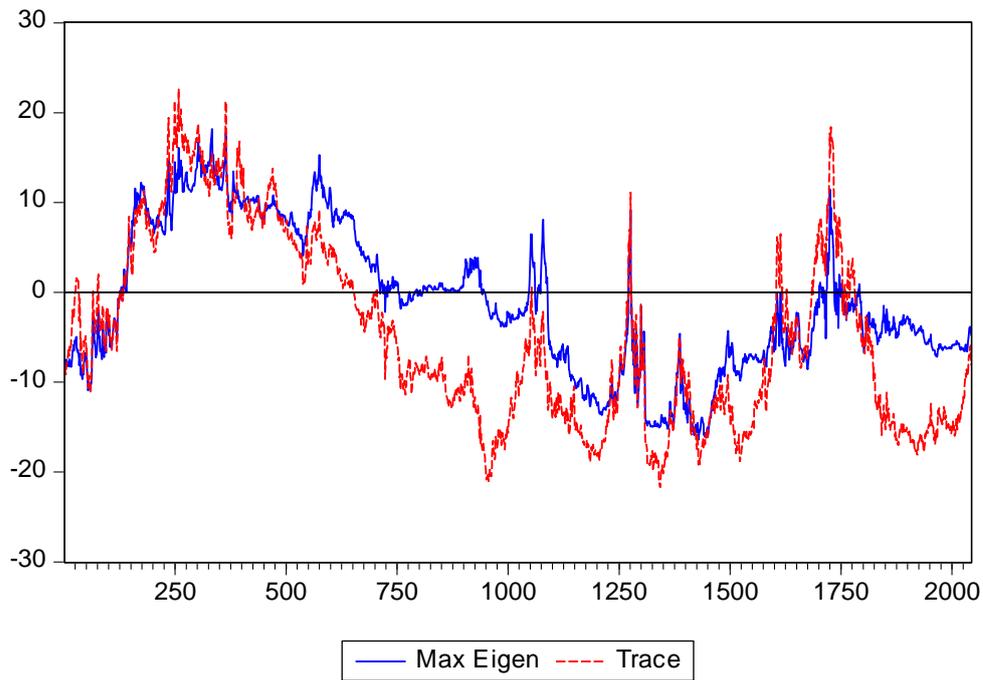
Appendix 3.5a 7-year Dynamic Cointegration Test Statistics for $r = 0$ (Local Currencies)



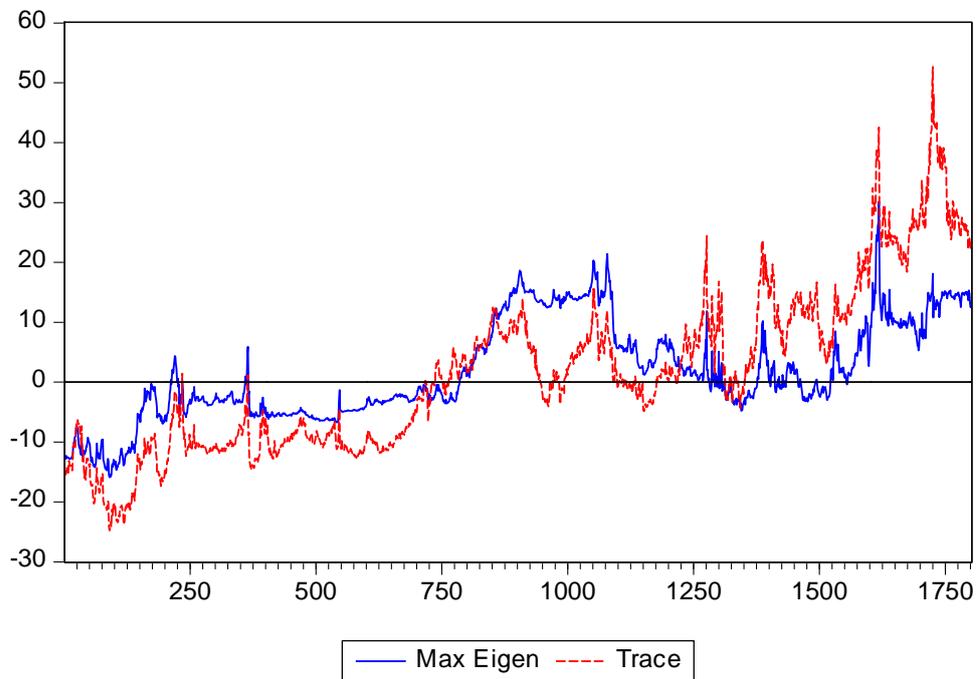
Appendix 3.5b 7-year Dynamic Cointegration Test Statistics for $r = 0$ (Common Currency)



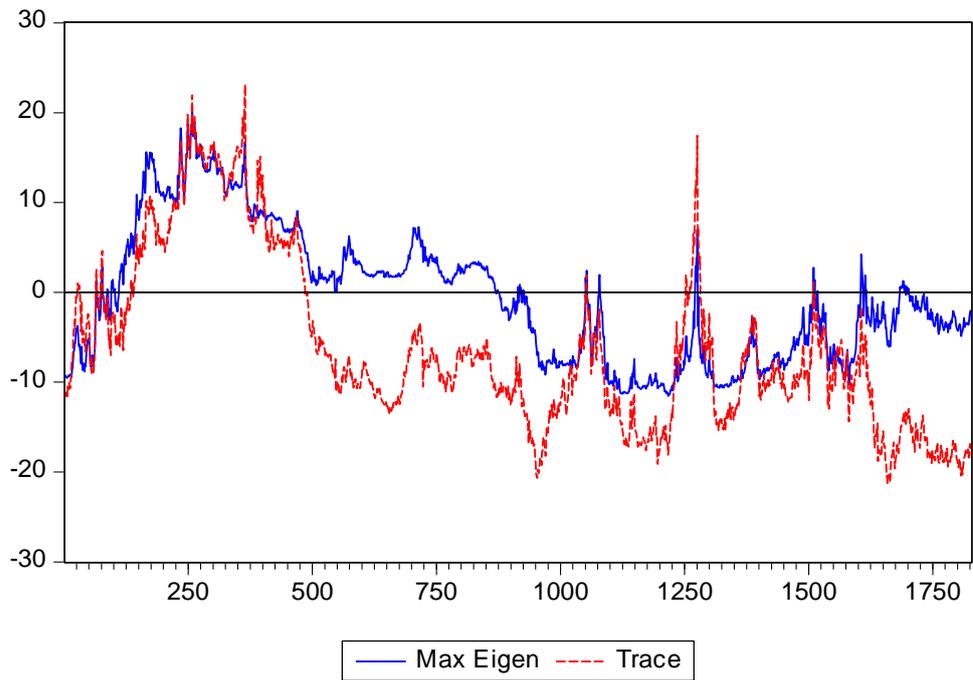
Appendix 3.6a 8-year Dynamic Cointegration Test Statistics for $r = 0$ (Local Currencies)



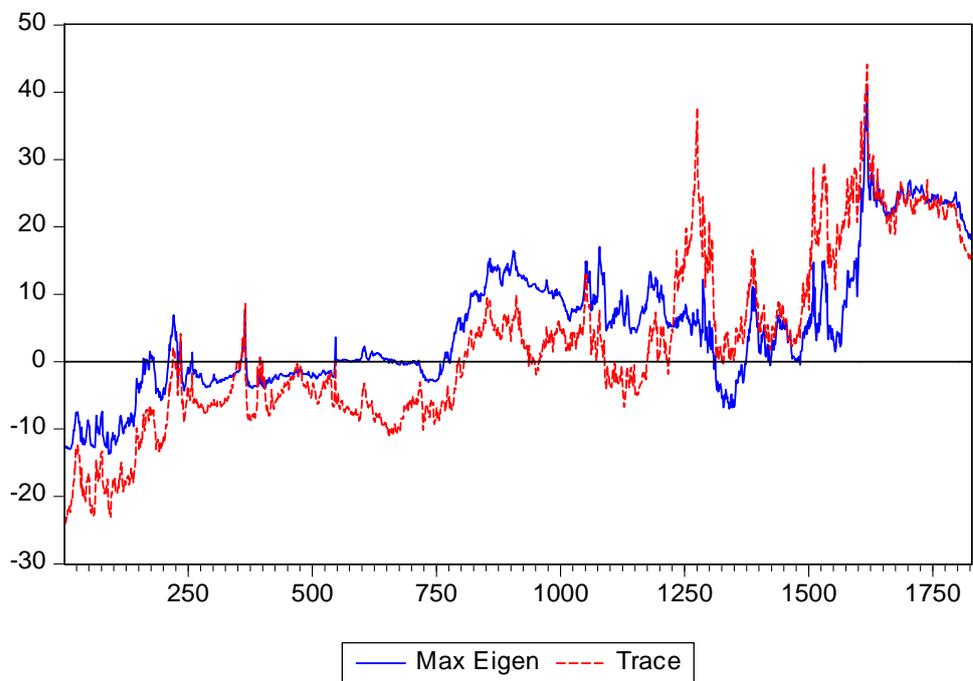
Appendix 3.6b 8-year Dynamic Cointegration Test Statistics for $r = 0$ (Common Currency)



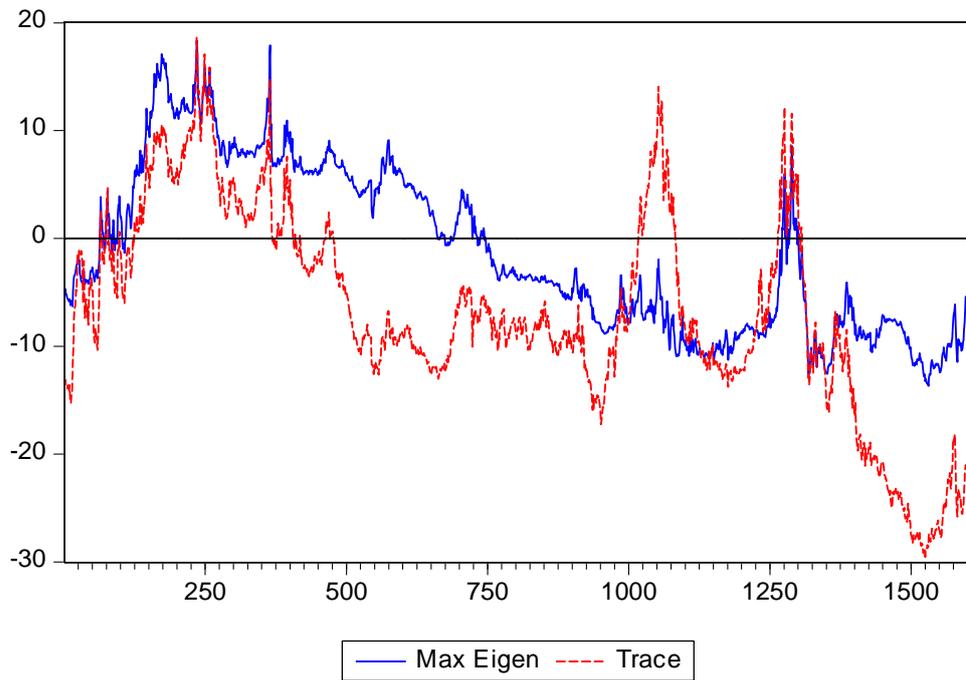
Appendix 3.7a 9-year Dynamic Cointegration Test Statistics for $r = 0$ (Local Currencies)



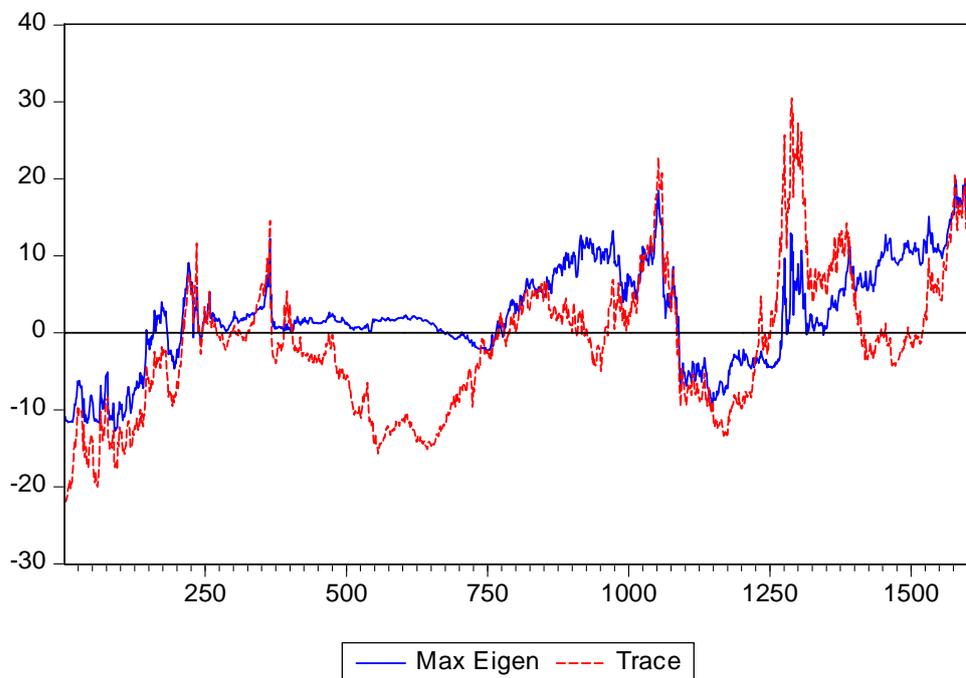
Appendix 3.7b 9-year Dynamic Cointegration Test Statistics for $r = 0$ (Common Currency)



Appendix 3.8a 10-year Dynamic Cointegration Test Statistics for $r = 0$ (Local Currencies)



Appendix 3.8b 10-year Dynamic Cointegration Test Statistics for $r = 0$ (Common Currency)



Chapter 4 – Return and Volatility Spillovers between Chinese Stock Markets and Developed Stock Markets

4.1 Introduction

Since the stock market crash of October 1987, there has been substantial interest in research on why and how stock returns and volatility are propagated across world markets. The analysis of such spillover effects between markets serves as the subject of interest for international portfolio management, the rationale being that if cross market information transmissions are indeed present, portfolio managers would not only utilise information of the market they conduct transactions, but also information from other stock markets which are relevant to the movement in the domestic markets (Koutmos and Booth, 1995). Therefore, a good understanding of the sources of return and volatility spillovers is critical for pricing domestic securities, for implementing global hedging strategies and asset allocation decisions. Furthermore, such information would also assist regulatory authorities in evaluating proposals to restrict international capital flows.

A sampling of early research in this area includes studies by Eun and Shim (1989), King and Wadhvani (1990), Hamao *et al.* (1990 and 1991), Ng *et al.* (1991), Engle and Susmel (1993), Lin *et al.* (1994), Karolyi (1995) and Koutmos and Booth (1995). These studies amass a substantial body of evidence that confirms the short-term interdependence among the world's largest stock markets and attributes this phenomenon to the growing connectedness of financial markets. Later studies have extended this line of inquiry to emerging stock markets, and between these and developed markets, see for example, Wei *et al.* (1995) on Taiwan, Hong Kong and three developed markets, Liu and Pan (1997) on four Asian markets, the US and Japan, Ng (2000) on six Pacific-Basin markets, the US and Japan, Kim (2003) on four advanced Asia-Pacific markets and the US, Chan and Karim (2010) on ASEAN-Five markets, the US and Japan, to name a few.

Despite extensive research effort in understanding the short-term transmission mechanism between Asian stock markets and the US and Japanese markets, studies concerning the two Mainland Chinese stock markets are primarily confined to a regional setting (i.e. the Greater China region), see for example, Yeh and Lee (2000), Qiao *et al.* (2008) and Johansson and Ljungwall (2009). The few exceptions include Hu *et al.* (1997) and Wang and Firth (2004), both of which examine spillover effects among the four markets in the Greater China region and selected developed international markets. The samples in both studies encompass a period when foreign investment into the Mainland China's stock markets was a virtual impossibility through legal channel. The launch of the Qualified Foreign Institutional Investor (QFII) scheme in late 2002 and subsequent introduction of the Qualified Domestic Institutional Investor (QDII) scheme have prompted capital flows into and out of Mainland China ever since. Against this background, it is of great interest to examine whether these recent financial liberalisation initiatives would alter the pattern of return and volatility spillovers between Mainland China and the rest of the world. There have been a number of studies which demonstrate that various financial liberalisation policies will facilitate greater information transmission across markets in the forms of return and volatility spillovers. For example, Kim and Roger (1995) find increased spillover effects in the Korean stock market since the market liberalisation; similarly, Darrat and Benkato (2003) identify the US and the UK as dominant sources of volatility spillover for the Istanbul Stock Exchange following the market liberalisation in Turkey. Given these evidence, we would expect greater spillover effects between Mainland Chinese stock markets and the world stock markets as the consequence of the recent financial liberalisation initiatives.

The purpose of this study is thus twofold: first, to remedy the gap in the literature by examining return and volatility spillover effects of Mainland Chinese stock markets in an international setting; second, to investigate possible change of behaviour in which the return and volatility of the two Mainland China's stock markets are related with market in the same economic region (Hong Kong)

and major developed markets (the US, the UK and Japan) following the partial financial liberalisation. Our empirical results will serve as the basis for evaluating the implications of cross-market influences in stock returns and volatility for pricing of securities within those markets, for hedging and other trading strategies and for regulatory policies within their financial markets.

The remainder of this chapter is organised as follows: Section 2 discusses the theories underlying the cross-market spillover effects followed by a review of the extant literature on the topic; Section 3 describes the sample data and report basic statistical results; Section 4 describes the two-stage procedure for testing spillover effects across markets; Section 5 presents and discusses the empirical results; and Section 6 provides concluding remarks.

4.2 Literature Review

4.2.1 Logic of Return and Volatility Spillovers

Ito and Lin (1994) put forward the informational efficiency and market contagion hypotheses to explain the cause of international transmission of stock returns and volatility. The informational efficiency hypothesis attributes interdependence of stock returns and volatility across markets to real and financial linkage of economies: news revealed in one country is perceived as informative to fundamentals of stock prices in another country. Under this hypothesis, return spillovers are likely to be positively influenced by foreign return volatility. On the other hand, the market contagion hypothesis posits that stock prices in one country can be affected by changes in another country beyond what is conceivable by connections through economic fundamentals. According to this view, cross-market spillover effects are caused by the contagion of liquidity traders' sentiments or by resolution of heterogeneous interpretation of foreign news. If this is the case,

returns correlations will be positively influenced by foreign trading volume, but not by foreign return volatility.

Decomposing close-to-close return into its overnight and daytime components, Hamao *et al.* (1990) further point out that return spillover effects from foreign markets to domestic overnight return are predicted by international asset pricing models, while return spillover effects to the daytime return are predicted not to occur, should informational efficiency hypothesis holds. They further elaborate that volatility spillovers could represent a causal phenomenon across markets that trade sequentially; or alternatively, they could reflect global economic changes that concurrently alter stock return volatility across international stock markets.

Researchers have identified a number of factors that could strengthen the real and financial linkage of economies, which in turn give rise to greater return and volatility spillovers among these markets. Spillovers from one market to another can be simply magnified by the advances in technology that allow speedy information transmission with lower transaction costs (Chan and Karim, 2000). Spillover effects may differ across countries owing to the degree of market openness and the volume of cross-market capital flows. This view is supported by Ng (2000) who suggests financial liberalisation events do have an impact on the spillover effects from Japan and the US to Pacific-Basin stock markets. Spillover effects are more pronounced in markets that are economically tied or in close geographical proximity. Janakiramanan and Lamba (1998) demonstrate that markets that are geographically and economically close tend to influence one another. Johansson and Ljungwall (2009) document strong spillover effects in both returns and volatility in the Greater China region (i.e. Mainland China, Hong Kong, and Taiwan). Cross-border stock multi-listing has also contributed a great deal to the return interaction and information transmission among stock markets, because it internationalises local enterprises and thus provides simultaneous shocks to both foreign and domestic markets (Yeh and Lee, 2000). For

example, Cotter (2004) finds that dual-listing of Irish stocks in the form of American Depositary Receipts (ADRs) has played an important role in the unidirectional spillover effect from the US to Irish stock market.

The presence of significant spillover effects between stock markets will attenuate the benefits of international portfolio diversification. Besides, the transmission of foreign shocks to the home market might create an adverse effect to both local and foreign investors. The existence of cross-market spillover effects implies that the analysis of a single market in isolation will ignore vital information and may lead to suboptimal global asset allocation decisions.

4.2.2 Empirical Evidence

A substantial body of evidence has now accumulated on the information transmission across different stock markets. For example, Eun and Shim (1989) find that innovations (shocks) in the US stock market are rapidly transmitted to the rest of the world, although innovations in other national markets do not have much effect on the US market. Applying a two-step procedure and GARCH type model, Hamao *et al.* (1990) study the short-run interdependence of returns and return volatility across Tokyo, London, and New York stock exchanges. They find evidence of unidirectional return and volatility spillovers from relatively advanced markets to less advanced markets, i.e. from New York to London and Tokyo, and from London to Tokyo, but neither London nor Tokyo stock return shocks had any effect on next-day New York stock returns. In contrast to Hamao *et al.* (1990), Lin *et al.* (1994) show that the earlier results were sensitive to measurement of the opening quotes in Tokyo and New York, and that cross-market interdependence in returns and volatility is much more balanced and generally bidirectional in nature across these markets. In a follow-up study, Hamao *et al.* (1991) review the evidence in the post-1987 Crash period and find that volatility spillover effects overall, but especially those

emanating from Japan to the US, had dissipated in magnitude and persistence over time. On balance, research on developed markets generally reports a negligible role of the Japanese market in information leadership among the markets of the US and Western Europe and an absence of significant market linkages between Japan and other major markets. Bae and Karolyi (1994) attribute this weak relationship to the misspecification of the returns and volatility generating process in those markets as asymmetric effect is not fully investigated. To this end, Koutmos and Booth (1995) examine asymmetric volatility transmission mechanism among the stock markets of New York, London, and Tokyo such that negative innovations in a given market increase volatility in the next market to trade considerably more than positive innovations. A pre- and post-1987 crash analysis reveals that the linkages and interactions among the three markets have increased substantially in the post-crash era, suggesting that national stock markets have grown more interdependent.

Similar patterns exist for Asia-Pacific stock markets in terms of significant first- and second-moment spillover effects. The US market has been providing a significant leading influence on the region. Despite close economic linkages between Japan and other regional countries, the influence of the Japanese market has not been very strong. For example, Liu and Pan (1997) investigate the return and volatility spillover effects from the US and Japan to Hong Kong, Singapore, Taiwan, and Thailand. They find that the US market is more influential than the Japanese market in transmitting returns and volatility to the four Asian markets. Although a lot of previous work has focused on Asian stock markets, the number of studies on Mainland China's emerging stock markets does not parallel their growing importance in the optimisation of global portfolio diversification and asset allocation. Hu *et al.* (1997) provide evidence that volatility of the two Mainland Chinese markets are less correlated with their domestic counterparts than they are with the US and Japanese market, leading to the conclusion that geographic proximity and economic ties do not necessarily warrant stronger information transmission. Wang and Firth (2004)

study the return and volatility spillovers between the four markets in Greater China, incorporating the markets of the US, the UK and Japan, through a univariate GARCH framework. Their findings point to unidirectional spillovers from more advanced stock markets to markets in the Greater China region. Mixed results are reported on the spillover effects within the Greater China region: Qiao *et al.* (2008) suggest the Mainland markets are more influential than Hong Kong in volatility transmission; on the contrary, Johansson and Ljungwall (2009) find that Mainland markets are influenced by Taiwan and Hong Kong, but not vice versa. Since both studies employ similar econometric framework and data sample, the conflicting results may be due to the difference in data frequency. Furthermore, the sample period in neither study goes beyond 2005. In light of the recent effort made by the Chinese government to further liberalise its capital markets (i.e. the launch of QFII and QDII schemes), the issue of return and volatility spillovers in Mainland China deserves to be revisited. To discern the impact of QFII and QDII on the pattern of return and volatility transmission, the whole sample period is partitioned into pre- and post-QFII periods, which are analysed separately. Since the degree of market openness is often cited as being positively related to the market's sensitivity to foreign shocks, we expect to see stronger return and volatility transmission between Mainland China and the rest of the world in the post-QFII period.

4.3 Data

We examine daily opening and closing stock prices of six stock market indices over the period from January 4th 1993 to March 31st 2010. The three stock indices for China are the Shanghai Stock Exchange A-Share Index (SH), Shenzhen Stock Exchange A-Share Index (SZ), and Hang Seng Index (HK). New York Stock Exchange Composite Index (US), London Stock Exchange 100 Index (UK),²⁰ and Tokyo Stock Price Index (JP) are used as the proxies for the stock markets in

²⁰ We substitute FTSE-100 Index for FTSE-All share Index since the opening price data for the latter index is not available on the Datastream until April 20th 2006.

the developed economies. The inclusion of these developed stock markets is important to our analysis since they are believed to exert influences over the stock markets in emerging economies. All price data are extracted from Datastream. Our sample period encompasses different episodes in the international transmission of large shocks in prices and volatility, including the periods of the 1997 Asian financial crisis, the forming and bursting of the dot.com bubble, and the outbreak of 2007-2009 global financial crisis.

To carry out the empirical analysis, we follow Hamao *et al.* (1990) and Lin *et al.* (1994) in using intradaily data of stock index returns in order to clearly define the daytime and overnight returns. Hamao *et al.* (1990) decompose daily (close-to-close) returns into overnight (close-to-open) and daytime (open-to-close) returns, and stress that using close-to-close returns to estimate spillover effects tends to confuse the causes of correlation in return processes across markets by inducing positive correlation in measured returns and possibly in return volatility. The significance of separating overnight and daytime returns is also highlighted by Martens and Poon (2001) and Burns *et al.* (1998). These authors show that studies of market linkages can be significantly biased by non-synchronous trading problems and overlapping measurement of returns.

Let OP_{it} and CP_{it} be the i th stock index's opening and closing price at time t , respectively. The daily close-to-close returns of each stock market index, R_{it} , is divided into close-to-open (overnight) returns, RN_{it} , and open-to-close (daytime) returns, RD_{it} :

$$R_{it} = RN_{it} + RD_{it} \tag{Eq.(4.1)}$$

where $RN_{it} = \ln \frac{OP_{it}}{CP_{it-1}}$, $RD_{it} = \ln \frac{CP_{it}}{OP_{it}}$, and $i = \text{SH, SZ, HK, US, UK, and JP}$. Suffixes N and D

denote overnight and daytime, respectively.

Since the trading hours of Chinese stock markets are not synchronous with the three major international stock markets, especially the US and the UK markets, the partitioning of overnight and daytime returns enables us to investigate return and volatility spillovers in a more precise manner.

Another technical problem in studying information transmission mechanism across markets is the existence of nonsynchronous holidays among these markets. As Chinese stock markets close for a week or more during the Lunar New Year holidays, usually in January or early February, the data of the three international stock markets for these periods are eliminated. Similarly, other holidays' data are also excluded from the sample. The holiday-adjusted sample contains 3732 observations.

Table 4.1 displays trading hours of the six exchanges in their local times and Greenwich times. Figure 4.1 illustrates the chronological sequence of opening and closing times of the six stock exchanges. The four Asian stock markets overlap in trading hours, but there is no overlap in trading hours between each of the four Asian stock markets and the US and UK stock markets. Note that the overnight return is ahead of the daytime return by definition.

Table 4.1 Trading Hours of the Six Stock Exchanges in Local and Greenwich Times

Stock Exchange	Local Time	Greenwich Time
Shanghai	9:30 – 11:30, 13:00 – 15:00	1:30 – 3:30, 5:00 – 7:00
Shenzhen	9:30 – 11:30, 13:00 – 15:00	1:30 – 3:30, 5:00 – 7:00
Hong Kong	10:00 – 12:30, 14:30 – 16:00	2:00 – 4:30, 6:30 – 8:00
New York	9:30 – 16:00	14:30 – 21:00
London	9:30 – 15:30	9:30 – 15:30
Tokyo	9:00 – 11:00, 13:00 – 15:00	0:00 – 2:00, 4:00 – 6:00

Figure 4.1 Sequence of Opening and Closing Times of the Six Stock Exchanges

Greenwich Time																							
0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
SHN _t	SHD _t					SHN _{t+1}																	
SZN _t	SZD _t					SZN _{t+1}																	
HKN _t	HKD _t					HKN _{t+1}																	
USN _t															USD _t					USN _{t+1}			
UKN _t									UKD _t						UKN _{t+1}								
JPD _t						JPN _{t+1}																	

Note: Grey bar indicates the market is closed.

Table 4.2 Summary Statistics of the Daytime and Overnight Index Returns

Index	Mean%	S.D.	Skew	Kurt	J-B	LB(1)	LB(5)	LB ² (1)	LB ² (5)
<i>SHD</i>	0.0046	0.0207	0.5605	13.4386	0.0000	65.245*	84.058*	273.87*	1568.1*
<i>SHN</i>	0.0325	0.0145	2.5732	70.3111	0.0000	3.0249†	27.165*	9.9707*	72.670*
<i>SZD</i>	0.0661	0.0219	0.7114	16.4507	0.0000	24.185*	30.230*	53.870*	502.48*
<i>SZN</i>	-0.0231	0.0117	0.7480	51.5429	0.0000	20.581*	38.286*	18.419*	99.800*
<i>HKD</i>	-0.0197	0.0133	0.1097	9.8778	0.0000	8.7524*	15.756*	635.94*	1462.6*
<i>HKN</i>	0.0559	0.0132	0.8001	26.1822	0.0000	7.4467*	24.092*	85.459*	289.58*
<i>USD</i>	0.0104	0.0115	-0.5479	13.1515	0.0000	10.138*	20.611*	250.93*	1839.9*
<i>USN</i>	0.0184	0.0049	1.6351	190.3264	0.0000	32.978*	100.46*	30.087*	558.76*
<i>UKD</i>	-0.0221	0.0115	-0.3164	9.4311	0.0000	0.1147	13.190*	221.14*	2039.6*
<i>UKN</i>	0.0406	0.0056	3.4874	74.5611	0.0000	0.9299	5.4289	2.0521	6.5770
<i>JPD</i>	-0.0519	0.0114	0.0042	10.2703	0.0000	0.0002	24.401*	198.23*	1355.0*
<i>JPN</i>	0.0441	0.0067	-1.0891	31.2112	0.0000	6.1765*	11.116*	19.034*	30.366*

Notes: * indicates significance at 5% level and † indicates significance at 10% level.

Table 4.2 reports some basic statistics for daily daytime and overnight returns for the six stock indices over the full sample period. It is notable that the daytime volatilities (measured by standard deviation) are much higher than the overnight volatilities for most of the indices except for HK, whose daytime and overnight volatilities are on par with each other. No particular pattern is observed between the daytime and overnight returns from their respective market indices. All return series are skewed and leptokurtic which indicate that their empirical distributions have fat

tails relative to the normal distribution. Ljung-Box statistics, $LB(k)$ and $LB^2(k)$ for $k = 1$ and $k = 5$ lags, calculated for both the return and the squared return series, indicate the presence of significant linear and non-linear dependencies, respectively, in the returns of all six markets, with only few exceptions. Linear dependencies may be due to either to non-synchronous trading of the stocks that make up each index (Scholes and Williams, 1977; and Lo and MacKinlay, 1988) or to some form of market inefficiency. Non-linear dependencies may be due to autoregressive conditional heteroskedasticity. Rejections of the null hypothesis of no serial correlation for most of the squared return series indicate that a GARCH type model will be an appropriate specification.

Table 4.3 Contemporaneous Correlation between Domestic Overnight and Daytime Returns

	SH	SZ	HK	US	UK	JP
Correlation	-0.0077	-0.0091	0.0676	0.0193	-0.0028	0.2472
<i>p</i> -value	0.6367	0.5799	0.0000	0.2379	0.8655	0.0000

As shown in Table 4.3, domestic daytime and overnight returns in HK and JP are significantly positively correlated instead of being mutually uncorrelated. This implies that both lagged overnight and daytime returns may have explanatory power on the current value of each other.

4.4 Methodology

In this study, we employ a two-stage procedure to investigate the short-run interdependence of returns and return volatilities of the stock indices across Shanghai, Shenzhen, Hong Kong, New York, London and Tokyo stock exchanges. In the first stage, we estimate the unexpected returns for each index that cannot be forecasted using currently available information within the exchange. In the second stage, we fit the unexpected returns to the proposed GARCH model to investigate the interdependence of returns and volatilities between the i th and the j th markets, $i \neq j$.

The purpose of the first-stage estimation is to extract the unpredictable part of the stock returns. To remove the predictable part from the index return, a procedure analogous to the one in Engle and Ng (1993) is adopted. This procedure involves a day-of-the-week effect adjustment and an autoregressive regression which removes the predictable part from the index return.

There have been a large number of empirical studies documenting significant day-of-the-week effect in both developed and emerging stock markets. Early studies by Cross (1973), French (1980), Gibbons and Hess (1981), and Keim and Stambaugh (1984), among others, all acknowledge consistently negative Monday returns for US stocks. There is also copious empirical evidence supporting the existence of weekday seasonality in European and Asian stock markets. Theobald and Price (1984) and Jaffe et al. (1989) observe significant negative returns on London Stock Exchange on Mondays. For the Asian markets, Jaffe and Westerfield (1985) and Lee et al. (1990) document negative returns of Japanese on Tuesdays; Aggarwal and Rivoli (1989) find that the Hang Seng index produces negative return on Tuesdays and Chen *et al.* (2001) report a similar Tuesday effect for China's stock markets since 1995. Researchers have also conjectured that the 'Tuesday effect' in Far Eastern markets is partially due to the spillover from the US. On the other hand, Connolly (1989) suggests that evidence of a significant Monday effect is a statistical anomaly and the strength of the effect is dependent on the estimation method and sample period. Similarly, Chang *et al.* (1993) finds that sample size and/or error term adjustments render US day-of-the-week effects statistically insignificant whereas day-of-the-week effects in the UK and Hong Kong remain robust to these adjustments. Given the lack of consistent evidence of day-of-the-week effect in the stock markets investigated in this study, we define five weekday dummies (through Monday to Friday) and allow up to four dummies in the regression equation for each index return:

$$D_{d,t} = \begin{cases} 1, & \text{if } t \text{ is } d \text{ (} d = \text{Monday, Tuesday, Wednesday, Thursday or Friday)} \\ 0, & \text{otherwise} \end{cases} \quad \text{Eq. (4.2)}$$

In addition to the day-of-the-week dummies, we also introduce a dummy variable, DA, to control for the effect of the Asian financial crisis. Between October 20th 1997 and October 23rd 1997, the Hang Seng Index dropped 23%. When the New York Stock Exchange opened on October 27th 1997, the Dow Jones Industrial Average (DJIA) dropped 7.18% in reaction to the Asian financial crisis and London Stock Exchange's FTSE-100 index also plunged substantially. Following the stock market collapse in New York and London, the Hang Seng Index dropped a further 13.7% on October 28th 1997. DA takes the value of unity between October 20th 1997 and October 28th 1997 and zero otherwise.

$$DA_t = \begin{cases} 1, & \text{if } t = \text{October 20th 1997 to October 28th 1997} \\ 0, & \text{otherwise} \end{cases} \quad \text{Eq. (4.3)}$$

We first regress each index return on a constant and dummies (i.e. the day-of-the-week and Asian financial crisis dummy variables) to get the residual, μ_t .²¹ The residuals for the overnight and daytime returns are denoted as $\mu_{t,RN}$ and $\mu_{t,RD}$, respectively. By allowing for a possible correlation between the preceding overnight return and daytime return, $\mu_{t,RN}$ is regressed on $\mu_{t-1,RN}, \dots, \mu_{t-10,RN}$, and $\mu_{t-1,RD}, \dots, \mu_{t-10,RD}$, to obtain the residual, $\varepsilon_{t,RN}$, which is the unexpected index overnight return. The unexpected index daytime return, $\varepsilon_{t,RD}$, is obtained in a similar fashion by regressing $\mu_{t,RD}$ on a constant, $\mu_{t,RN}, \dots, \mu_{t-9,RN}$, and $\mu_{t-1,RD}, \dots, \mu_{t-10,RD}$. We restrict the autoregressive terms of $\mu_{t,RN}$ and $\mu_{t,RD}$ to ten lags. Our estimation results show that this setting suffices in most cases as higher order of lags provide no incremental explanatory power.

²¹ The day-of-the-week dummy variables are entered into the regression equation one by one, starting with Monday dummy, those that are insignificant at 5% level are dropped out until all the remaining dummies variables are significant at 5% level.

The unexpected stock return, ε_t , is used for the estimation of GARCH model. The GARCH approach to capturing the phenomenon of volatility clustering is very popular in modeling the second moments of financial data. The GARCH model comprises two parts – the mean equation and the variance equation, which allows us to examine the mean and volatility spillovers simultaneously. The simplest GARCH (1, 1) specification takes the form:

$$\varepsilon_t = X_t' \gamma + \epsilon_t \quad \text{Eq. (4.4)}$$

$$\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 \quad \text{Eq. (4.5)}$$

in which the conditional mean of ε_t given in Eq.(4.4) is written as a function of exogenous variables with an error term. The conditional variance at time t , σ_t^2 , is modeled as a positive function of the last period's error squared and its conditional variance.

Following Lin *et al.* (1994), the fitted value of the unexpected overnight and daytime return of foreign market j , $\hat{\varepsilon}_{jt-l}$, are substituted into Eq. (4.4) as exogenous variables to capture return spillover effects from j th markets to the i th market. Squared residuals, $\hat{\varepsilon}_{jt-l}^2$, are incorporated into Eq. (4.5) to capture the potential volatility spillover effect from j th markets to the i th market. According to Engle *et al.* (1990), Hamao *et al.* (1990), and Koutmos and Booth (1995), the squared residual term, $\hat{\varepsilon}_{jt-l}^2$, can be interpreted as a volatility surprise, and the coefficient for this exogenous variable measures the volatility spillover effect from j th markets to the i th market. Due to non-synchronous trading times between the stock exchanges, the added variables have a different time subscript l . Recall that the four Asian stock markets overlap in trading hours and there is one-hour overlap between New York and London, there is a need to distinguish between

lead-lag and contemporaneous spillover effects in the model specification.²² Non-overlapping trading implies that the estimation of the mean and variance in each market is conditional on own past information as well as information generated by the last markets to trade. For markets whose trading hours do overlap, if market A closes trading after market B, the contemporaneous innovations from market B will be included in the estimated equations for market A instead. For instance, considering the unexpected daytime return of Shanghai, ε_{SHD} , $l = 0$ for $j \in \{SZN, HKN, JPD, JPN\}$; $l = 1$, for $j \in \{SZD, HKD, USD, USN, UKD, UKN\}$. In other words, the current period return and volatility surprises from the overnight returns of SZ, HK and JP, and the daytime returns of JP are known by the time the daytime return of SH is calculated. In contrast, SH on day t only knows the return and volatility surprises from US and UK on day $t-1$, so $l = 1$. Since SH closes trading simultaneously with SZ and one hour earlier than HK, SH will not learn the closing prices of SZ and HK by the time it closes, the innovations originated from SZ and HK during the daytime trading would only be partially felt by SH, l is therefore set to 1 to avoid potentially spurious relationship. The formations and orderings of the added exogenous variables for each unexpected return series are detailed in Table 4.4. A significant contemporaneous or lagged return spillover coefficient or a significant contemporaneous or lagged volatility spillover coefficient suggests that the j th stock market's unexpected return and volatility spillovers provide additional information in formulating i th market's return and volatility process.

Table 4.4 Formations of Exogenous Variables in the Mean Equation

Return Series	Ordering of the Exogenous Variables									
	1	2	3	4	5	6	7	8	9	10
<i>SHD</i>	ε_{JPD}	ε_{HKN}	ε_{SZN}	ε_{JPN}	$\varepsilon_{USD(-1)}$	$\varepsilon_{UKD(-1)}$	$\varepsilon_{USN(-1)}$	$\varepsilon_{UKN(-1)}$	$\varepsilon_{HKD(-1)}$	$\varepsilon_{SZD(-1)}$
<i>SHN</i>	ε_{JPN}	$\varepsilon_{USD(-1)}$	$\varepsilon_{UKD(-1)}$	$\varepsilon_{USN(-1)}$	$\varepsilon_{UKN(-1)}$	$\varepsilon_{HKD(-1)}$	$\varepsilon_{SZD(-1)}$	$\varepsilon_{JPD(-1)}$	$\varepsilon_{HKN(-1)}$	$\varepsilon_{SZN(-1)}$
<i>SZD</i>	ε_{JPD}	ε_{HKN}	ε_{SHN}	ε_{JPN}	$\varepsilon_{USD(-1)}$	$\varepsilon_{UKD(-1)}$	$\varepsilon_{USN(-1)}$	$\varepsilon_{UKN(-1)}$	$\varepsilon_{HKD(-1)}$	$\varepsilon_{SHD(-1)}$

²² There is two-hour trading overlap between New York and London during the period of British Summer Time.

<i>SZN</i>	ε_{JPN}	$\varepsilon_{USD(-1)}$	$\varepsilon_{UKD(-1)}$	$\varepsilon_{USN(-1)}$	$\varepsilon_{UKN(-1)}$	$\varepsilon_{HKD(-1)}$	$\varepsilon_{SHD(-1)}$	$\varepsilon_{JPD(-1)}$	$\varepsilon_{HKN(-1)}$	$\varepsilon_{SHN(-1)}$
<i>HKD</i>	ε_{SHD}	ε_{SZD}	ε_{JPD}	ε_{SHN}	ε_{SZN}	ε_{JPN}	$\varepsilon_{USD(-1)}$	$\varepsilon_{UKD(-1)}$	$\varepsilon_{USN(-1)}$	$\varepsilon_{UKN(-1)}$
<i>HKN</i>	ε_{SHN}	ε_{SZN}	ε_{JPN}	$\varepsilon_{USD(-1)}$	$\varepsilon_{UKD(-1)}$	$\varepsilon_{USN(-1)}$	$\varepsilon_{UKN(-1)}$	$\varepsilon_{SHD(-1)}$	$\varepsilon_{SZD(-1)}$	$\varepsilon_{JPD(-1)}$
<i>USD</i>	ε_{UKD}	ε_{UKN}	ε_{HKD}	ε_{SHD}	ε_{SZD}	ε_{JPD}	ε_{HKN}	ε_{SHN}	ε_{SZN}	ε_{JPN}
<i>USN</i>	ε_{UKN}	ε_{HKD}	ε_{SHD}	ε_{SZD}	ε_{JPD}	ε_{HKN}	ε_{SHN}	ε_{SZN}	ε_{JPN}	$\varepsilon_{UKD(-1)}$
<i>UKD</i>	ε_{USN}	ε_{HKD}	ε_{SHD}	ε_{SZD}	ε_{JPD}	ε_{HKN}	ε_{SHN}	ε_{SZN}	ε_{JPN}	$\varepsilon_{USD(-1)}$
<i>UKN</i>	ε_{HKD}	ε_{SHD}	ε_{SZD}	ε_{JPD}	ε_{HKN}	ε_{SHN}	ε_{SZN}	ε_{JPN}	$\varepsilon_{USD(-1)}$	$\varepsilon_{USN(-1)}$
<i>JPD</i>	ε_{HKN}	ε_{SHN}	ε_{SZN}	$\varepsilon_{USD(-1)}$	$\varepsilon_{UKD(-1)}$	$\varepsilon_{USN(-1)}$	$\varepsilon_{UKN(-1)}$	$\varepsilon_{HKD(-1)}$	$\varepsilon_{SHD(-1)}$	$\varepsilon_{SZD(-1)}$
<i>JPN</i>	$\varepsilon_{USD(-1)}$	$\varepsilon_{UKD(-1)}$	$\varepsilon_{USN(-1)}$	$\varepsilon_{UKN(-1)}$	$\varepsilon_{HKD(-1)}$	$\varepsilon_{SHD(-1)}$	$\varepsilon_{SZD(-1)}$	$\varepsilon_{HKN(-1)}$	$\varepsilon_{SHN(-1)}$	$\varepsilon_{SZN(-1)}$

If the spillover reflects the influence of an economic effect common to more than one market, then the residuals and squared residuals of these markets will be correlated. Simultaneous presence of these residuals and squared residuals will inevitably impair their individual explanatory power to the conditional mean and variance. The ordering of the residuals and squared residuals in the mean and variance equations may affect our results on the relative strength of spillover effects from the markets concerned. Instead of appending all residuals and squared residuals at once, we add them one by one, starting first with the residual from the most recently observed index return. Subsequently introduced residual (or squared residual) will be dropped out of the estimated equation if it renders no incremental explanatory power (i.e. statistically insignificant at our pre-specified significance level). The model specifications for the unexpected overnight and daytime returns are expressed respectively as:

$$\begin{cases} \varepsilon_{it,RN} = \sum_{j=1}^5 \lambda_j \hat{\varepsilon}_{jt-L,RN} + \sum_{j=1}^5 \varphi_j \hat{\varepsilon}_{jt-L,RD} \\ \sigma_{it,RN}^2 = \omega_i + \alpha \varepsilon_{it-1,RN}^2 + \beta \sigma_{it-1,RN}^2 + \sum_{j=1}^5 \delta_j \hat{\varepsilon}_{jt-L,RN}^2 + \sum_{j=1}^5 \psi_j \hat{\varepsilon}_{jt-L,RD}^2 \end{cases} \quad \text{Eq. (4.6)}$$

$$\begin{cases} \varepsilon_{it,RD} = \sum_{j=1}^5 \lambda_j \hat{\varepsilon}_{jt-L,RN} + \sum_{j=1}^5 \varphi_j \hat{\varepsilon}_{jt-L,RD} \\ \sigma_{it,RD}^2 = \omega_i + \alpha \varepsilon_{it-1,RD}^2 + \beta \sigma_{it-1,RD}^2 + \sum_{j=1}^5 \delta_j \hat{\varepsilon}_{jt-L,RN}^2 + \sum_{j=1}^5 \psi_j \hat{\varepsilon}_{jt-L,RD}^2 \end{cases} \quad \text{Eq. (4.7)}$$

where i and $j = \text{SH, SZ, HK, US, UK, and JP, } i \neq j$.

The standard GARCH model is symmetric in its response to past innovations. However, there are theoretical arguments that suggest a different response in conditional variance to positive and negative innovations. The need for an asymmetric approach as opposed to the simple GARCH specification is underscored by Bae and Karolyi (1994) and Koutmos and Booth (1995), who collectively report that the volatility transmission among US, UK and Japanese stock markets is asymmetric. The asymmetric GARCH model employed in this study is the threshold GARCH model introduced by Glosten *et al.* (1993), hereafter GJR-GARCH. Engle and Ng (1993) show that the GJR-GARCH is the best at parsimoniously capturing the asymmetric or ‘leverage’ effect. The GJR-GARCH model yields the following modification for the variance equations:

$$\sigma_{it,RN}^2 = \omega_i + \alpha \varepsilon_{it-1,RN}^2 + \beta \sigma_{it-1,RN}^2 + \theta_i (I_{it-1} \varepsilon_{it-1,RN}^2) + \sum_{j=1}^5 \delta_j \varepsilon_{jt-l,RN}^2 + \sum_{j=1}^5 \psi_j \varepsilon_{jt-l,RD}^2 \quad \text{Eq. (4.8)}$$

$$\sigma_{it,RD}^2 = \omega_i + \alpha \varepsilon_{it-1,RD}^2 + \beta \sigma_{it-1,RD}^2 + \theta_i (I_{it-1} \varepsilon_{it-1,RD}^2) + \sum_{j=1}^5 \delta_j \varepsilon_{jt-l,RN}^2 + \sum_{j=1}^5 \psi_j \varepsilon_{jt-l,RD}^2 \quad \text{Eq. (4.9)}$$

The term $I_{it-1} \varepsilon_{it-1}^2$ captures the asymmetric effect on the conditional variance, where I_{it-1} is a dummy variable:

$$I_{it-1} = \begin{cases} 1, & \text{if } \varepsilon_{it-1} < 0, \\ 0, & \text{otherwise} \end{cases} \quad \text{Eq. (4.10)}$$

While there is ample evidence that the volatility process of developed stock markets are better characterised by asymmetric GARCH model, there is little agreement on whether volatility asymmetry is a prominent feature in the emerging stock markets. For example, Lee *et al.* (2001) show that the EGARCH model does not produce a better description of China’s stock market data

than the GARCH model. The empirical validity of the proposed GJR-GARCH model, particularly on overnight returns, is yet to be seen. For this reason, we allow different parameterisations for the variance equation of each stock market index return under investigation. Symmetric GARCH is preferred over the GJR-GARCH model if the asymmetry parameter – θ_i in Eq. (4.8 and 4.9), is statistically insignificant. The finalised GARCH estimation is achieved by eliminating insignificant exogenous variables from the mean and variance equations while satisfying the diagnostic tests. The primary diagnostic test involves the Ljung-Box statistics, which is used to test for remaining serial correlation in the model residuals and residuals squared. The statistics are calculated for up to 5 and 10 lags respectively. Finally, all GARCH-type models are estimated based on the Berndt-Hall-Hausman algorithm (see Berndt *et al.*, 1974).

Conceptually our approach resembles the GARCH-in-mean model employed by Hamao *et al.* (1990) and aggregate shock model employed by Lin *et al.* (1994). While all three approaches involve two-stage estimation, the difference lies in the method of extracting unpredictable return in the first stage, which is done under the GARCH framework in the latter two approaches. Moreover, our second-stage GARCH estimation explicitly allows for asymmetric spillover effects among markets, through the use of GJR-GARCH model.

Later studies, for example, Koutmos and Booth (1995), among others, utilise the multivariate version of GARCH method to examine the issue. They argue that the multivariate GARCH model has several advantages over the univariate approach: first, it eliminates the two-step procedure, thereby avoiding problems associated with estimated regressors; second, it improves the efficiency and the power of the tests for cross market spillovers; third, it is methodologically consistent with the notion that spillovers are essentially manifestations of the impact of global news on any given market (Koutmos and Booth, 1995).

Despite its methodological appeal, the use of multivariate GARCH framework is not a viable option for this study. The estimation of multivariate GARCH model can be computationally costly as the number of variables in the model increases. Given we have six stock markets to analyse, the estimation of such model would be a formidable task and the difficulty is further compounded by the separation of overnight and daytime returns. Lin *et al.* (1994) point out that the two-stage univariate approach is asymptotically equivalent to a multivariate procedure if the return process is correctly specified. By assuming the observed residuals from the first stage model as the unobservable innovations in the second stage model, we effectively avoid the complexity associated with multivariate model while still being able to obtain consistent estimated coefficients, though the estimated covariance matrix might not be consistent.

4.5 Empirical Results

Table 4.5 reports the results of the adjustment procedure to remove the day-of-the-week and Asian financial crisis effects from the daily index returns. Only constants and dummy variables that are significant at 5% level are reported.

Table 4.5 Day-of-the-Week Effect and Asian Financial Crisis Adjustments (Full Sample)

	c	D_{Mon}	D_{Tue}	D_{Wed}	D_{Thu}	D_{Fri}	DA
<i>SHN</i>	0.000578*	–	–	–	–	-0.001254*	0.002345*
<i>SHD</i>	0.001484*	-0.002168*	-0.002414*	–	-0.002752*	–	–
<i>SZN</i>	–	–	–	–	–	-0.000975*	–
<i>SZD</i>	–	–	–	0.001870*	–	0.001835*	–
<i>HKN</i>	0.000816*	–	–	–	–	-0.001001*	-0.027911*
<i>HKD</i>	–	–	–	–	-0.001167*	–	–
<i>USN</i>	–	–	–	–	0.000443*	–	–
<i>USD</i>	–	–	–	–	–	–	–
<i>UKN</i>	0.000408*	–	–	–	–	–	-0.000750*

<i>UKD</i>	–	–	–	-0.000893*	–	–	-0.014238*
<i>JPN</i>	0.000441*	–	–	–	–	–	–
<i>JPD</i>	–	-0.001460*	–	–	–	–	–

Notes: D_{Mon} , D_{Tue} , D_{Wed} , D_{Thu} , and D_{Fri} are dummy variables for Monday, Tuesday, Wednesday, Thursday, and Friday respectively. * denotes significance at 5% level when heteroskedasticity-robust standard errors are used.

As shown in Table 4.5, the pattern of day-of-the-week anomaly differs from one market to another and rarely conforms to those documented in the day-of-the-week literature. The Asian crisis dummy is significant and negative for HKN, UKN and UKD, suggesting HK and UK suffered negative returns during the period of Asian financial crisis. Surprisingly, the SH index registered slightly positive overnight return during the same period. This to some extent lends support to the assertion that Mainland China was unaffected by the Asian crisis.

Table 4.6 reports the results of autocorrelation adjustments which remove the predictable part of the return series. The estimated equations contain the lagged returns that are significant at 5% level.

Table 4.6 Autocorrelation Adjustments (Full Sample)

Autocorrelation Adjustments	
$\mu_{t,SHN}$	$= 0.112211\mu_{t-1,SHD} + 0.049257\mu_{t-4,SHD} + 0.070979\mu_{t-4,SHN}$
$\mu_{t,SHD}$	$= -0.127210\mu_{t-1,SHD} - 0.053979\mu_{t-10,SHD} - 0.089077\mu_{t-5,SHN}$
$\mu_{t,SZN}$	$= 0.086598\mu_{t-1,SZD} + 0.035184\mu_{t-4,SZD} + 0.076289\mu_{t-1,SZN} + 0.049804\mu_{t-9,SZN}$
$\mu_{t,SZD}$	$= -0.078750\mu_{t-1,SZD} - 0.086820\mu_{t-5,SZN}$
$\mu_{t,HKN}$	$= 0.075846\mu_{t-1,HKD}$
$\mu_{t,HKD}$	$= 0.064683\mu_{t,HKN} - 0.066507\mu_{t-3,HKN} + 0.063821\mu_{t-7,HKN}$
$\mu_{t,USN}$	<i>N/A</i>
$\mu_{t,USD}$	$= -0.167242\mu_{t-6,UKN}$
$\mu_{t,UKN}$	$= -0.025567\mu_{t-2,UKD} - 0.035195\mu_{t-9,UKN}$
$\mu_{t,UKD}$	<i>N/A</i>
$\mu_{t,JPN}$	$= 0.029248\mu_{t-1,JPD} - 0.027662\mu_{t-6,JPD}$
$\mu_{t,JPD}$	$= 0.420336\mu_{t,JPN}$

Note: ‘N/A’ indicates none of the lagged variables is significant at 5% level when heteroskedasticity-robust standard errors are used.

With the exceptions of USN and UKD, index returns are dependent on either the past values of its own or alternative returns or both. In particular, overnight and daytime returns of HK and JP as well as USD can only be explained by the past values of its alternative returns but not its own returns.

Having obtained the fitted values of unexpected returns, we proceed to the second-stage GARCH estimation. Table 4.7 presents the mean and volatility spillover for the overnight returns. A parallel investigation on the daytime returns is presented in Table 4.8.

Table 4.7 Mean and Volatility Spillovers for the Overnight Returns (Full Sample)

	$\hat{\epsilon}_{SHN}$	$\hat{\epsilon}_{SZN}$	$\hat{\epsilon}_{HKN}$	$\hat{\epsilon}_{USN}$	$\hat{\epsilon}_{UKN}$	$\hat{\epsilon}_{JPN}$
$\hat{\epsilon}_{SHD}/SHD(-1)$	–	–	–	–	–	–
$\hat{\epsilon}_{SHN}/SHN(-1)$	–	-0.045941*	–	–	–	–
$\hat{\epsilon}_{SZD}/SZD(-1)$	–	–	–	–	–	–
$\hat{\epsilon}_{SZN}/SZN(-1)$	–	–	0.035829*	–	-0.005214*	–
$\hat{\epsilon}_{HKD}/HKD(-1)$	0.011594*	0.012906*	–	-0.001611*	0.008351*	–
$\hat{\epsilon}_{HKN}/HKN(-1)$	–	–	–	-0.005759*	0.024155*	–
$\hat{\epsilon}_{USD}(-1)$	0.026116*	0.022175*	0.380260*	–	–	0.244080*
$\hat{\epsilon}_{USN}(-1)$	–	–	–	–	-0.013765*	–
$\hat{\epsilon}_{UKD}(-1)$	–	–	0.061970*	-0.001909*	–	0.053853*
$\hat{\epsilon}_{UKN}/UKN(-1)$	–	–	–	0.304603*	–	-0.025720*
$\hat{\epsilon}_{JPD}/JPD(-1)$	–	–	-0.051317*	–	–	–
$\hat{\epsilon}_{JPN}$	0.023610*	0.023586*	0.399011*	0.015102*	-0.009424†	–
ω	-2.37E-07*	-2.27E-08†	1.61E-06†	8.94E-09*	-6.07E-08*	7.17E-08*
α	0.010212*	0.008129*	0.101278*	-0.000107*	-0.000895*	0.025006*
β	0.904773*	0.965736*	0.796904*	0.555436*	0.628141*	0.953107*
θ	–	–	0.122048*	0.014091*	0.137205*	–
$\hat{\epsilon}_{SHD}^2/SHD(-1)$	–	–	–	–	0.001790*	–
$\hat{\epsilon}_{SHN}^2/SHN(-1)$	–	0.000569*	–	–	–	–
$\hat{\epsilon}_{SZD}^2/SZD(-1)$	0.007058*	–	–	–	–	–

$\hat{\varepsilon}_{SZN/SZN(-1)}^2$	—	—	—	—	—	—
$\hat{\varepsilon}_{HKD/HKD(-1)}^2$	0.000988*	0.000672*	—	—	0.001046*	—
$\hat{\varepsilon}_{HKN/HKN(-1)}^2$	—	—	—	—	0.003429*	—
$\hat{\varepsilon}_{USD(-1)}^2$	—	—	0.136599*	—	—	0.003135*
$\hat{\varepsilon}_{USN(-1)}^2$	—	—	—	—	—	—
$\hat{\varepsilon}_{UKD(-1)}^2$	—	—	0.034761†	—	—	—
$\hat{\varepsilon}_{UKN/UKN(-1)}^2$	—	—	—	0.045773*	—	—
$\hat{\varepsilon}_{JPD/JPD(-1)}^2$	—	—	—	—	0.000494*	—
$\hat{\varepsilon}_{JPN}^2$	—	—	—	0.000222*	—	—
LB(5)	7.7540	9.1309	1.7933	0.9935	6.0243	6.2284
LB(10)	12.886	12.271	13.945	4.6310	8.8355	11.850
LB ² (5)	0.1864	0.3407	0.5573	0.2125	1.9460	1.6383
LB ² (10)	0.7926	0.7671	6.3708	0.4392	4.4910	2.9647

Note: * indicates significance at 5% level and † indicates significance at 10% level.

Table 4.8 Mean and Volatility Spillover for the Daytime Returns (Full Sample)

	$\hat{\varepsilon}_{SHD}$	$\hat{\varepsilon}_{SZD}$	$\hat{\varepsilon}_{HKD}$	$\hat{\varepsilon}_{USD}$	$\hat{\varepsilon}_{UKD}$	$\hat{\varepsilon}_{JPD}$
$\hat{\varepsilon}_{SHD/SHD(-1)}$	—	—	0.049511*	—	—	—
$\hat{\varepsilon}_{SHN/SHN(-1)}$	—	0.076190*	—	—	—	—
$\hat{\varepsilon}_{SZD/SZD(-1)}$	0.038160*	—	—	—	—	—
$\hat{\varepsilon}_{SZN/SZN(-1)}$	—	—	-0.024135†	—	—	—
$\hat{\varepsilon}_{HKD/HKD(-1)}$	—	—	—	0.074282*	0.097040*	—
$\hat{\varepsilon}_{HKN/HKN(-1)}$	0.059752*	0.059048*	—	—	—	0.149796*
$\hat{\varepsilon}_{USD(-1)}$	-0.060655*	-0.062724*	-0.036887*	—	—	-0.101769*
$\hat{\varepsilon}_{USN/USN(-1)}$	—	—	—	—	0.097577*	—
$\hat{\varepsilon}_{UKD/UKD(-1)}$	0.041086†	0.039588†	—	—	—	0.032810†
$\hat{\varepsilon}_{UKN/UKN(-1)}$	—	—	—	0.068569*	—	—
$\hat{\varepsilon}_{JPD}$	—	—	0.276666*	0.069412*	0.093311*	—
$\hat{\varepsilon}_{JPN}$	0.088842*	0.073525†	—	—	—	—
ω	7.27E-06*	7.23E-06*	4.44E-07*	7.39E-07*	6.04E-07*	2.58E-06*
α	0.078245*	0.154745*	0.045286*	0.002879	-0.000128	0.043317*
β	0.843160*	0.838705*	0.927089*	0.903558*	0.916216*	0.880612*
θ	—	—	0.028504*	0.136833*	0.111456*	0.044463*
$\hat{\varepsilon}_{SHD/SHD(-1)}^2$	—	—	—	—	—	—
$\hat{\varepsilon}_{SHN/SHN(-1)}^2$	—	—	0.001064*	—	—	—
$\hat{\varepsilon}_{SZD/SZD(-1)}^2$	0.047261*	—	—	—	—	—
$\hat{\varepsilon}_{SZN/SZN(-1)}^2$	0.040670*	—	—	0.001431*	—	—

$\hat{\varepsilon}_{HKD/HKD(-1)}^2$	–	–	–	0.002922*	0.007640*	–
$\hat{\varepsilon}_{HKN/HKN(-1)}^2$	–	0.012750*	–	–	–	0.013473*
$\hat{\varepsilon}_{USD(-1)}^2$	–	–	–	–	–	0.007948*
$\hat{\varepsilon}_{USN/USN(-1)}^2$	–	–	–	–	0.014544†	–
$\hat{\varepsilon}_{UKD/UKD(-1)}^2$	–	–	0.003096*	–	–	–
$\hat{\varepsilon}_{UKN/UKN(-1)}^2$	–	–	–	–	–	–
$\hat{\varepsilon}_{JPD}^2$	–	–	0.007765*	–	–	–
$\hat{\varepsilon}_{JPN}^2$	–	–	–	0.025654*	0.017658*	–
LB(5)	8.8192	9.0937	6.5944	8.6977	4.9513	6.4715
LB(10)	25.074*	17.858†	13.106	10.212	14.405	8.9313
LB ² (5)	3.4888	1.5699	3.5648	6.0180	6.4741	5.6194
LB ² (10)	7.5567	11.364	10.377	7.5577	9.1922	8.3202

Note: * indicates significance at 5% level and † indicates significance at 10% level.

In terms of first-moment interdependencies (return spillovers), the estimated mean equations show a quite rich transmission pattern from the more developed markets (US, UK, JP and HK) to Mainland China (SH and SZ), but not vice versa. More specifically, the unexpected overnight returns of SH and SZ ($\hat{\varepsilon}_{SHN}$ and $\hat{\varepsilon}_{SZN}$) are influenced by surprises from lagged daytime returns of HK and US ($\hat{\varepsilon}_{HKD(-1)}$ and $\hat{\varepsilon}_{USD(-1)}$) and contemporaneous overnight return of JP ($\hat{\varepsilon}_{JPN}$); the daytime returns of SH and SZ ($\hat{\varepsilon}_{SHD}$ and $\hat{\varepsilon}_{SZD}$) are sensitive to the realisations of lagged unexpected daytime returns of US and UK ($\hat{\varepsilon}_{USD(-1)}$ and $\hat{\varepsilon}_{UKD(-1)}$) and contemporaneous unexpected overnight return of JP and HK ($\hat{\varepsilon}_{JPN}$ and $\hat{\varepsilon}_{HKN}$). The coefficients for $\hat{\varepsilon}_{UKD(-1)}$ in the conditional mean equations of $\hat{\varepsilon}_{SHD}$ and $\hat{\varepsilon}_{SZD}$ are only marginally significant at 10% level, pointing to a less influential role of UK relative to US and JP in unexpected return information leadership to Mainland China's stock markets. It should be noted that Mainland index returns only react to the most recent innovations originated in HK but they react twice to the same innovations from $\hat{\varepsilon}_{USD(-1)}$ and $\hat{\varepsilon}_{JPN}$. The spillover effect from $\hat{\varepsilon}_{USD(-1)}$ is responded positively by $\hat{\varepsilon}_{SHN}$ and $\hat{\varepsilon}_{SZN}$ and negatively by $\hat{\varepsilon}_{SHD}$ and $\hat{\varepsilon}_{SZD}$. This indicates that Mainland indices initially overreact to observed price changes in the US in their overnight returns and reverse their prior responses to the same information in the subsequent daytime returns. Quite the contrary, the two

consecutive positive responses to shocks from $\hat{\varepsilon}_{JPN}$ by the overnight and daytime returns of Mainland indices can be inferred as the underreaction by the Mainland indices. The differing patterns of responses to spillover effects imply that the Mainland Chinese markets adjust to information from HK in a more efficient manner than to US and JP. There is also evidence of domestic return spillovers among the three Chinese stock markets. In addition to the spillovers from HK to Mainland, we also find a complex array of significant spillovers from $\hat{\varepsilon}_{SHN(-1)}$ to $\hat{\varepsilon}_{SZN}$, from $\hat{\varepsilon}_{SZN}$ to $\hat{\varepsilon}_{HKN}$, from $\hat{\varepsilon}_{SZD(-1)}$ to $\hat{\varepsilon}_{SHD}$, from $\hat{\varepsilon}_{SHN}$ to $\hat{\varepsilon}_{SZD}$, and from $\hat{\varepsilon}_{SHD}$ and $\hat{\varepsilon}_{SZN}$ to $\hat{\varepsilon}_{HKD}$. It is easy to recognise that returns in HK are influenced by the unexpected movement from one of the Mainland markets but not both. This is due to the fact that the unexpected return innovations between SH and SZ are highly correlated so that spillover effect from one market is overshadowed by spillover effect from another market.²³ The unexpected return spillovers from the three more developed markets (US, UK and JP) to Mainland China are in general unidirectional, as the latter hardly exert any influence to the former. On the other hand, the spillovers between HK and the three more developed markets are mainly bidirectional. The spillover effects on the daytime returns suggest some informational inefficiency among the market indices considered. According to Hamao *et al.* (1990), spillover effects from other markets on the conditional means of the overnight return are consistent with international financial integration and predicted by international asset pricing models, while spillover effects on the conditional means of the daytime returns are predicted not to occur.

In terms of the second moment interdependencies (return spillovers), the volatility spillovers from more developed markets to the emerging Mainland Chinese stock markets are virtually non-existent – return volatility of the two Mainland indices are unaffected by the volatility surprises of the three major international exchanges. Rather, the volatility spillovers are

²³ The correlation between $\hat{\varepsilon}_{SHN}$ and $\hat{\varepsilon}_{SZN}$ is around 0.75 and the correlation between $\hat{\varepsilon}_{SHD}$ and $\hat{\varepsilon}_{SZD}$ is as high as 0.80.

concentrated within the domestic territory of China. Despite the absence of significant spillovers from the three more developed markets to Mainland China, we observe reverse volatility spillovers from $\hat{\varepsilon}_{SZN}^2$ to $\hat{\varepsilon}_{USD}^2$, and $\hat{\varepsilon}_{SHD}^2$ to $\hat{\varepsilon}_{UKN}^2$. This finding is contrary to the conventional wisdom that short-term volatility spillovers run only unidirectionally from developed to emerging markets.

Turning to the estimated variance equations, most of the GARCH coefficients α and β are positive and statistically significant at 5%. The magnitude of α is relatively small and the positivity constraint is violated in several occasions. The degree of volatility persistence (measured by $\alpha + \beta$) is reduced as the squared residual terms are included in the variance equation. The proposed GJR-GARCH specification is proven to be more suitable in modelling returns of the four more developed indices for which the coefficients of the GJR term are significantly positive. This indicates volatility transmission mechanism is asymmetric in these markets (except for the overnight return of JP). The empirical validity of the GJR-GARCH model for Mainland China's index returns is brought into question, as none of the GJR terms are even statistically significant at 10% level. The coefficients of significant squared residuals in the variance equations unanimously have positive signs which indicate that unexpected volatility shocks from foreign markets will induce greater volatility in the home market.

Our empirical investigation of the full sample period leads to the following conclusion: significant return spillover effects occur in the direction of, but not from, the Mainland Chinese markets. HK plays the most influential role among the three Chinese markets in that it elicits significant first- and second-moment influences on its domestic neighbouring exchanges. Furthermore, being a vibrant originator and absorbent of spillover effects, HK is clearly more active in the international information transmission mechanism than its Mainland counterparts. Since HK is more open to the world markets than SH and SZ, our results support the view that the extent to which an

emerging market can influence or be influenced by the developed stock markets is associated with the degree of openness of the emerging market.

To control for the possible impact of exchange rates on our estimates, we convert all non-US index returns into US dollars using the daily spot exchange rates. This conversion allows us to assess whether our findings are mitigated or exacerbated by the conversion into a single currency. We repeat the two-stage estimation procedure for the dollar-denominated indices. The first stage adjustments are presented in Appendix 4.1 and the second stage estimations are shown in Table 4.9 and 4.10 below.

Table 4.9 Mean and Volatility Spillover for the Overnight Returns (in USD)

	<i>SHN</i>	<i>SZN</i>	<i>HKN</i>	<i>USN</i>	<i>UKN</i>	<i>JPN</i>
$\hat{\epsilon}_{SHD/SHD(-1)}$	–	0.008830*	-0.008010*	–	–	–
$\hat{\epsilon}_{SHN/SHN(-1)}$	–	–	–	–	–	–
$\hat{\epsilon}_{SZD/SZD(-1)}$	–	–	–	–	–	–
$\hat{\epsilon}_{SZN/SZN(-1)}$	–	–	0.038173*	–	–	–
$\hat{\epsilon}_{HKD/HKD(-1)}$	0.012417†	0.013045*	–	–	0.049380*	-0.021759*
$\hat{\epsilon}_{HKN/HKN(-1)}$	–	–	–	–	0.165424*	–
$\hat{\epsilon}_{USD(-1)}$	–	0.027347*	0.486596*	–	–	0.241843*
$\hat{\epsilon}_{USN(-1)}$	–	–	–	–	–	–
$\hat{\epsilon}_{UKD(-1)}$	0.018880*	–	0.085897*	–	–	0.093823*
$\hat{\epsilon}_{UKN/UKN(-1)}$	–	–	–	–	–	-0.038552*
$\hat{\epsilon}_{JPD/JPD(-1)}$	–	–	-0.063860*	–	–	–
$\hat{\epsilon}_{JPN}$	0.021431*	0.011017*	0.091565*	–	0.149318*	–
ω	-2.58E-07*	-1.79E-07	5.07E-08	-8.48E-09*	4.17E-07*	1.53E-06*
α	0.008724*	0.088740*	0.114058*	0.088978*	0.039882*	0.030119*
β	0.928976*	0.978545*	0.766998*	0.442726*	0.908205*	0.938746*
θ	-0.004177*	-0.070320*	0.161888*	0.023127*	–	–
$\hat{\epsilon}_{SHD/SHD(-1)}^2$	–	–	–	–	–	–
$\hat{\epsilon}_{SHN/SHN(-1)}^2$	–	–	–	–	–	–
$\hat{\epsilon}_{SZD/SZD(-1)}^2$	0.006569*	–	–	–	–	–
$\hat{\epsilon}_{SZN/SZN(-1)}^2$	–	–	–	–	–	–
$\hat{\epsilon}_{HKD/HKD(-1)}^2$	0.000945*	0.002313†	–	–	0.001542*	0.003536*

$\hat{\varepsilon}_{HKN/HKN(-1)}^2$	—	—	—	—	—	—
$\hat{\varepsilon}_{USD(-1)}^2$	—	—	0.092827*	—	—	0.003557*
$\hat{\varepsilon}_{USN(-1)}^2$	—	—	—	—	—	—
$\hat{\varepsilon}_{UKD(-1)}^2$	—	—	0.038944*	—	—	—
$\hat{\varepsilon}_{UKN/UKN(-1)}^2$	—	—	—	0.000797*	—	—
$\hat{\varepsilon}_{JPD/JPD(-1)}^2$	—	—	—	0.000759*	0.008252*	—
$\hat{\varepsilon}_{JPN}^2$	—	—	0.061223*	—	0.011791*	—
LB(5)	3.9647	5.6998	3.3204	0.6065	2.3789	0.8297
LB(10)	13.746	9.4081	16.924†	4.1450	7.9072	9.3426
LB ² (5)	0.0931	0.0307	1.0402	1.4903	6.5326	0.8321
LB ² (10)	9.1592	0.0960	9.6761	2.6677	9.0723	2.7088

Notes: * indicates significance at 5% level and † indicates significance at 10% level.

Table 4.10 Mean and Volatility Spillover for the Daytime Returns (in USD)

	SHD	SZD	HKD	USD	UKD	JPD
$\hat{\varepsilon}_{SHD/SHD(-1)}$	—	—	0.050423*	—	—	—
$\hat{\varepsilon}_{SHN/SHN(-1)}$	—	0.057092*	—	—	—	—
$\hat{\varepsilon}_{SZD/SZD(-1)}$	0.041850*	—	—	—	—	—
$\hat{\varepsilon}_{SZN/SZN(-1)}$	—	—	—	—	—	—
$\hat{\varepsilon}_{HKD/HKD(-1)}$	0.127891*	—	—	0.077489*	0.094037*	—
$\hat{\varepsilon}_{HKN/HKN(-1)}$	—	0.069093*	—	0.032734*	—	0.189586*
$\hat{\varepsilon}_{USD(-1)}$	—	—	-0.070302*	—	—	—
$\hat{\varepsilon}_{USN/USN(-1)}$	—	—	—	—	0.090380*	—
$\hat{\varepsilon}_{UKD/UKD(-1)}$	0.042034*	—	—	—	—	0.032644*
$\hat{\varepsilon}_{UKN/UKN(-1)}$	—	—	—	0.057976*	—	—
$\hat{\varepsilon}_{JPD}$	—	—	0.270122*	0.069134*	0.112512*	—
$\hat{\varepsilon}_{JPN}$	0.048082*	—	—	-0.036291*	—	—
ω	8.64E-06*	7.53E-06	4.43E-07†	8.35E-07*	7.23E-07*	2.46E-06*
α	0.080732*	0.159634*	0.045002*	0.007661	0.000293	0.043015*
β	0.831846*	0.833642*	0.924103*	0.907317*	0.913951*	0.880371*
θ	—	—	0.030515*	0.131274*	0.108660*	0.054098*
$\hat{\varepsilon}_{SHD/SHD(-1)}^2$	—	—	—	—	—	—
$\hat{\varepsilon}_{SHN/SHN(-1)}^2$	—	—	0.001475*	—	—	—
$\hat{\varepsilon}_{SZD/SZD(-1)}^2$	0.051143*	—	—	—	—	—
$\hat{\varepsilon}_{SZN/SZN(-1)}^2$	0.033367*	—	—	—	—	—
$\hat{\varepsilon}_{HKD/HKD(-1)}^2$	—	—	—	0.002382*	0.007042*	—
$\hat{\varepsilon}_{HKN/HKN(-1)}^2$	—	0.013940*	—	—	—	0.010901*

$\hat{\varepsilon}_{USD(-1)}^2$	–	–	0.003802†	–	0.009658*	–
$\hat{\varepsilon}_{USN/USN(-1)}^2$	–	–	–	0.011063*	0.018497*	–
$\hat{\varepsilon}_{UKD/UKD(-1)}^2$	–	–	–	–	–	0.008498*
$\hat{\varepsilon}_{UKN/UKN(-1)}^2$	–	–	–	–	–	–
$\hat{\varepsilon}_{JPD}^2$	–	–	0.008931*	–	–	–
$\hat{\varepsilon}_{JPN}^2$	–	–	–	–	–	–
LB(5)	9.8108†	8.7850	6.6783	8.2595	6.8867	5.3591
LB(10)	27.691*	16.891†	13.330	9.6659	15.298	8.0276
LB ² (5)	2.9245	1.6659	3.4849	5.4671	5.1939	7.0831
LB ² (10)	7.0231	11.238	9.3036	7.4037	7.9643	10.249

Notes: * indicates significance at 5% level and † indicates significance at 10% level.

From Table 4.9, we note that the patterns of return spillovers are subject to certain changes. In terms of the number of significant spillover effects, the US is relatively less influential to the rest of the five markets once the exchange rate fluctuations have been properly accounted for. The daytime return of US appears to be more vulnerable to spillovers from HK and JP while its overnight return is totally independent from the unexpected price movements from the other five markets. The outcomes for volatility spillovers are broadly in line with the local currency case.

On the basis of the conditional variance equations, one salient result emerges. The GJR terms for $\hat{\varepsilon}_{SHN}$ and $\hat{\varepsilon}_{SZN}$ turn to be significantly negative from being previously insignificant, while the one for $\hat{\varepsilon}_{UKN}$ becomes statistically insignificant. When returns are denominated in RMB (i.e. the official currency of Mainland China), the two Mainland China' stock markets respond indifferently to good and bad news, as shown in Table 4.7 and 4.8. A significant negative GJR term implies good-news-chasing behaviour of the investors such that positive innovations increase volatility more than negative innovations with equal magnitude. The likely explanation for this particular finding lies in the trend of exchange rate movements. The value of the RMB was determined with reference to the US dollar through most of its history and has been strengthened continuously against world's major currencies in recent years. The US dollar adjusted returns are

therefore inflated as the result of gradually appreciated RMB, which in turn lead to the reverse asymmetric behaviour. Since the GBP has experienced similar appreciation against the USD in recent years, the asymmetry effect in the UK is neutralised by the large swing in exchange rate. On the other hand, the GJR term for $\hat{\varepsilon}_{HKN}$ remains largely unchanged in the single currency scenario. This is due to the fact that HKD is pegged to USD and is only allowed to float in a narrow margin. However, it is intriguing why the GARCH parameterisations for unexpected daytime returns are immune from exchange rate movements. We suspect it could be because that the exchange rate shocks are fully absorbed in daytime returns, but this belief would require further investigation. After all, this exercise does demonstrate the importance of taking exchange rate into consideration when studying the international information transmission mechanism across national stock markets. In particular, our results show that some of the return spillover effects are to some degree caused by fluctuations in exchange rates. This is consistent with Roll (1992) that a portion of national equity index behaviour can be ascribed to exchange rate behaviour and policies.

Finally, none of the Ljung-Box test statistics for the squared standardised residuals are significant at conventional levels, indicating the adequacy of the fitted models to successfully capture the non-linear dependencies in index return series. Of somewhat greater concern are the standardised residuals for models underlying $\hat{\varepsilon}_{SHD}$ and $\hat{\varepsilon}_{SZD}$ which fail the diagnostic test at 5% significance level, as shown in Table 4.8. Although we tried other specifications for the conditional mean of these two series, the results do not improve. However, no indications of model misspecification are observed for models estimated on the second subsample period (verified in subsequent tables).

To examine whether the return and volatility spillover patterns are altered after the partial relaxation of stock ownership by foreign institutional investors, we split the whole period into two subsample periods: from January 4th 1993 to August 31st 2006 and September 1st 2006 to March

31st 2010. The first subsample period allows us to address an interesting issue, that is, how the return and volatility of markets that were totally closed to foreign investors are related to the information from foreign markets. The starting date of the second subsample period marks the effective date of ‘Regulation on Domestic Securities Investment by Qualified Foreign Institutional Investor’ which replaced the ‘Temporary Regulation on Domestic Securities Investment by Qualified Foreign Institutional Investor’. Although the QFII program was introduced way back in November 2002, the scope of the program had been quite limited in terms of the number of participants and the total trading volume represented by these participants. In addition, the second subsample period commences three months after the introduction of the parallel QDII scheme which permits qualified Mainland financial institutions to invest in the overseas capital markets. Of particular interest is the impact of these transitional arrangements on the way in which return and volatility spillovers move across borders. These initiatives have encouraged cross-country investing between Mainland China and other markets, particularly Hong Kong. As a result, the increased presence of foreign investors would facilitate the transmission of foreign sentiments into the Mainland stock markets; domestic investors with foreign equity holdings would become more responsive to changes in other world’s major stock markets. It would be reasonable to hypothesise that a market with fewer foreign investment restrictions would show greater influence from other markets. Hence, we expect to observe a stronger spillover effect for the two Mainland indices in the second subsample period. For the sake of brevity, we only present the results for local currencies cases. The first stage adjustments for the first subsample period are presented in Appendix 4.2 and the second stage estimations are shown in Table 4.11 and 4.12 below.

Table 4.11 Mean and Volatility Spillover for the Overnight Returns (First Subsample)

	<i>SHN</i>	<i>SZN</i>	<i>HKN</i>	<i>USN</i>	<i>UKN</i>	<i>JPN</i>
$\hat{\epsilon}_{SHD/SHD(-1)}$	–	–	–	–	–	–
$\hat{\epsilon}_{SHN/SHN(-1)}$	–	-0.051830*	–	–	–	–
$\hat{\epsilon}_{SZD/SZD(-1)}$	–	–	–	–	–	–

$\hat{\epsilon}_{SZN/SZN(-1)}$	—	—	—	—	—	—
$\hat{\epsilon}_{HKD/HKD(-1)}$	0.012208†	0.010194†	—	—	0.007709*	—
$\hat{\epsilon}_{HKN/HKN(-1)}$	—	—	—	—	0.009368*	—
$\hat{\epsilon}_{USD(-1)}$	—	—	0.344362*	—	—	0.182710*
$\hat{\epsilon}_{USN(-1)}$	—	—	—	—	—	-0.035701*
$\hat{\epsilon}_{UKD(-1)}$	—	—	0.104952*	—	—	0.048297*
$\hat{\epsilon}_{UKN/UKN(-1)}$	—	—	—	0.031623*	—	-0.024803*
$\hat{\epsilon}_{JPD/JPD(-1)}$	—	—	—	—	—	—
$\hat{\epsilon}_{JPN}$	—	—	0.486532*	—	—	—
ω	1.90E-07*	4.78E-08*	6.74E-07*	1.41E-08*	3.28E-07†	-3.50E-08
α	0.016068*	0.006434*	0.099225*	0.000140†	-0.004204†	0.027165*
β	0.941198*	0.957767*	0.832904*	0.364829*	0.798315*	0.997259*
θ	—	—	—	—	1.260098*	—
$\hat{\epsilon}_{SHD}^2/SHD(-1)$	—	—	—	—	—	—
$\hat{\epsilon}_{SHN}^2/SHN(-1)$	—	0.000888*	—	—	—	—
$\hat{\epsilon}_{SZD}^2/SZD(-1)$	—	—	—	—	—	—
$\hat{\epsilon}_{SZN}^2/SZN(-1)$	—	—	—	—	—	—
$\hat{\epsilon}_{HKD}^2/HKD(-1)$	0.000438*	0.000465*	—	—	0.003423†	—
$\hat{\epsilon}_{HKN}^2/HKN(-1)$	—	—	—	0.000245*	0.004646*	—
$\hat{\epsilon}_{USD}^2(-1)$	—	—	0.019791*	—	—	—
$\hat{\epsilon}_{USN}^2(-1)$	—	—	—	—	—	—
$\hat{\epsilon}_{UKD}^2(-1)$	—	—	0.009689*	—	—	—
$\hat{\epsilon}_{UKN}^2/UKN(-1)$	—	—	—	0.009382*	—	—
$\hat{\epsilon}_{JPD}^2/JPD(-1)$	—	—	0.033183*	—	—	—
$\hat{\epsilon}_{JPN}^2$	—	—	—	0.001471*	—	—
LB(5)	6.9988	5.6353	1.5224	3.8681	7.1942	2.9554
LB(10)	14.355	8.5526	4.7918	13.162	13.652	8.3968
LB ² (5)	0.3052	0.1517	1.3887	0.0678	1.1215	1.1443
LB ² (10)	1.0176	0.3793	6.9291	6.2579	3.1427	1.7895

Notes: * indicates significance at 5% level and † indicates significance at 10% level.

Table 4.12 Mean and Volatility Spillover for the Daytime Returns (First Subsample)

	<i>SHD</i>	<i>SZD</i>	<i>HKD</i>	<i>USD</i>	<i>UKD</i>	<i>JPD</i>
$\hat{\epsilon}_{SHD}/SHD(-1)$	—	—	0.020446*	—	—	—
$\hat{\epsilon}_{SHN}/SHN(-1)$	—	0.102152*	—	—	—	—
$\hat{\epsilon}_{SZD}/SZD(-1)$	0.036357*	—	—	—	—	—
$\hat{\epsilon}_{SZN}/SZN(-1)$	—	—	—	—	—	—

$\hat{\epsilon}_{HKD/HKD(-1)}$	—	—	—	0.055949*	0.083026*	—
$\hat{\epsilon}_{HKN/HKN(-1)}$	0.038391†	0.047836*	—	0.029974*	0.056762*	0.114064*
$\hat{\epsilon}_{USD(-1)}$	—	—	—	—	—	—
$\hat{\epsilon}_{USN/USN(-1)}$	—	—	—	—	—	—
$\hat{\epsilon}_{UKD/UKD(-1)}$	—	—	—	—	—	0.035484†
$\hat{\epsilon}_{UKN/UKN(-1)}$	—	—	—	—	—	—
$\hat{\epsilon}_{JPD}$	—	—	0.256580*	0.059342*	0.083361*	—
$\hat{\epsilon}_{JPN}$	—	—	—	—	—	—
ω	9.71E-06*	8.90E-06*	5.26E-07*	1.19E-06*	5.11E-07*	1.59E-06*
α	0.102117*	0.162390*	0.041530*	0.010612	0.001000	0.037679*
β	0.807911*	0.830500*	0.939449*	0.915480*	0.924681*	0.900615*
θ	—	—	0.023426*	0.137957*	0.096180*	0.047402*
$\hat{\epsilon}_{SHD/SHD(-1)}^2$	—	—	—	—	—	—
$\hat{\epsilon}_{SHN/SHN(-1)}^2$	—	—	0.000765*	—	—	—
$\hat{\epsilon}_{SZD/SZD(-1)}^2$	0.052874*	—	—	—	—	—
$\hat{\epsilon}_{SZN/SZN(-1)}^2$	0.045709*	—	—	—	—	—
$\hat{\epsilon}_{HKD/HKD(-1)}^2$	—	—	—	—	0.006253*	—
$\hat{\epsilon}_{HKN/HKN(-1)}^2$	—	—	—	—	—	0.008898*
$\hat{\epsilon}_{USD(-1)}^2$	—	—	—	—	—	0.012928*
$\hat{\epsilon}_{USN/USN(-1)}^2$	—	—	—	—	0.016401†	—
$\hat{\epsilon}_{UKD/UKD(-1)}^2$	—	—	0.002483*	—	—	—
$\hat{\epsilon}_{UKN/UKN(-1)}^2$	—	—	—	—	—	—
$\hat{\epsilon}_{JPD}^2$	—	—	—	—	—	—
$\hat{\epsilon}_{JPN}^2$	—	—	—	—	0.009899*	—
LB(5)	6.9567	5.0189	2.8887	5.2563	6.7727	5.0547
LB(10)	19.027*	14.951	8.3611	14.084	13.280	8.8872
LB ² (5)	4.0945	1.1183	2.3707	5.5090	2.1254	4.3385
LB ² (10)	7.2071	7.5294	11.151	9.2130	6.9486	6.7021

Notes: * indicates significance at 5% level and † indicates significance at 10% level.

Broadly speaking, the extent to which return and volatility surprises are transmitted among the six markets investigated is less extensive in the two subsamples, measured by the occurrence of significant coefficients in the mean and variance equations. In the first subsample period, the three developed stock markets hardly have any influence on Mainland China's stock markets, in terms of both return and volatility transmission. The transmission of pricing and volatility information

among the three Chinese markets is dominated by HK such that it not only passes return realisations to SH and SZ but it also leads in the transmission of their volatilities.

The first stage adjustments for the second subsample period are presented in Appendix 4.3 and the second stage estimations are shown in Table 4.13 and 4.14 below.

Table 4.13 Mean and Volatility Spillover for the Overnight Returns (Second Subsample)

	<i>SHN</i>	<i>SZN</i>	<i>HKN</i>	<i>USN</i>	<i>UKN</i>	<i>JPN</i>
$\hat{\epsilon}_{SHD/SHD(-1)}$	–	–	–	–	–	–
$\hat{\epsilon}_{SHN/SHN(-1)}$	–	–	0.676074*	–	–	–
$\hat{\epsilon}_{SZD/SZD(-1)}$	–	–	–	–	–	–
$\hat{\epsilon}_{SZN/SZN(-1)}$	–	–	–	–	–	–
$\hat{\epsilon}_{HKD/HKD(-1)}$	–	–	–	–	–	-0.082473*
$\hat{\epsilon}_{HKN/HKN(-1)}$	–	–	–	–	–	–
$\hat{\epsilon}_{USD(-1)}$	0.154417*	0.139185*	–	–	–	0.357679*
$\hat{\epsilon}_{USN(-1)}$	–	–	–	–	–	–
$\hat{\epsilon}_{UKD(-1)}$	–	–	–	–	–	0.119722*
$\hat{\epsilon}_{UKN/UKN(-1)}$	–	–	–	0.520476*	–	–
$\hat{\epsilon}_{JPD/JPD(-1)}$	–	–	–	–	–	–
$\hat{\epsilon}_{JPN}$	0.352898*	0.227188*	–	–	0.023945*	–
ω	2.29E-06*	-1.15E-06*	2.91E-06	-4.73E-08*	4.25E-07*	1.51E-06*
α	0.028078*	-0.008489*	0.122707*	2.66E-05	0.046511*	0.029183*
β	0.917421*	0.982559*	0.797550*	0.404209*	0.612106*	0.863387*
θ	–	–	–	0.084311*	-0.048083*	0.145440*
$\hat{\epsilon}_{SHD/SHD(-1)}^2$	–	0.009497*	–	–	–	–
$\hat{\epsilon}_{SHN/SHN(-1)}^2$	–	–	0.094392*	0.000176*	–	–
$\hat{\epsilon}_{SZD/SZD(-1)}^2$	–	–	–	–	–	–
$\hat{\epsilon}_{SZN/SZN(-1)}^2$	–	–	–	–	–	–
$\hat{\epsilon}_{HKD/HKD(-1)}^2$	–	–	–	–	0.000959*	–
$\hat{\epsilon}_{HKN/HKN(-1)}^2$	–	–	–	3.34E-05*	–	–
$\hat{\epsilon}_{USD(-1)}^2$	–	–	–	–	–	0.005944*
$\hat{\epsilon}_{USN(-1)}^2$	–	–	–	–	–	–
$\hat{\epsilon}_{UKD(-1)}^2$	–	–	–	–	–	–
$\hat{\epsilon}_{UKN/UKN(-1)}^2$	–	–	–	0.148643*	–	–
$\hat{\epsilon}_{JPD/JPD(-1)}^2$	0.010241*	–	–	–	0.001844*	–

$\hat{\epsilon}_{JPN}^2$	—	—	—	—	—	—
LB(5)	2.3669	2.0646	5.3604	0.5779	4.7030	5.3655
LB(10)	5.7054	5.5350	10.174	1.3095	10.852	7.0303
LB ² (5)	0.6970	3.6877	2.9614	0.0205	0.8651	1.5592
LB ² (10)	5.5371	6.9397	7.2147	0.0403	2.0923	5.6020

Notes: * indicates significance at 5% level and † indicates significance at 10% level.

Table 4.14 Mean and Volatility Spillover for the Daytime Returns (Second Subsample)

	<i>SHD</i>	<i>SZD</i>	<i>HKD</i>	<i>USD</i>	<i>UKD</i>	<i>JPD</i>
$\hat{\epsilon}_{SHD/SHD(-1)}$	—	—	0.188187*	—	—	—
$\hat{\epsilon}_{SHN/SHN(-1)}$	—	—	—	—	—	—
$\hat{\epsilon}_{SZD/SZD(-1)}$	—	—	—	—	—	—
$\hat{\epsilon}_{SZN/SZN(-1)}$	—	—	—	—	—	—
$\hat{\epsilon}_{HKD/HKD(-1)}$	—	—	—	0.237780*	0.196172*	—
$\hat{\epsilon}_{HKN/HKN(-1)}$	0.175481*	0.224788*	—	0.092717*	—	0.199536*
$\hat{\epsilon}_{USD(-1)}$	-0.130508*	-0.179359*	-0.058561*	—	—	-0.241108*
$\hat{\epsilon}_{USN/USN(-1)}$	—	—	0.142465*	—	0.269086*	—
$\hat{\epsilon}_{UKD/UKD(-1)}$	—	—	—	—	—	—
$\hat{\epsilon}_{UKN/UKN(-1)}$	—	—	—	—	—	—
$\hat{\epsilon}_{JPD}$	0.162619*	0.142670*	0.328974*	0.101916*	0.092756*	—
$\hat{\epsilon}_{JPN}$	—	—	—	—	—	—
ω	7.59E-06†	9.41E-06*	-1.86E-07	2.68E-08	1.61E-06	3.82E-06*
α	0.055804*	0.091682*	0.076351*	-0.005645	-0.052413*	0.076890*
β	0.913781*	0.872580*	0.853640*	0.902907*	0.836364*	0.794876*
θ	—	—	—	0.101826*	0.180418*	—
$\hat{\epsilon}_{SHD/SHD(-1)}^2$	—	—	—	—	0.004991†	—
$\hat{\epsilon}_{SHN/SHN(-1)}^2$	—	0.074936†	0.013939*	—	—	—
$\hat{\epsilon}_{SZD/SZD(-1)}^2$	—	—	—	—	—	—
$\hat{\epsilon}_{SZN/SZN(-1)}^2$	—	—	—	—	—	—
$\hat{\epsilon}_{HKD/HKD(-1)}^2$	—	—	—	0.036804*	0.052108*	—
$\hat{\epsilon}_{HKN/HKN(-1)}^2$	—	—	—	—	—	0.018023*
$\hat{\epsilon}_{USD(-1)}^2$	—	—	—	—	0.028400†	—
$\hat{\epsilon}_{USN/USN(-1)}^2$	—	—	—	—	0.047479†	—
$\hat{\epsilon}_{UKD/UKD(-1)}^2$	—	—	—	—	—	0.039176*
$\hat{\epsilon}_{UKN/UKN(-1)}^2$	—	—	—	—	—	—
$\hat{\epsilon}_{JPD}^2$	0.026344*	—	0.060366*	—	—	—
$\hat{\epsilon}_{JPN}^2$	—	—	—	0.039393*	—	—

LB(5)	3.1505	2.3180	3.4382	1.7740	1.9186	6.8152
LB(10)	6.6116	6.1105	9.1603	3.1702	3.0280	12.772
LB ² (5)	1.0428	4.0928	4.5241	4.1686	4.7588	5.3286
LB ² (10)	4.8672	11.219	6.7335	8.5246	7.5242	10.452

Notes: * indicates significance at 5% level and † indicates significance at 10% level.

A quite different picture emerges for the spillover effects in the second subsample period. There are noticeable increases in the strength of those significant spillover effects, as shown by the magnitudes of the corresponding coefficients. Fewer spillover effects in the overnight returns allow us to portray the dissemination and circulation of spillover effects among the six stock markets: being the first overnight return realisation of the day, $\hat{\varepsilon}_{JPN}$ takes influence from previous day's day returns surprises of US, UK and HK ($\hat{\varepsilon}_{USD(-1)}$, $\hat{\varepsilon}_{UKD(-1)}$, and $\hat{\varepsilon}_{HKD(-1)}$); the next realised pair of overnight returns $\hat{\varepsilon}_{SHN}$ and $\hat{\varepsilon}_{SZN}$ are positively influenced by innovations from $\hat{\varepsilon}_{JPN}$ which was just released one and half hour ago, and $\hat{\varepsilon}_{USD(-1)}$; they are closely followed by the overnight return in HK $\hat{\varepsilon}_{HKN}$, which is heavily driven by shocks from $\hat{\varepsilon}_{SHN}$ and the correlation is as high as 0.68; $\hat{\varepsilon}_{UKN}$ receives the a relatively weak spillover from $\hat{\varepsilon}_{JPN}$; and the circle is completed by $\hat{\varepsilon}_{USN}$, which is an exclusive recipient of shocks from $\hat{\varepsilon}_{UKN}$ and the correlation between which is over 0.52. For daytime return spillovers, it seems that daytime returns largely inherit the spillover pattern of the full sample period. Overreaction to shocks from the US is still evident in the two Mainland stock markets. However, SH and SZ have improved their efficiency in digesting the shocks from JP – the daytime returns of SH and SZ no longer respond to shocks from $\hat{\varepsilon}_{JPN}$, instead, they have become more reactive to contemporaneous shocks from $\hat{\varepsilon}_{JPD}$. We also observe the lack of interactions between the SH and SZ. This result is not surprising, since both markets reside in the same economic and political environment, news from one market mainly reflects information related to economic and financial factors that are common to both markets, thus hardly has any marginal impact on the other. The Mainland stock markets appear to be more sensitive to price movements in the US, JP and HK than to price

movement of the UK. The absence of spillovers from UK to Mainland China may be explained by the lesser degree of real economic linkage between the two countries. The US, JP and HK have been the three top trade partners of Mainland China for over a decade whereas the UK is ranked outside the top ten over the most of our sample period. Alternatively, one may argue that the information content embedded in the shocks of UK and US reflect common economic effect, and such information is passed over to Mainland China by the more recently traded market (i.e. the US market) thus making the spillovers effect from UK less visible. We test this proposition by substituting significant US residual terms in the mean equation with otherwise similar UK residual terms. This proposition finds support in overnight return spillovers but not in daytime return spillovers – our results show that US residuals can be replaced by UK residuals in explaining the overnight returns of SH and SZ but UK residuals fail to generate any significant spillover effect to the daytime returns of SH and SZ in the absence of US residuals.

Examining the conditional variance equations, we find unidirectional volatility spillovers from SH to SZ and HK. The overnight and daytime volatilities of SH are solely dependent on the unexpected daytime volatility of JP, which indicate that information from JP has become an important source of return volatility for SH. The volatility spillovers radiate from foreign markets to SZ remains scarce. Surprisingly, HK is only influenced by spillovers from JP and SH in the second subsample period. This finding leads us to conjecture that SH has taken over the position of HK and emerged as the main driving force of domestic volatility transmission. We believe this transition is associated with two parallel developments in the Chinese stock markets. The first development is the surge in the number of H-shares dual-listed in the Mainland China stock exchanges (predominantly the Shanghai Stock Exchange) beginning in year 2006.²⁴ As of March 31st 2010, 120 companies had issued H-shares on the Hong Kong Stock Exchange Main Board.

²⁴ H-shares refer to the shares of companies incorporated in Mainland China that are traded on the Hong Kong Stock Exchange.

Of all the H-shares, 53 companies have listings on either Shanghai or Shenzhen Stock Exchange in Mainland China. Almost half of these companies took debuts in Mainland China between 2006 and 2008. Majority of them are China's elite stated-owned corporation with gigantic market capitalisation and ten of which are the current constituent stocks of the Hang Seng Index of Hong Kong.²⁵ The domination of dual-listed stocks will make the Hang Seng Index vulnerable to the unexpected movements in the Mainland stock indices, particularly SH index. This view is further supported by the finding of Chong and Su (2006) that Mainland China stock market plays a major role in finding the implicit efficient price for those dual-listed A- and H-shares characterised by high market capitalisation and liquidity. In the language of Garbade and Silber (1979), Mainland China stock markets have now become the 'dominant' markets and Hong Kong is likely to be the 'satellite' market.

The second development is the introduction of QFII and QDII schemes, which does not only facilitate cross-border capital flows but also allow speculators to take advantage of the price discrepancy between dual-listed A- and H-shares. More specifically, the unidirectional volatility spillover from SH to HK may be caused by the speculative trading strategy reported in Peng *et al.* (2008). The reported trading strategy is to acquire H-shares of a dual-listed company first, which will have limited impact on prices owing to the market depth; and simultaneously use a relatively small order to push up A-share prices as A-share market is shallower. This strategy pays off if the A-share prices rise and the widening price gap over corresponding H-share induce buying interest from international investors in the respective H-shares, creating a pulling effect on H-shares and thus causing excessive volatility in the Hong Kong stock index.

We also find evidence that unexpected volatility of SH spills over to US, and UK through either the overnight and daytime channels. The scope of spillovers originated in Mainland China seems

²⁵ There are 45 constituent stocks in total for the Hang Seng Index.

to have extended beyond its domestic territory. In a similar vein, this phenomenon may be rationalised by the two parallel developments mentioned above. The return of the H-shares has aligned the Mainland stock markets more closely with other regional and international counterparts in terms of its responsiveness to common regional and worldwide financial and macroeconomic factors. Likewise, the return of the H-shares has also enhanced Mainland markets' ability to generate shocks that will be digested by other developed markets. The lack of spillovers from Mainland China to the other developed markets observed in the first subsample period may be due to the fact that the shocks from Mainland markets mainly reflect country-specific information. The reversed volatility spillover from Mainland China to the US and UK may be the consequence of participation by foreign institutional investors under the QFII scheme. With significant ownership of A-shares, these financial institutions may become more aware of the unexpected movement in Mainland Chinese stock market and act on these information when trading in other developed markets.

4.6 Conclusion

Motivated by the recent financial liberalisation initiatives prompted by the Chinese government, we re-examine the pattern of return and volatility spillovers between the two Mainland Chinese stock markets (SH and SZ) and their regional (HK and JP) and international (US and UK) counterparts. The full sample analysis reveals a complex array of return spillovers among the six stock markets with significant return spillover effects occurring in the direction of, but not from, the Mainland Chinese markets. The analysis also provides evidence that the two Mainland Chinese markets digest shocks of HK in a more efficient manner than that of US and JP. In terms of second moment interdependence, the degree of volatility persistence of each market index is moderately attenuated by conditioning on the shocks originated from other markets. In addition, the observed spillover effects are exacerbated by the fluctuation in the exchanges rates. The degree

of asymmetry effect in volatility is also likely to be overstated if we do not adjust for exchange rate movements.

A comparison of the results from the pre- and post-QFII periods indicates spillover effects have become more accentuated in the post-QFII period. Our results suggest that Mainland China's stock markets fluctuations are collectively explained by regional shocks from JP and HK, and global shocks from US. Although volatility spillovers into Mainland China remain primarily regional in nature, there is sign that Mainland China has become active on the scene of international volatility transmission in the post-QFII period. More striking is the finding that the leadership of HK among the three Chinese stock markets has been weakened in the wake of the rising prominence of SH. The changing nature of return and volatility spillovers in the post-QFII period will have a profound impact on the diversification strategies pursued by both Mainland China and foreign institutional investors. Overall, stronger return spillovers will weaken the marginal benefit of cross-border diversification. Given the significant positive return and volatility spillovers between Mainland China and its neighbouring markets in Asia, QDII participants (i.e. domestic Chinese institutional investors) may favour the advanced Western stock markets (e.g. US and UK) for the purpose of portfolio diversification. QFII participants (foreign institutional investors) may need to be more prudent about investing in Mainland China and Hong Kong – increasing the weight of Mainland equity holding would require a compromise on the amount of capital diverted to Hong Kong if the portfolio manager intends to maintain a fixed exposure to the systematic risk of China. The reverse volatility spillovers from Mainland China to HK, US and UK pose a new challenge to the pricing of securities in these markets. Similarly, regulatory authorities of these markets should be more alert to stock price movements, volatility, and policy changes related to the Mainland Chinese stock markets. On the other hand, the new source of volatility spillovers will benefit more active global portfolio managers who seek to speculate on short-term volatility movements with a diverse set of derivative contracts written on the underlying stock indices of these markets.

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Appendices:

Appendix 4.1a Day-of-the-Week Effect and Asian Financial Crisis Adjustments (in USD)

	<i>c</i>	<i>D_{Mon}</i>	<i>D_{Tue}</i>	<i>D_{Wed}</i>	<i>D_{Thu}</i>	<i>D_{Fri}</i>	<i>DA</i>
<i>SHN</i>	–	–	–	–	–	–	0.002753*
<i>SHD</i>	–	–	–	–	–	0.001776*	–
<i>SZN</i>	–	–	–	–	–	-0.000963*	–
<i>SZD</i>	–	–	–	0.001870*	–	0.001835*	–
<i>HKN</i>	0.000818*	–	–	–	–	-0.001013*	-0.027758*
<i>HKD</i>	–	–	–	–	-0.001167*	–	–
<i>USN</i>	–	–	–	–	0.000443*	–	–
<i>USD</i>	–	–	–	–	–	–	–
<i>UKN</i>	–	–	–	–	–	–	–
<i>UKD</i>	–	–	–	-0.000893*	–	–	-0.014238*
<i>JPN</i>	0.000519*	–	–	–	–	–	–
<i>JPD</i>	–	–	–	–	–	–	–

Notes: *D_{Mon}*, *D_{Tue}*, *D_{Wed}*, *D_{Thu}*, and *D_{Fri}* are dummy variables for Monday, Tuesday, Wednesday, Thursday, and Friday respectively. * denotes significance at 5% level.

Appendix 4.1b Autocorrelation Adjustments (in USD)

Autocorrelation Adjustments

$$\mu_{t,SHN} = 0.117415\mu_{t-1,SHD} + 0.052090\mu_{t-4,SHD} + 0.050075\mu_{t-4,SHN}$$

$$\mu_{t,SHD} = -0.126981\mu_{t-1,SHD} - 0.055114\mu_{t-10,SHD} - 0.072386\mu_{t-5,SHN}$$

$$\mu_{t,SZN} = 0.086153\mu_{t-1,SZD} + 0.044920\mu_{t-4,SZD} + 0.064660\mu_{t-1,SZN} + 0.033601\mu_{t-9,SZN}$$

$$\mu_{t,SZD} = -0.078821\mu_{t-1,SZD}$$

$$\mu_{t,HKN} = 0.074792\mu_{t-1,HKD}$$

$$\mu_{t,HKD} = 0.065707\mu_{t,HKN} - 0.067158\mu_{t-3,HKN} + 0.063696\mu_{t-7,HKN}$$

$$\mu_{t,USN} \quad N/A$$

$$\mu_{t,USD} = -0.167242\mu_{t-6,UKN}$$

$$\mu_{t,UKN} = -0.037115\mu_{t-2,UKD}$$

$$\mu_{t,UKD} \quad N/A$$

$$\mu_{t,JPN} = 0.046034\mu_{t-1,JPD} - 0.038542\mu_{t-9,JPD} + 0.040837\mu_{t-6,JPN}$$

$$\mu_{t,JPD} = 0.109131\mu_{t,JPN} - 0.060210\mu_{t-1,JPN}$$

Appendix 4.2a Day-of-the-Week Effect and Asian Financial Crisis Adjustments (Second Subsample)

	<i>c</i>	<i>D_{Mon}</i>	<i>D_{Tue}</i>	<i>D_{Wed}</i>	<i>D_{Thu}</i>	<i>D_{Fri}</i>
<i>SHN</i>	–	–	–	–	–	–
<i>SHD</i>	–	–	–	0.003447*	–	–
<i>SZN</i>	–	–	–	–	–	–
<i>SZD</i>	–	–	–	0.004670*	–	–
<i>HKN</i>	–	–	–	–	–	–
<i>HKD</i>	–	–	–	–	–	–
<i>USN</i>	–	–	–	–	–	–
<i>USD</i>	–	–	–	–	–	–
<i>UKN</i>	0.001028*	–	–	-0.001236*	–	-0.001126*
<i>UKD</i>	–	–	–	–	–	–
<i>JPN</i>	–	–	–	–	–	–
<i>JPD</i>	–	–	–	–	–	–

Notes: D_{Mon} , D_{Tue} , D_{Wed} , D_{Thu} , and D_{Fri} are dummy variables for Monday, Tuesday, Wednesday, Thursday, and Friday respectively. Asterisk denotes significance at 5% level. The dummy variable DA is excluded from the estimated equation since the subsample does not include the episode of Asian financial crisis.

Appendix 4.2b Autocorrelation Adjustments (Second Subsample)

Autocorrelation Adjustments

$$\mu_{t,SHN} = 0.104544\mu_{t-1,SHD} + 0.090231\mu_{t-10,SHD}$$

$$\mu_{t,SHD} = -0.126105\mu_{t-1,SHD} + 0.139651\mu_{t-2,SHN} - 0.119903\mu_{t-6,SHN}$$

$$\begin{aligned} \mu_{t,SZN} = & 0.108717\mu_{t-1,SZD} - 0.044707\mu_{t-5,SZD} - 0.047426\mu_{t-6,SZD} + 0.085193\mu_{t-10,SZD} + 0.084378\mu_{t-3,SZN} + \\ & 0.077921\mu_{t-4,SZN} \end{aligned}$$

$$\mu_{t,SZD} = -0.141457\mu_{t-9,SZD}$$

$$\mu_{t,HKN} = 0.133273\mu_{t-7,HKD} + 0.130023\mu_{t-8,HKD} - 0.148942\mu_{t-9,HKD}$$

$$\mu_{t,HKD} = 0.127828\mu_{t-7,HKN}$$

$$\mu_{t,USN} \quad N/A$$

$$\mu_{t,USD} = -0.134062\mu_{t-1,USD} - 0.286903\mu_{t-6,USN}$$

$$\mu_{t,UKN} \quad N/A$$

$$\mu_{t,UKD} = 0.244970\mu_{t-4,UKN}$$

$$\mu_{t,JPN} = -0.061658\mu_{t-6,JPD} + 0.094229\mu_{t-6,JPN}$$

$$\mu_{t,JPD} = -0.000985 + 0.566804\mu_{t,JPN}$$

Chapter 5 – Dynamic Return Correlation Structure between the Two Mainland Chinese Stock Markets and Four Developed Stock Markets

5.1 Introduction

This empirical chapter revisits the issue of stock market integration by examining the dynamic correlation structure between the Shanghai Stock Exchange A-share Index of Mainland China and several other domestic and international stock market indices. We explore three different types of correlation coefficients – unconditional, realised, and conditional correlations, and possible shifts in these correlation patterns over time.

Cross-market correlation coefficient is a straightforward approach to quantify the degree of bilateral stock market linkage.²⁶ Estimating and analysing the return correlation between national stock markets will provide us with a simple, yet informative indicator that reveals the collective reaction of heterogeneous investors within these markets. The correlation structure of international equity returns plays a crucial role in asset management, particularly in the area of portfolio management. It is an indispensable part of the financial tools used to construct an optimal portfolio. The lower the return correlation between two stock indices (or any two assets), the greater the potential benefit to be obtained by diversification. Understanding changes in correlation is potentially useful in deciding on appropriate market weightings in global portfolio allocation.

However, the estimation of correlations using conventional approach or in business practice is

²⁶ Unlike many previous studies which examine covariance structure between national stock markets, we only analyse the correlation structure. The covariance between national markets could change because the interdependence across market changes, but also because the volatility of national markets evolves over time. Looking at the market correlation allows us to focus on the interdependence between markets.

often based on the constant correlation method. This fails to reflect the potential market dynamics and time-varying nature of correlation, which in turn can misguide decisions about portfolio selections. In response to this pitfall, we estimate the monthly rolling unconditional correlation and the realised correlation; for conditional correlations, we implement the Baba-Engle-Kraft-Kroner (BEKK)-GARCH and dynamic conditional correlation (DCC)-GARCH models to account for the potential time-variation in conditional correlations, in addition to the constant conditional correlation (CCC)-GARCH model.

Empirical results generally suggest that average pairwise correlations between developed stock markets behave strongly countercyclical. This implies that the benefits of diversification go down exactly when they are most desirable. In recent years, cross-border diversification has increasingly relied on investment in emerging markets. As one of the largest emerging markets in the world, Mainland China has become a very attractive investment destination in the eyes of global investors. The combined market capitalisation of the Shanghai and Shenzhen Stock Exchanges reached \$4 trillion at the end of year 2010, second only to the New York Stock Exchange. Parallel to the growing interest of foreign investors, is the increasing desire of Mainland China's domestic investors to explore other investment options overseas. However, Chinese Mainland A-share stock markets (i.e. Shanghai and Shenzhen Stock Exchanges) were closed off to foreign investors before November 2002 due to China's tight capital controls which restrict the movement of fund in and out of the country; likewise, domestic investors could not access the overseas markets before April 2006. The research on the correlation structure between Mainland China and other national stock markets prior to the above-mentioned partial removal of foreign investment restrictions therefore has little practical implication because neither side of investors could take advantage of the low correlation (should there be any). This explains the scarcity of relevant research on the subject concerning the Mainland Chinese stock markets. From the foreign investor's perspective, it is curious to see how well the emerging Mainland Chinese stock markets serve the purpose of

cross-border diversification following the gradual removal of investment impediments. The same argument holds for the Chinese domestic investors. The empirical evidence emerging from this study will not only serve the interests of both domestic and foreign investors who are seeking to optimise the risk-return profile of their equity investment, but also have important policy implication for the future development of the Mainland Chinese stock markets, for example, the knowledge of the correlation structure will allow the Chinese financial regulators to assess to what extent domestic and foreign investors are deprived of opportunities for diversification.

In connection with our investigation of stock market integration, we employ Bai and Perron (1998, 2003a, b) breakpoint test and nonlinear smooth transition regression model to time the phases of such process. The former technique allows us to detect multiple unknown abrupt structural breaks in the unconditional and realised correlation series while the latter models the structural change as a smooth transition between regimes over time.

5.2 Literature Review

The main purpose of carrying out correlation analysis is to assess the potential benefits associated with portfolio diversification. Early studies acknowledge the benefits of diversification by amassing evidence of low correlations between index returns in different countries. These studies overwhelmingly suggest that the benefits of international diversification outweigh the numerous costs, including higher direct trading costs, regulatory and cultural differences, and currency and political risks. For example, Grubel (1968) show that between 1959 and 1966, US investors could have achieved better risk and return opportunities by investing part of their portfolio in foreign equity markets. Levy and Sarnat (1970) analyse international correlations in the 1951-67 period and report diversification benefits from investing in both developed and developing equity markets. Grubel and Fadner (1971) show that correlation is an increasing function of holding

periods and correlation between country index returns was smaller than correlation between domestic assets. The general finding from these papers is that correlations between national stock markets are significant but small in magnitude before 1970s.

This empirical regularity has broken down in the past two decades. Rapid removal of impediments to international investment as well as the growing political, economic and financial integration during the following three or four decades has led to a progressive increase in the international correlation of equity markets. Koch and Koch (1991) look at the correlation of eight markets using daily data for the years 1972, 1980 and 1987 and conclude from simple Chow tests that international markets have recently grown more interdependent in the form of higher correlations. As shown by Brooks and Del Negro (2004), the correlation of US stock returns with equity returns in other developed countries has risen from a relatively stable level of around 0.4 from the mid-1980s through the mid-1990s to close to 0.9 at the turn of the millennium.

Later studies began to test the stability of the correlation and covariance matrices over time since many researchers started to speculate that the assumption of constant correlation may not always hold. A variety of papers have confirmed this belief. Makridakis and Wheelwright (1974) and Bennett and Kelleher (1988) find that international correlations are unstable over time. Kaplanis (1988) compares the correlation and covariance matrices of monthly returns of ten major stock markets over a 15 year period (1967-1982). She finds evidence of stable correlation but less stable covariance of real international equity returns. Unlike previous works which only consider unconditional correlation, Longin and Solnik (1995) analyse conditional correlation from the bivariate GARCH model and impose the null hypothesis of constant conditional correlation between equity markets. They reject the null hypothesis and conclude that international correlation had been increasing through the period 1960-1990. The later study of Longin and Solnik (2001) focuses on the correlation during extreme months and find evidence of positive international

equity market correlation shifts conditional on market drops over the past 38 years. Goetzmann *et al.* (2005) assemble the largest time series data sample to date, covering 150 years of global equity market history, to evaluate the stability of correlation matrix through time. They find that roughly half the benefits of diversification available today to the international investors are due to the increasing number of world markets and available and half to a lower average correlation among the available markets.

Another frequently studied question is whether international correlation increases in periods of high turbulence. The rationale behind this proposition is that international correlation increases when global factors dominate domestic ones and affect all financial markets, and the dominance of global factors tends to be associated with very volatile markets. Using high-frequency data surrounding the crash of 1987, King and Wadhvani (1990) and Bertero and Mayer (1990) find that international correlation tends to increase during the stock market crisis. This phenomenon, as in the language of King and Wadhvani (1990), is described as ‘contagion’. According to Forbes and Rigobon (2002), contagion is defined as significant increases in cross-market comovements, while any continued market correlation at high levels is considered to be interdependence. To distinguish between contagion and interdependence is a difficult exercise and misleading results have often been reported in the past because of a spurious relationship between correlation and volatility. For example, Forbes and Rigobon (2002) cast doubt on the validity of earlier results on contagion based on increased unconditional or conditional (GARCH) cross-market correlations during periods of market turmoil. They argue that increases in market volatility will give rise to increased correlation coefficients and thus it becomes difficult to separate the effects of market interdependence from those of contagion. They find no evidence for contagion in the aftermath of major crises such as the 1987 US market crash, the 1994 Mexican Peso crisis or the 1997/1998 Asian financial crisis once the correlation coefficients are adjusted for changing volatility in market returns. The strong result of ‘no contagion, only interdependence’ from Forbes and

Rigobon (2002) is brought into question since they take the variance of stock returns of the crisis originating country as a proxy for the volatility of the common factor affecting all markets. The failure to distinguish between common and country-specific components of market returns induces a bias towards the null hypothesis of 'no contagion'. Focusing on the international transmission of shocks from the Hong Kong stock market crisis in October 1997 as a case study, Corsetti *et al.* (2002) find evidence of contagion from Hong Kong to at least five other countries.

More recent studies devote greater effort in modelling directly time-variation within correlation coefficients between series. Raganathan and Mitchell (1997) compare the correlations estimated using CCC-GARCH and the diagonal VECH-GARCH models of eighteen country indices relative to the US and the World index. They reject the normality assumption and do not overwhelmingly reject the hypothesis of constant correlation. Berben and Jansen (2005) formulate a smooth transition correlation GARCH model, which is applied to both market level and industry level weekly data from Germany, Japan, the UK and the US in the period 1980 – 2000. They find that correlations among the German, UK and US stock markets have doubled with a great variety in timing and speed of the correlation shifts, whereas Japanese correlations have remained the same. Chelley-Steeley (2004 and 2005) calculates the unconditional correlations and fit them into the Logistic Smooth Transition Regression (LSTR) model of Granger and Teräsvirta (1993) to analyse changes to the stock markets of four Asia-Pacific and four Eastern European countries respectively. The author finds that the markets of Korea, Singapore and Thailand are becoming progressively less segmented, both locally and globally, whereas Taiwanese stock market is not showing evidence of either local or global integration (Chelley-Steeley, 2004). From a selection of four emerging Eastern European markets, she reports significant declines in the degree of market segmentation for Poland, Hungary and the Czech Republic while the Russian stock market remains heavily segmented (Chelley-Steeley, 2005). Égert and Kočenda (2007) study the correlation structure between three Western European and three Central and Eastern (CE)

European stock markets. By applying the DCC-GARCH model to the intraday data, they find limited evidence of comovement between CE and Western European markets and conclude that stock market integration is less than complete. Evans and McMillan (2009) provide a comprehensive analysis of the time-varying correlations using the data set of 33 international stock market indices from different regions and report the importance of accounting for time-variation in portfolio construction, the benefit of which is more pronounced for the larger markets but only marginal for the smaller markets. While there is a general upward trend in the correlation between the US and the G7 economies, no such trending behaviour is observed between the US and the rest of the world; greater evidence of positive trending behaviour in correlations is found on a more regional basis, notably for the European markets. This study is among the very few that consider Mainland China, which yields the lowest correlation with both the US and Japan among the ten Asian countries included in the panel.

Studies dealing with the return correlations between the stock markets of Mainland China and other countries are very scarce while previous research overwhelmingly focuses on the correlation structure between the two domestic stock markets – the Shanghai and Shenzhen Stock Exchanges or between the two classes of shares available on these two markets – the A-share and B-share. Chiang *et al.* (2007) document the time-varying correlations between A-share and B-share stock returns, which are not only significantly related to the trend factor but also associated with excessive trading activity. The correlation between these two classes of shares has also increased since the relaxation of the restriction on B-share market investments by domestic investors. In the sample period covering 15-year history of Chinese markets up to December 2006, Lin *et al.* (2009) show that the Mainland Chinese A-share indices have never been correlated with world markets while the B-share indices exhibit a low degree of correlation with Western markets and a slightly higher degree of correlation with other Asian markets – a finding in sharp contrast to their expectation of a general upward trending correlation consistent with the Gordon's growth model.

On another front, researchers have attempted to address the underlying causes for changes in cross-country correlations, since the better understanding of which is crucial for evaluating the potential benefits of international portfolio diversification. Erb *et al.* (1994) have shown that correlations between returns on national stock market indices tend to change through time in relation to the coherence between business cycles in the respective countries such that correlations are higher when the macroeconomic policies and business cycles of countries have become more closely aligned and lower when two countries' business cycles are out of phase. They also find that correlations are not symmetric in up (recovery or growth) and down (recession) markets and the higher correlations in down markets are not just a function of the influential October 1987 observation. Based on their findings, Longin and Solnik (1995) conjecture that correlation is likely to be affected by the industry mix of each national market as well as the correlation of the countries' business cycles. Cappiello *et al.* (2006) generalise the DCC-GARCH model to accommodate the possible asymmetry in volatilities and correlations and demonstrate the superiority of the asymmetric DCC model over scalar and/or symmetric representations. Aslanidis *et al.* (2009) examine the role of macroeconomic and financial variables for explaining stock returns of the US and the UK and find high correlation between these two stock markets before 2000 can be attributed to the substantial communality in response to changes in US Federal Funds rate, UK bond yield and oil price inflation.

5.3 Methodology

Correlation analysis has been widely used to measure the degree of stock market interdependence. A variety of methods of generating correlations exist in the academic literature and among practitioners. These methods range from the conventional ones that rely on a simple regression analysis or take an unconditional correlation based on a specific sample period, such as rolling

window correlation estimation, to those derived from an array of the multivariate GARCH models.

5.3.1 Unconditional Correlation

In this study, we first employ a monthly rolling window to compute unconditional correlation. The calculation of simple unconditional correlation is given as:

$$\rho_{ij,t} = \frac{\sum_{t=1}^n (r_{it} - \bar{r}_i)(r_{jt} - \bar{r}_j)}{\sqrt{\sum_{t=1}^n (r_{it} - \bar{r}_i)^2 (r_{jt} - \bar{r}_j)^2}} \quad \text{Eq. (5.1)}$$

5.3.2 Realised Variance and Correlation

Here we introduce the recently developed realised variance methodology and how it can be applied to the estimation of return correlation.²⁷ To set out the basic idea and intuition assume that the logarithmic $N \times 1$ vector price process, p_t , follows a multivariate continuous time stochastic volatility diffusion:

$$dp = \mu_t dt + \sigma_t dW_t \quad \text{Eq. (5.2)}$$

where W_t denotes a standard N -dimensional Brownian motion, and σ the $N \times N$ positive definite diffusion matrix. Further, normalising the unit time interval to represent one trading day, i.e. $h=1$, and conditional on the past realisations of μ_t and σ_t , the continuously compounded h -period returns

$r_{t+h,h} \equiv p_{t+h} - p_t$ is then:

²⁷ See Andersen *et al.* (1999) for a discussion.

$$r_{t+h,h} = \int_0^h \mu_{t+\tau} d\tau + \int_0^h \sigma_{t+\tau} dW(\tau) \quad \text{Eq. (5.3)}$$

which constitutes a decomposition into a predictable or ‘drift’ component of finite variation and a local martingale. Finally, using the theory of quadratic variation, increments to the quadratic return variation process are of the form:

$$[r,r]_{t+h} - [r,r]_t = \int_0^h \sigma_{t+\tau}^2 d\tau \quad \text{Eq. (5.4)}$$

which defines integrated volatility and provides a natural measure of the true latent h -period volatility. This measure contrasts sharply with the common use of the squared h -period return as the simple ex post volatility measure which, although provides an unbiased estimate for realised integrated volatility, is an extremely noisy estimator. Furthermore, for longer horizons any conditional mean dependence will tend to contaminate this latter variance measure, whereas the mean component is irrelevant for the quadratic variation.

The realised variance on day t is defined as:

$$\sigma_{rv,t}^2 = \sum_{k=1}^{1/\Delta} r_{t-1+k\Delta}^2 \quad \text{Eq. (5.5)}$$

where $t=1, \dots, T$, with T the total number of observations and Δ in our case, is the daily frequency, such that $1/\Delta$ the number of daily intervals within a month. In principle, as Δ approaches zero, that is continuous sampling, then the measure approaches the true integrated volatility of the underlying continuous time process, and theoretically free from measurement error. This measure

thus allows market participants to treat volatility as an observed variable and to allow direct estimation.

Generalising the realised volatility idea, we can similarly obtain realised covariances between two assets, say asset i and asset j , in the following fashion:

$$\sigma_{rcv,t} = \sum_{k=1}^{1/\Delta} r_{i,t-1+k\Delta} r_{j,t-1+k\Delta} \quad \text{Eq. (5.6)}$$

As with the realised variance term, the realised covariance can be treated as observed and directly used in estimation. Finally, we can use the realised variances and covariances to construct the realised correlation:

$$\rho_{rc,t} = \frac{\sigma_{rcv,ij,t}}{\sqrt{\sigma_{rv,it}^2 \cdot \sigma_{rv,jt}^2}} \quad \text{Eq. (5.7)}$$

5.3.3 Multiple Structural Breaks Test

As discussed at length in *Chapter Three*, the Mainland Chinese stock market has experienced different phases of stock market integration which are evident in the Gregory and Hansen (1996) cointegration and rolling cointegration analyses. We expect similar pattern to show up in the estimated unconditional and realised correlation series. To confirm this belief, we implement the method of Bai and Perron (1998, 2003a, b) on the unconditional and realised correlation series. The breakpoint test of Bai and Perron is able to detect multiple breaks by allowing the data to ‘speak for itself’ without imposing any prior beliefs. The test involves regressing the variable of interest on a constant and testing for breaks within that constant. Consider the model with m breaks ($m + 1$ regimes):

$$x_t = \beta_j + \varepsilon_t; \quad t = T_{j-1} + 1, \dots, T_j \quad \text{Eq. (5.8)}$$

For $j=1, \dots, m+1$, where x_t is the variable of interest and β_j ($j = 1, \dots, m+1$) is the mean level in the j th regime. The m -partition represents the breakpoints for the different regimes and is treated as unknown. Each partition is estimated by OLS with the estimate of β_j ($j = 1, \dots, m+1$) generated by the usual minimisation of the sum of squared residuals. Moreover, the breakpoint estimators correspond to the global minimum sum of squared residuals. The testing procedure aims to identify the number of break m . In particular, the testing procedure first assumes there is no break within the data against an alternate that there is up to b breaks in the data, where b is specified by the user. Furthermore, a minimum distance between breaks can also be specified. In the results reported below we allow for up to four breakpoints (five regimes), with a minimum distance of 36 observations.

5.3.4 Smooth Transition Regression (STR) Model

The use of smooth transition models as a means of representing deterministic structural change in a time series regression was originally proposed by Bacon and Watts (1971) and Maddala (1977). More recently, it has been reconsidered by Granger and Teräsvirta (1993) and Lin and Teräsvirta (1994) among others. It models structural change as a smooth transition between different regimes over time instead of an instantaneous one. Putting in the context of stock market integration, this approach allows data itself to determine the speed and timing of the integration in contrast to previous approaches which have sought to use institutional information to pre-determine the causes, speed and duration of the process.

In general, the STR model estimated against a time trend can take three forms:

$$\text{Model 1: } \rho_t = \alpha + \beta S_t(\gamma, \tau) + v_t \quad \text{Eq.(5.9)}$$

$$\text{Model 2: } \rho_t = \alpha_1 + \alpha_2 t + \beta S_t(\gamma, \tau) + v_t \quad \text{Eq. (5.10)}$$

$$\text{Model 3: } \rho_t = \alpha_1 + \alpha_2 t + \beta_1 S_t(\gamma, \tau) + \beta_2 S_t(\gamma, \tau) t + v_t \quad \text{Eq. (5.11)}$$

where ρ_t is the monthly bivariate monthly unconditional correlation coefficient between SH and five other stock indices; $S_t(\gamma, \tau)$ is a smooth transition function, based on a sample size T , which can be first-order logistic (LSTR):

$$S_t(\gamma, \tau) = \{1 + \exp[-\gamma(t - \tau T)]\}^{-1}, \gamma > 0 \quad \text{Eq.(5.12)}$$

or exponential (ESTR):

$$S_t(\gamma, \tau) = 1 - \exp[-\gamma(t - \tau T)^2], \gamma > 0 \quad \text{Eq.(5.13)}$$

or second-order logistic:

$$S_t(\gamma, \tau) = \{1 + \exp[-\gamma(t - \tau_1 T)(t - \tau_2 T)]\}^{-1}, \tau_1 < \tau_2, \gamma > 0 \quad \text{Eq.(5.14)}$$

The above three transition functions control the transition between regimes, which can be a smooth process, and by convention is bounded by zero and one. Different choices for the transition function $S_t(\gamma, \tau)$ give rise to different types of regime-switching behaviour.

The interpretation of the parameters of $S_t(\gamma, \tau)$ in LSTR form is as follows (Leybourne *et al.*, 1998: p.85; and Franses and van Dijk, 2000: p.72-73): the parameter τ determines the timing of the

transition midpoint since, for $\gamma > 0$, we have $S_{-\infty}(\gamma, \tau) = 0$, $S_{+\infty}(\gamma, \tau) = 1$ and $S_{\tau T}(\gamma, \tau) = 0.5$. The parameter γ determines the smoothness of the change in the value of the logistic function, thus the speed of transition from one regime to the other. If γ is small then $S_t(\gamma, \tau)$ takes a long period time of traverse the interval (0, 1), suggesting a gradual movement towards integration. On the other hand, for large values of γ , $S_t(\gamma, \tau)$ traverses the interval (0, 1) rapidly, and as γ approaches $+\infty$ this function changes value from 0 to 1 instantaneously at time $t = \tau T$, consequently, the logistic function approaches the indicator function and the LSTR model becomes a Threshold model. In the limiting case with $\gamma = 0$, $S_t(\gamma, \tau) = 0.5$ for all t , the first-order logistic model reduces to a linear model and no integration takes place.

The exponential smooth transition function has the property that $S_{-\infty}(\gamma, \tau) = 0$, $S_{+\infty}(\gamma, \tau) = 1$ and $S_{\tau T}(\gamma, \tau) = 0$. Under this specification, the regimes are associated with small and large absolute values of t , as opposed to small and large values of t under the logistic function. A drawback of the exponential function is that for either $\gamma = 0$ or ∞ , the function collapses to a constant equal to 0 and 1, respectively. Hence, the model becomes linear in both cases and the model does not nest a Threshold model as a special case (van Dijk, *et al.*, 2002).

The second-order logistic function is thought to be more desirable in that the model becomes linear when $\gamma = 0$, whereas if $\gamma = \infty$ and $\tau_1 \neq \tau_2$, the transition function $S_t(\gamma, \tau)$ is equal to 1 for $t < \tau_1 T$ and $t > \tau_2 T$ and equal to 0 in between.

Since equity market integration cannot drift upward indefinitely, the trend component $\beta_1 t$ and the smooth transition trend component $\beta_2 S_t(\gamma, \tau) t$ have to be dropped from the estimating equation so that Model 2 and Model 3 is not applicable for the purpose of this study.

In all three cases, if we assume that v_t is a zero-mean $I(0)$ process, then ρ_t is stationary around a

mean which changes from initial value α (prior to integration) to $\alpha + \beta$. Thus, α is a measure of market integration in the first regime and β is the increase (if β is positive) or decrease (if β is negative) in market integration in the second regime. If we allow $\gamma < 0$ then the initial and final model states are reversed but the interpretation of the parameters remains the same.

5.3.5 Bivariate GARCH Models

The development of GARCH model is a great leap forward in time series analysis. Multivariate GARCH models have been extensively applied to examine the structure of covariances and correlations among various return series of stock indices and the interaction between variances and covariances of these series.

The formulation of bivariate GARCH model is given as:

$$y_t = \mu_t + \varepsilon_t \quad \text{Eq. (5.14)}$$

where y_t is a 2×1 vector of random variables incorporating the returns on two stock indices. The 2×1 error vector ε_t is normally distributed with zero mean and conditional variance-covariance matrix given by $H_t = E(\varepsilon_t \varepsilon_t' | \psi_{t-1})$ where ψ_{t-1} is the information set up to time $t-1$. H_t is structured as follows:

$$H_t = \begin{bmatrix} h_{11,t} & h_{12,t} \\ h_{21,t} & h_{22,t} \end{bmatrix} \quad \text{Eq. (5.15)}$$

The general bivariate GARCH model, initially due to Bollerslev *et al.* (1988), is then given by:

$$vech(H_t) = C + A_1 vech(\varepsilon_{t-1})^2 + B_1 vech(H_{t-1}) \quad \text{Eq. (5.16)}$$

where C is a (3×1) parameter vector of constants, A_i, B_i are (3×3) parameter matrices, and $vech$ denotes the operator that takes the upper triangular portion of a matrix and stacks each element into a vector with a single column. In case of $vech(H_t)$, this becomes:

$$vech(H_t) = \begin{bmatrix} h_{11t} \\ h_{22t} \\ h_{12t} \end{bmatrix} \quad \text{Eq. (5.17)}$$

where h_{ii} represent the conditional variances at time t of the two stock index return series ($i = 1, 2$) used in the model, and h_{ij} ($i \neq j$) represent the conditional covariances between the index returns.

The problem normally encountered using a bivariate GARCH model is the number of parameters that need to be estimated.²⁸ In case of an unrestricted bivariate VECH model, the conditional variance and covariance equations contain 21 parameters. Bollerslev *et al.* (1988) introduce a restricted version of the full bivariate VECH model such that each variance and covariance element depends only upon its past values, which effectively reduces the number of parameters to be estimated to nine and the model, known as diagonal VECH, is now characterised by:

$$H_{it} = A_0 + \sum_{i=1}^p A_i \otimes (\varepsilon_{t-1} \varepsilon_{t-i}^T) + \sum_{i=1}^q B_i \otimes H_{i,t-1} \quad \text{Eq. (5.18)}$$

where \otimes is the Hadamard product (element by element product). The matrices A_0, A_i , and B_i are constrained to be symmetric and hence the covariance matrix, H_{it} is also symmetric.

²⁸ The number of parameters to be estimated is given by $\{[n(n+1)][1+n(n+1)(p+q)/2]\}/2$.

A disadvantage of this specification is that there is no guarantee of a positive semi-definite covariance matrix – a property that is important for many applications in finance since variances can never be negative. The Baba-Engle-Kraft-Kroner (BEKK) model by Engle and Kroner (1995) addresses the difficulty of with VECH ensuring that the conditional variance and covariance matrix is always positive definite.

A further simplification is Bollerslev's (1990) model in which the conditional correlation is assumed to be constant. The conditional covariance is thus given by:

$$h_{ij,t} = \rho \times \sqrt{h_{ii,t}h_{jj,t}} \quad \text{Eq. (5.19)}$$

Rather than allowing the correlation ρ to vary over time, it is assumed to be constant with only the conditional covariances varying over time relative to the conditional variances. Whilst the assumption of a constant correlation may be useful in certain circumstances it may not be of practical use if the correlation between stock index returns is potentially time-varying.

The most recent addition in the class of multivariate GARCH models is the dynamic conditional correlation (DCC) model of Engle and Sheppard (2001) and Engle (2002). This specification builds upon the earlier constant conditional correlation (CCC) model of Bollerslev (1990), and has a clear advantage over the previous models as it ensures non-negativity while avoids computational complexities. Furthermore, the strength of the DCC model over competing models is its capability to resolve the problem of heteroskedasticity, since the estimation of correlation coefficients is based on the standardised residuals. Thus, the conditional correlation derived from DCC model will not only exhibit time variation in a manner similar to the GARCH (1,1) model,

but also alleviate the effect of a parametric impact resulting from variations in volatility. The estimation of the DCC-GARCH model encompasses two stages. In the first stage, a univariate GARCH model is estimated for the individual time series. In the second stage, the standardised residuals obtained from the first stage are used to derive the conditional correlation estimator. In this model the conditional covariance matrix is expressed in terms of the following decomposition:

$$\Omega_t = D_t \Gamma_t D_t \quad \text{Eq. (5.20)}$$

where D_t refer to the diagonal matrix of the conditional standard deviations and Γ_t is the matrix of conditional correlations. Bollerslev (1990) assumed that the correlations were constant, i.e. $\Gamma_t = \Gamma$. In order to estimate the model individual GARCH (1,1) models are estimated for each series with the standardised residuals (ξ_t) computed in the usual way:

$$\xi_t = D_t^{-1} \varepsilon_t \quad \text{Eq. (5.21)}$$

The (assumed constant) unconditional correlations are given by:

$$\Gamma = \frac{1}{T} \sum_{t=1}^T \xi_t \xi_t' \quad \text{Eq. (5.22)}$$

More specifically, conditional correlations are allowed to fluctuate around their constant (unconditional) values as such:

$$Q_{ij,t} = (1 - \alpha - \beta)\Gamma_{ij} + \alpha \xi_{i,t-1} \xi_{j,t-1}' + \beta Q_{ij,t-1}, \quad i, j = 1, 2 \quad \text{Eq. (5.23)}$$

where $Q_{ij,t}$ is the time-varying correlation matrix, α is the news coefficient and β is the decay coefficient. Finally, in order to ensure the estimated correlations between -1 and 1 we standardise the correlations:

$$\rho_{ij,t} = \Gamma_{t,ij} = Q_{t,ij} / \sqrt{Q_{ii}} \sqrt{Q_{jj}} \quad \text{Eq. (5.24)}$$

The model is mean-reverting provided $\alpha + \beta < 1$, while the conditional correlation process in Eq. (5.23) is integrated when the sum equals 1. However, the latter case violates the assumption of a constant unconditional correlation Γ_{ij} . The DCC-GARCH method ensures both a positive definite matrix, and readily interpretable correlations, whilst allowing for a relatively tractable estimation procedure.

5.4 Data

This study employs daily and monthly returns of six national stock indices. They are Shanghai Stock Exchange A-Share Index (SH) and Shenzhen Stock Exchange A-Share Index (SZ) for Mainland China, New York Stock Exchange Composite Index (US) for the US, Financial Times Stock Exchange All-Share Index (UK) for the UK, Tokyo Stock Price Index (JP) for Japan, and Hang Seng Index (HK) for Hong Kong. Similar to the previous chapters, the sample period is from January 1st 1993 to March 31st 2010, resulting in 3845 daily and 208 monthly price observations after holiday adjustment.

Table 5.1 Summary Statistics of Monthly Stock Index Returns

Index	Mean	Max	Min	Std. Dev.	Skew.	Kurt.
SH	0.0067	0.8988	-0.3809	0.1257	0.5603	15.6788

SZ	0.0078	0.5327	-0.2710	0.1129	0.5851	5.5554
HK	0.0065	0.2645	-0.3482	0.0800	-0.2838	5.2960
US	0.0052	0.1019	-0.2174	0.0433	-1.2183	6.6948
UK	0.0037	0.0909	-0.1441	0.0414	-0.9158	4.2188
JP	-0.0014	0.1239	-0.2264	0.0537	-0.3821	4.1726

The summary statistics in Table 5.1 reveal the usual characteristics of monthly stock returns – a relatively small mean value and a larger standard deviation. Over the full sample period, SZ index exhibits the highest average monthly return across all markets, closely followed by SH and HK. The highest variability occurs in SH as measured by standard deviation. The range of fluctuations in the monthly return for the two Mainland China’s stock indices is also large in the form of enormous disparity between the maximum and minimum returns. The return distributions for US, UK, JP and HK are skewed to the left whereas the two Mainland Chinese stock market indices have positively skewed distributions which are indicative of the existence of large, positive monthly returns. Non-normality and in particular excess kurtosis is also evident and more pronounced for SH. This indicates that extreme return volatility is more prevalent in this market than the rest. A general message derived from these statistics is that the Mainland Chinese stock indices yield higher returns but are exposed to higher risks.

Table 5.2 Summary Statistics for Monthly Stock Index Returns (Continued)

Index	JB	ADF	LB(1)	LB(12)	LB ² (1)	LB ² (12)
SH	1470.480*	-17.517*	6.359*	25.945*	5.950*	10.010
SZ	68.132*	-13.571*	0.631	17.864	2.410	19.137†
HK	48.249*	-13.378*	0.904	18.479	0.003	22.642*
US	168.948*	-11.846*	6.817*	18.173	12.182*	44.278*
UK	41.748*	-12.960*	1.749	18.139	9.624*	41.329*
JP	16.896*	-11.605*	7.9644*	17.351	3.778†	11.387

Notes: JB is the Jarque-Bera normality test. ADF is the augmented Dickey-Fuller test (performed with constant). LB is the Ljung-Box Q test applied to the residuals. The numbers in parentheses refer to the lag length. Asterisks denote the rejection at 5% significance level on the basis of the tests.

As shown in Table 5.2, Jarque-Bera statistics strongly reject the normality of all six index returns and ADF unit root tests confirm the stationarity of these series. To test for the presence of linear and nonlinear dependencies, we compute the Ljung-Box statistics for both the return and the squared return series, $LB(k)$ and $LB^2(k)$ for $k = 1$ and $k = 12$ lags. The absence of return dependency is strongly rejected for US and JP at their first lags, and for SH at both lag lengths, as indicated by significant Ljung-Box statistics. Due to strong autocorrelation patterns in these series, lags will be added to the mean equation of the GARCH models. The Ljung-Box statistics of the squared returns are (marginally) significant for at least one lag length, implying that GARCH parameterisation is appropriate for the conditional variance processes.

5.5 Empirical Results

5.5.1 Unconditional Correlations

We begin our investigation by calculating the simple pair-wise unconditional correlations between the returns of SH and other five indices under investigation. Instead of dividing the full sample into pre-determined number of subsamples with equal length, we employ the Bai-Perron method to identify the optimal number of structural breaks as well as their locations in each correlation series. The location and corresponding date of the breakpoints within each correlation series are reported in Table 5.3.

Table 5.3 Optimal Breakpoints for the Monthly Unconditional Correlations

	vs. SZ	vs. HK	vs. US	vs. UK	vs. JP
Breakpoint 1	48 (12/1996)	46 (10/1996)	53 (05/1997)	65 (05/1998)	36 (12/1995)
Breakpoint 2	84 (12/1999)	82 (10/1999)	96 (12/2000)	101 (05/2001)	78 (06/1999)
Breakpoint 3	121 (01/2003)	128 (08/2003)	135(03/2004)	164 (08/2006)	128 (08/2003)
Breakpoint 4	157 (01/2006)	170 (02/2007)	171 (03/2007)	N/A	170 (02/2007)

The Bai-Perron tests suggest that the unconditional correlations series considered are subject to several breaks – four breakpoints are found for correlation series of US, JP, HK and SZ, while the correlation series of UK has three breaks. Some of these identified breakpoints can be associated with significant regional or global market events. The first breakpoints all occur before the Asian financial crisis²⁹ except for UK which occurs in May 1998; the second breakpoints for the three Asian stock indices (i.e. JP, HK and SZ) occur before the dot-com bubble burst whereas those for US and UK are identified after the climax of dot-com boom;³⁰ the third breakpoints occur during the recovery from the bear market between 2003 and 2004; the final breakpoints are marked around 2006 and 2007 – the period when the global housing bubble peaked in the US. The summary statistics for the full sample and the mean correlation for each identified regime (subsample) are calculated and presented in Table 5.4. To get a visual impression of the trend behaviour of the correlations, the monthly unconditional correlations as well as their breakpoints are depicted in Figure 5.1.

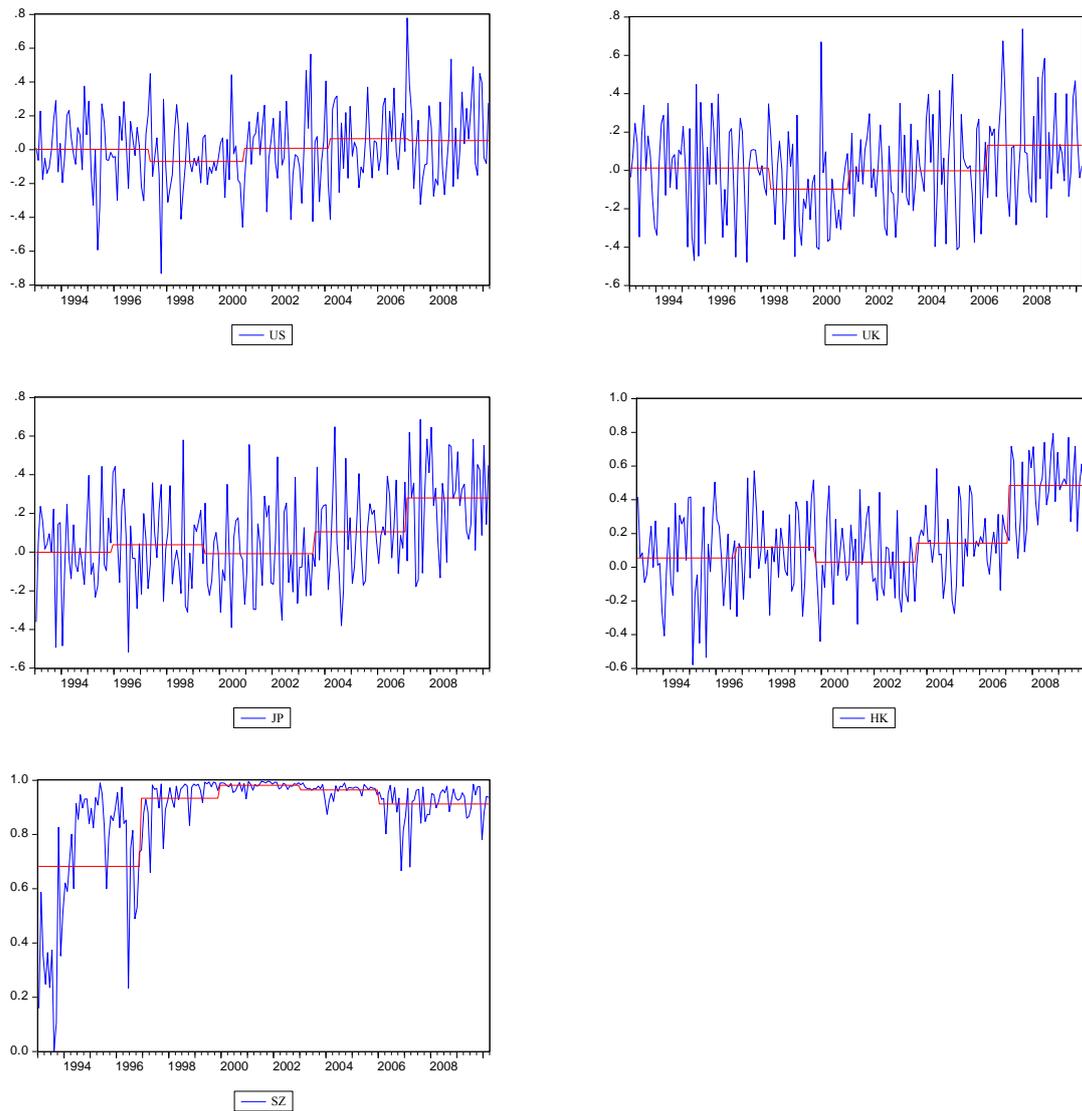
Table 5.4 Summary Statistics for Monthly Unconditional Correlations

	vs. SZ	vs. HK	vs. US	vs. UK	vs. JP
Mean	0.8852	0.1570	0.0085	0.0145	0.0783
Maximum	0.9962	0.7921	0.7782	0.7376	0.6849
Minimum	0.0011	-0.5788	-0.7324	-0.4776	-0.5166
1st subsample	0.6826	0.0549	0.0017	0.0126	-0.0005
2nd subsample	0.9336	0.1180	-0.0691	-0.0976	0.0379
3rd subsample	0.9811	0.0299	0.0089	-0.0012	-0.0081
4th subsample	0.9644	0.1423	0.0647	0.1315	0.1045
5th subsample	0.9123	0.4851	0.0534	N/A	0.2801

²⁹ The starting date of the Asian financial crisis is subject to debate since no single event acts as a clear catalyst behind this turmoil. The general consensus is that the Crisis started in July 1997 when Thailand announced a managed float of the baht.

³⁰ The climax of the dot-com boom is dated to March 10th 2000 when the NASDAQ peaked at 5132.5 points.

Figure 5.1 Plots of Monthly Unconditional Correlations and Breakpoints



Turning first to US, it has the lowest correlation with SH among all five stock indices. The correlation is just a little above zero in the first regime; then it falls to negative in the second regime which commences one month before the breakout of the Asian financial crisis. This period also marks the occurrence of the dot-com boom and bust. The negative mean correlation somehow reflects the fact that the cycle of dot-com boom and bust was not experienced by China's stock markets. The correlation moves back to positive regime in the third subsample. The last two subsample periods witness modest increase in correlation for which it reaches a level of 0.065 during the period of US housing bubble build-up and drops slightly to 0.053 once the problem of

sub-prime mortgage lending started to unveil in early 2007.

The behaviour of return correlation for UK shares the common feature with that for US – a negligible positive correlation at the beginning of the sample, followed by a negative correlation of -0.098 during the dot-com boom and bust period; the mean correlation in the third subsample period returns to a level that is barely below zero; it then bounces back to positive regime at a level of 0.132 towards the end of the sample.

The correlation series of JP and HK share similar trending behaviour as the locations of the breakpoints are almost identical. The first subsample for JP is characterised by a small negative mean correlation while the one for HK starts as positive figure. There are notable increases for both correlation series in the second regime, which may be associated with the period of the Asian financial crisis. Both series turn around to their initial states in the post-crisis period which begins in the second half of 1999 and ends in August 2003. This confirms the assertion that the Asian financial crisis prompts greater linkage between the countries' stock markets within the region. The intensified correlation does not sustain and is therefore short-lived. In addition, the temporary increases in correlation with JP and HK over this time interval are much smaller than those of other affected Asian stock markets (see example, Chiang *et al.*, 2007). This is consistent with the anecdotal evidence that the Mainland China's stock markets are resistant to potentially contagious effects. After a period of relative tranquillity, both series start to trend upward quite significantly since 2004 and the level of correlation is heightened amid the sub-prime mortgage crisis and the global recession thereafter. The increases in correlation in the last two subsample periods are more pronounced for HK than for JP.

The correlation between the two Mainland China's stock indices has been very high historically – the mean correlation is above 0.90 in four out of five subsample periods. The close-to-perfect

correlation is not surprising since the returns in both markets are driven by the same macroeconomic factors. The lower correlation in the first subsample (a mean correlation of 0.683) is probably due to the lack of listed companies on both exchanges so that much of the return can still be explained by idiosyncratic risks; as more companies are listed on these two exchanges, the proportion of return driven by idiosyncratic risks is diluted which in turn give rises to higher correlation. Another interesting finding is the subtle decrease in correlation between SH and SZ over the recent years. A possible explanation would be the growing difference in constituent stock composition between the two stock exchanges due to the Chinese government's initiative to transit SZ into a NASDAQ-style stock exchange aimed at private and technology companies.

The graphical evidence points towards the weak time-variation in the unconditional correlations of US and UK while those of JP and HK exhibit considerable time-variation. If the Asian financial crisis episode suggests that the Mainland Chinese stock markets were to offer significant diversification benefits as it was, to some degree, insulated from external shocks, then diversification into the Mainland stock markets would be less effective in light of the higher correlations in recent years, particular during the latest financial crisis.

5.5.2 Results from Smooth Transition Models

In this section, we investigate the integration experience of the Mainland China's stock market by employing variations of Smooth Transition Regression (STR) model suggested by Granger and Teräsvirta (1993). Given that we have previously computed monthly unconditional correlations at disposal, we can make use of this data and estimate three smooth transition models which would allow us to gauge the speed at which the market is becoming integrated.

By visualising the dynamic time paths of the unconditional correlations in Figure 5.1, some

correlation series seem to display upward trending and nonlinear behaviours. This suggests nonlinear models with time trend being the explanatory variable may be plausible if we want to characterise the movement of correlations. Furthermore, linear characterisation of correlation is not feasible since correlation cannot increase indefinitely as a function of time. The results from the LSTR models given by Eq. (5.9 and 5.12) are presented in Table 5.5.

Table 5.5 Results from LSTR Model

	α	β	γ	τT	ν	Adj. R ²
SH/SZ	0.3490**	0.5760**	0.3262*	13.8426**	-4.3886*	0.5143
SH/HK	0.0858**	0.5661**	0.1017*	171.9840**	-11.7060**	0.3299
SH/US	-0.0267	0.1621**	0.0759	135.0337**	-14.1027**	0.0525
SH/UK	-0.0178	0.1557**	9.0008	164.4952**	-6.1907**	0.0519
SH/JP	0.0139	0.3086**	0.0844	164.6720**	-13.1811**	0.1590

Notes: The table presents the results obtained from the estimation of the logistic trend model where α is a constant, β is the coefficient on the logistic time trend, γ captures the speed of adjustment, τT reflects the transition midpoint and figures in the column of ' ν ' are the ADF unit root test statistics, which are compared against the critical values by Leybourne *et al.* (1998). * and ** denote significant at 5% and 1% level of significance respectively.

Table 5.6 Results from ESTR Model

	α	β	γ	τT	ν	Adj. R ²
SH/SZ	0.5918**	0.2983**	1.1866**	32.1672**	-4.1778*	0.0025
SH/HK	-0.2349**	0.4218**	1.2154**	127.1198**	-4.8924**	-0.0038
SH/US	0.2834**	-0.2721**	0.0154	166.6352**	-13.8329**	0.0360
SH/UK	0.6427**	-0.6167**	0.2874**	171.1068**	-12.9091**	0.0423
SH/JP	0.0406	0.0528	2.0896	103.5305	-12.5230**	-0.0137

Table 5.7 Results from Second-Order LSTR Model

	α	β	γ	$\tau_1 T$	$\tau_2 T$	ν	Adj. R ²
SH/SZ	0.9256**	-0.5875**	4.9768	13.6029**	227.2016*	-4.2397	0.5237
SH/HK	0.6948**	-0.5744**	4.0373	193.6514**	231.4241**	-10.9741**	0.2669
SH/US	-0.2591**	0.4006**	1.0874	70.0067	70.0067	-14.2016**	0.0812

SH/UK	-0.3866**	0.6271**	0.7861	83.9048	83.9048	-13.7453**	0.1173
SH/JP	0.6766**	-0.6597**	3.5582	193.3578	193.3578	-13.4666**	0.1883

From Table 5.5, it appears that the correlations series of US, UK and JP are poorly fitted into the LSTR model as shown by the low adjusted R^2 . Parameter α represents the initial return correlation and β measures the change in correlation in the second regime. A positive β implies an upward trend in correlation (a sign of increasing integration). Positive β is reported in all five equations with four out of five being highly statistically significant except the one for US. The main analytical interest is the parameter γ , whose magnitude determines the pace of integration. Had we failed to reject the null hypothesis $H_0: \gamma = 0$, the estimated LSTR model collapses to a linear model and no integration is taking place between the two stock markets. Statistically significant γ are found in HK and SZ correlation series. Along with their positive β values, this suggests that SH with both HK and SZ are moving towards integration and away from segmentation. The magnitude of γ suggests that the pace of integration with SH is faster in SZ than in HK. The correlation between SH and SZ will eventually increase to 0.93 in the second regime (i.e. the sum of α and β) while the correlation for HK will be stationary around 0.54 once integration process completed. Considering the values of τT , it is possible to find the transition midpoints. These are February 1994 for SZ and March 2007 for HK. The poor explanatory power of LSTR model for the correlations with the other three stock indices are not beyond our expectation due to their static nature. Lastly, after the smooth transition model has been estimated, it is then important to test the residual of this process, which now no longer contain the deterministic component. If the residuals are stationary, there is justification for the series being described as stationary, having a permanent change, which is a smooth transition process. The ADF statistic from the residuals of the model is computed and compared against the critical values suggested by Leybourne *et al.* (1998), which are appropriate given the nonlinear form of the smooth transition model. The ADF test statistics for the residuals from HK and SZ's LSTR models are found to be -13.76 and -4.91. The

corresponding critical values at 5% and 1% significance levels are -4.161 and -4.761 (T=200), according to Leybourne *et al.* (1998). Since the test statistics exceed their critical value, the residual series are stationary and the smooth transition processes in these two markets are therefore justified.

The estimation of ESTR and second-order LSTR models yields little success. The adjusted R^2 were extremely low for the estimated ESTR models suggesting the model is not appropriate for explaining the data. Although many of the estimated parameters in the ESTR models are statistically significant, they rarely impart any economic meanings. For the second-order LSTR models, the models produce adjusted R^2 that are in acceptable range. Nevertheless, none of the key parameters (i.e. γ) are statistically significant and so the proposed models collapse to a linear one.

To sum up, despite the relatively low frequency and noise data, we are still able to capture the non-linearity embedded in some of the correlation series using the LSTR model. While the smooth transition analysis suggests the segmentation of SH from the three major developed stock indices, there is marginal evidence that regional integration is taking place steadily.

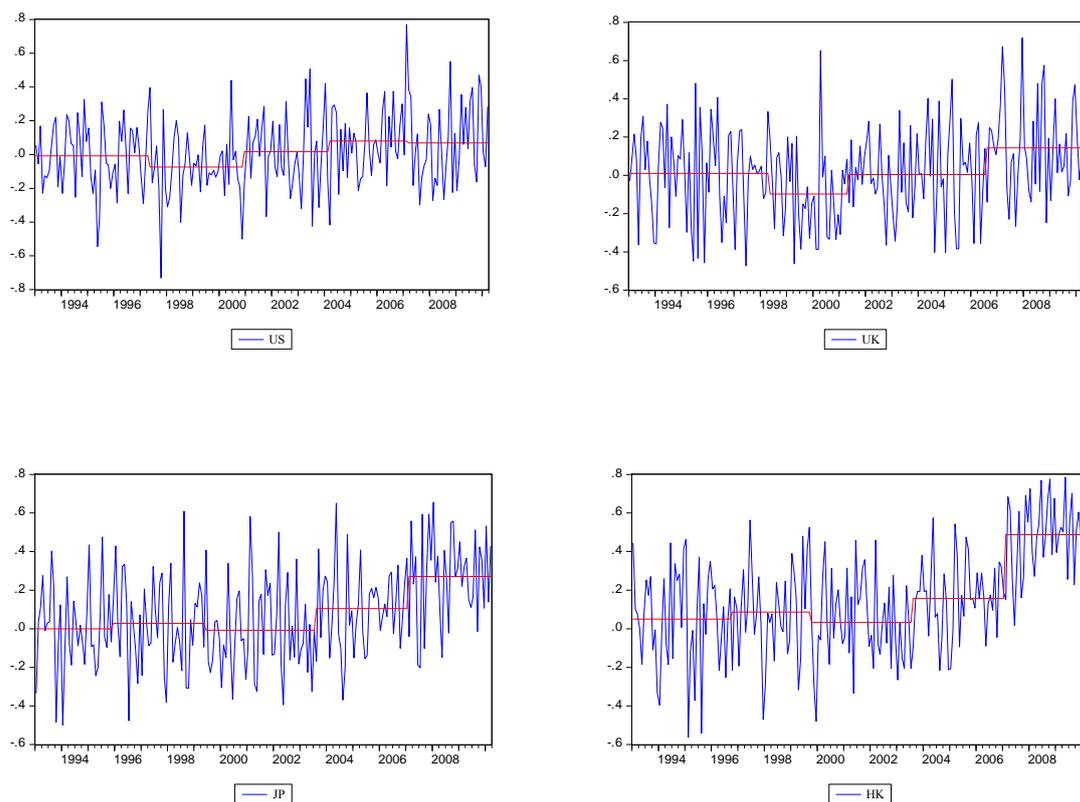
5.5.3 Realised Correlations

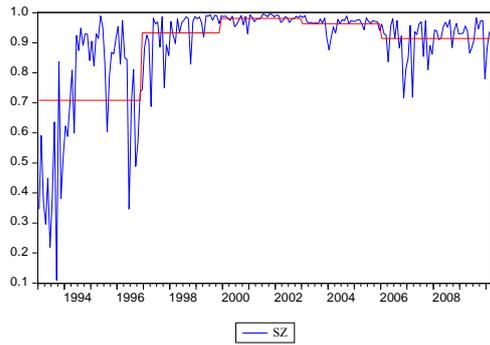
We now implement the realised variance methodology to generate correlation coefficients. This measure is regarded as free from measurement error and provides a model-free nonparametric framework in which to examine time-variation in correlation coefficient. The realised monthly correlation estimates have broadly similar pattern as the corresponding unconditional correlations and yield identical breakpoints. The summary statistics and graphs for the monthly realised correlations are presented in Table 5.8 and Figure 5.2 respectively.

Table 5.8 Summary Statistics for Monthly Realised Correlations

	vs. SZ	vs. HK	vs. US	vs. UK	vs. JP
Mean	0.8914	0.1548	0.0120	0.0179	0.0750
Maximum	0.9964	0.7846	0.7701	0.7181	0.6546
Minimum	0.1094	-0.5634	-0.7310	-0.4734	-0.4999
1st subsample	0.7084	0.0507	-0.0076	0.0104	-0.0002
2nd subsample	0.9331	0.0872	-0.0743	-0.0973	0.0283
3rd subsample	0.9812	0.0329	0.0163	0.0038	-0.0073
4th subsample	0.9638	0.1562	0.0805	0.1432	0.1049
5th subsample	0.9145	0.4881	0.0684	N/A	0.2710

Figure 5.2 Plots of Monthly Realised Correlations and Breakpoints

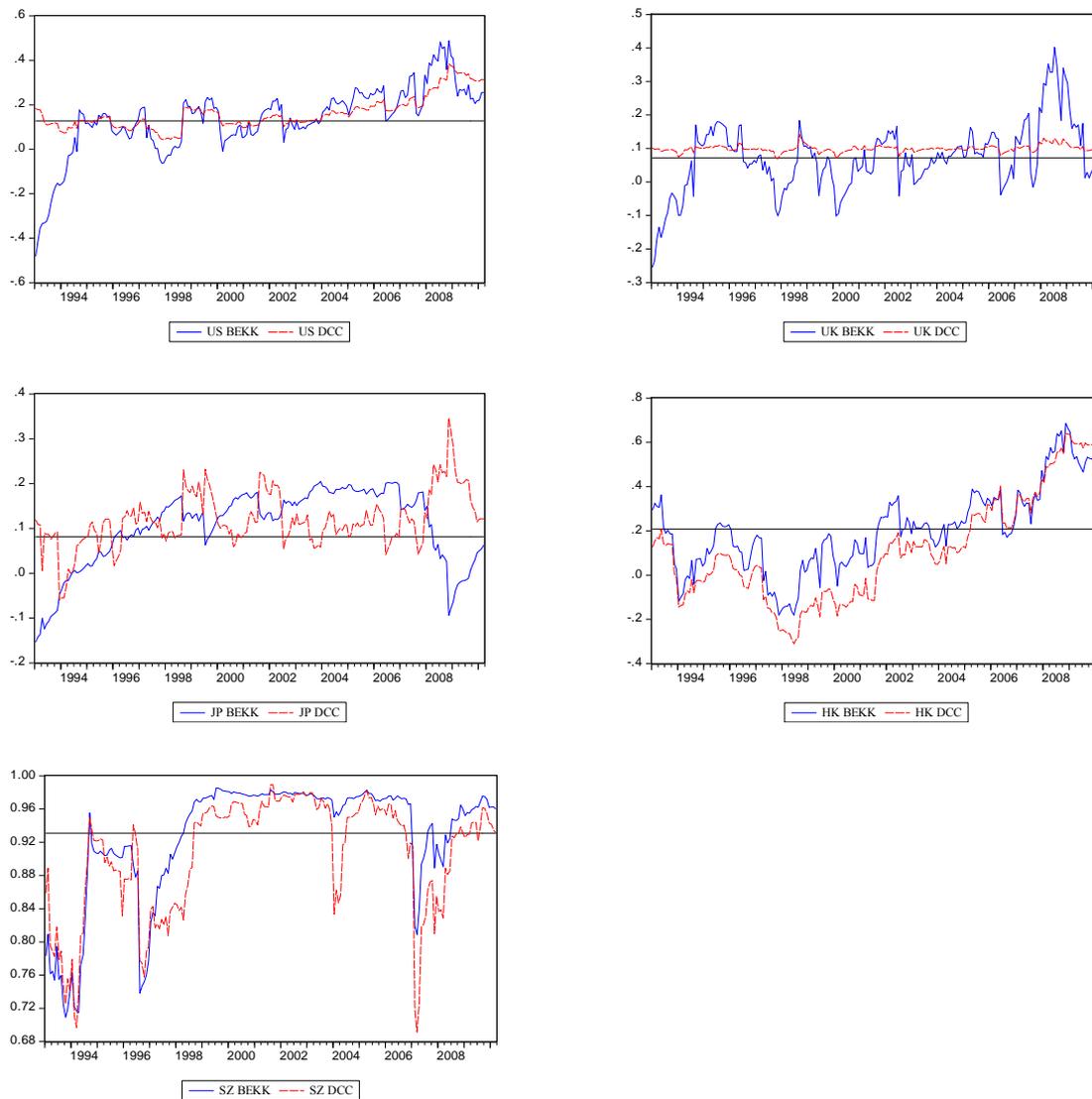




5.5.4 Conditional Correlations

The rolling monthly unconditional correlations are appealing since they are easy to construct and simple to understand. The main drawback of this approach, however, is that it gives an equal weight to all of the sample points under a fixed window. Realised correlation method performs the best when returns are sampled sufficiently frequently. With daily data, realised correlations largely resemble unconditional correlations. Therefore, it is more instructive to look at the conditional correlations from which the evolution of correlation is modelled by placing more weight on recent information; and the observed instability of the unconditional and realised correlations does not necessarily imply the conditional correlations follow the same suit. For conditional correlations, we start by estimating the CCC-GARCH model and proceed to the more advanced BEKK-GARCH model and the DCC-GARCH model in an attempt to capture possible time-variation in the correlations between the Shanghai A-share index and five other stock indices. The conditional correlations obtained from the CCC-, BEKK- and DCC-GARCH models are plotted in Figure 5.3.

Figure 5.3 Plots of GARCH Estimated Monthly Correlations



Notes: the horizontal lines represent the CCC-GARCH correlations, the blue lines represent the BEKK-GARCH correlations and the red lines represent the DCC-GARCH correlations.

At first glance, the conditional correlations have rather narrow bands and appear to be relatively smooth compared to the unconditional correlations which have very volatile paths. Even though the unconditional correlations vary erratically, these frequent variations have a very short half-life. We suspect the following reason to be responsible for the different magnitudes of fluctuations between conditional and unconditional/realised correlations. The conditional correlations are obtained using a time series model that requires correlations to change slowly over time so the

correlation series tend to be smoother and more persistent. On the other hand, the estimates of unconditional correlation are obtained separately for each point in time and can take on some rather extreme values which result in erratic fluctuations.

With the assumption of constant conditional correlation, the CCC-GARCH model seems to be a good starting point for our analysis. The constant conditional correlations as shown by the horizontal lines in Figure 5.3 suggest the correlations of UK and JP are both below 0.10 (0.07 for UK and 0.08 for JP), the one for US is around 0.13, the one for HK is just a little above 0.20, and the one between SH and SZ is very close to perfect correlation which stands at a level of 0.93. As noted earlier, the CCC-GARCH model offers only parametric information and ignores potential time-varying nature of the correlation by imposing a fixed value over the entire data sample and thus may lack practical significance for making portfolio diversification decisions. To this end, the BEKK- and DCC-GARCH correlation measures are more appealing since they are able to model the dynamic trajectories of correlation behaviour over time. In our case, they indeed reveal something quite different from the CCC-GARCH and unconditional correlation estimates.

The BEKK correlations for US, UK and JP all start in the negative regime and climb up in the following the two year interval. Apart from the correlation for JP which stays above zero for a considerable period, US and UK take frequent dips and soar during the latest financial crisis but plummet to their pre-crisis levels shortly after. The DCC correlation for US has been hovering around zero for the first half of the sample period and starts to take off gradually and reach its peak at the end of year 2008. The DCC correlation for UK is stationary around 0.10 without any substantial deviation, which implies that the correlation between SH and UK may well be time invariant. While the DCC correlations for US and UK do not move as much as do their BEKK alternates, the DCC correlation for JP displays remarkable ups and downs. The correlation behaviour for JP from 2007 onwards is even more intriguing as BEKK and DCC measures are in

sharp contrast to each other – the BEKK model suggests a dramatic fall in correlation during this period whereas the DCC model shows the exact opposite movement.

The DCC correlation for HK is broadly in line with the corresponding BEKK correlation for which both exhibit apparent upward trending behaviour. It is also notable that the correlations for HKSE do not fall in the aftermath of the global economic meltdown as much as do the correlations for the other markets; instead, they become stable at their current levels. The BEKK and DCC correlations between SH and SZ display very similar patterns, positing common turning points. The BEKK estimated correlation is consistently higher than that of DCC model for the majority of the sample period. The DCC estimate suggests that the sharp falls at the end of 2003 and at the beginning of 2007 are of greater magnitude than those estimated by the BEKK model.

The difference between BEKK and DCC estimated correlations can be reconciled since overestimated correlations are more heavily penalised and underestimated correlations are only moderately penalised by the likelihood function under the DCC-GARCH model. This causes DCC correlation estimates to be downward biased and only change slowly over time. Since the DCC approach puts too much emphasis on fitting the correlation dynamics during tranquil times as opposed to turbulent times (i.e. high volatilities and correlations), it would presumably result in the underestimation of VaR.

5.6 Conclusion

The major findings from the correlation analysis are summarised as follows: the analysis, which uses a longer span of data, finds supportive evidence that the relations between SH and other stock indices have been rather unstable over time, which is clear evidence against constant correlation hypothesis. The time-varying correlation GARCH models seem to give a better description of the

data than the CCC-GARCH model. The unconditional and realised correlation estimates appear to be considerably more unpredictable than the conditional correlations produced by the GARCH models. The apparent time variation and discrepancies between different correlation measures may pose challenges for portfolio diversification and risk management procedures. On balance, SH has not been strongly correlated with US, UK and JP. There is some evidence of correlations systematically changing around the periods of international market stress, particularly during the 2007-2009 global financial crisis. SH and SZ have been in close-to-perfect correlation throughout the sample period. The correlation between SH and HK has unambiguously trended upwards following the Asian financial crisis as suggested by both the unconditional and conditional correlations. The relatively low correlations between the SH and the three major stock markets imply that there is still plenty room for obtaining diversified portfolios through investing in Chinese A-share market, though the extent to which such benefit can be realised may be lessened by the current size of the quota for QFII.

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Chapter 6 – Market Risk Monitoring in the Mainland Chinese Stock Markets: Comparative Evidence from Symmetric, Asymmetric, and Long-memory GARCH Models in Value-at-Risk Estimation

6.1 Introduction

An important area of portfolio management concerns the measurement of market risk exposure. Following the success of the J.P. Morgan RiskMetrics system, the Value-at-Risk (hereafter, VaR) has become a standard measure of market risk and nowadays forms the basis of the determination of market risk capital requirements for financial institutions, since the 1996 Amendment to the Basel Accord.

The introduction of the ground-breaking initiative of the Qualified Foreign Institutional Investors (QFII) by the Chinese government has led to a surge in foreign equity investment in recent years. As foreign institutional investors enter the lucrative Chinese stock markets in search of higher returns and better international portfolio diversification opportunities, they should exercise caution when quantifying the market risk associated with the equity investments in China. An important area concerns the model selection for VaR reporting. There are a wide variety of alternative models which can be used for estimating VaR. Every real-world application of VaR is faced with the need to choose among these alternatives. This is a non-trivial problem, since models can yield substantially different VaR estimates, which consequently would result in suboptimal allocation of bank's economic capital. Although established domestic financial institutions in China are increasingly following international standards when building their risk management systems, the application of VaR to the financial market risk management in China is still in the pioneer stage. Not surprisingly, the empirical effectiveness of various VaR approaches in the emerging Chinese markets has not been examined in great detail. The present empirical chapter attempts to fill this

gap.

The purpose of this empirical chapter is threefold. First, to implement a number of univariate GARCH models under three distributional assumptions and two rolling window lengths in order to estimate daily 1% VaR. The different distributions will allow the selection of a model for the fat-tailness and skewness of returns, while the two rolling window lengths will reveal the importance of past data. Second, our empirical analysis provides new insights into the VaR application in the three Chinese stock markets for which there appears to be limited evidence with respect to the superiority of a spectrum of GARCH models in the computation of VaR estimates. We also conduct our analysis on stock indices from the markets of the US, the UK and Japan for purpose of comparison. Third, we address the specific concern of risk manager regarding the choice among a set of adequate models by quantifying and comparing the magnitude of under- and over-estimation of VaR by each model, which in turn allow us to effectively find the best performing models.

The remainder of this empirical chapter is organised as follows. Section 2 describes the concept of VaR and its calculation in the context of the regulatory framework of Basel Accord. Section 3 presents the GARCH models considered here. Section 4 describes the evaluation methods of VaR in the literature as well as the construction of the proposed two-stage backtesting procedure. Section 5 and 6 describe the data utilised and the specification of empirical models, respectively. Section 7 reports the out-of-sample performance and the evaluation results of the VaR models. Section 8 summarises our findings.

6.2 Value-at-Risk

According to Jorion (2007), VaR summarises the worst loss (or the highest gain) of a portfolio

over a target horizon that will not be exceeded with a given level of confidence, which practitioners have found very useful and easily interpreted as a measure of market risk. Using the ‘delta-normal’ approach, VaR is calculated as:

$$VaR = kN_{\alpha}\sigma V \quad \text{Eq.(6.1)}$$

where k is the multiplicative factor imposed by the regulator, α represents the specified probability level, N_{α} is the corresponding value from the standard normal table, σ is the volatility estimate, and V is the portfolio value. VaR is also commonly expressed as a proportion of the asset or portfolio value, and this convention is adopted in this study. The calculation of VaR simply boils down to the estimation of the volatility of the asset or portfolio.

Despite several other competing risk measures proposed in the literature, VaR has gained its popularity over the years and has been adopted by Bank for International Settlements for determining the Minimum Capital Risk Requirement (MCR) against market risk exposure of financial institutions since the 1996 Amendment of the Basel Accord.

For the purpose of determining regulatory capital, the Basel Committee on Banking Supervision stipulates VaR to be estimated at the 99% confidence level, using daily data over a minimum length of one year (250 trading days), with the estimates being updated at least every quarter. The rules do leave the bank a broad degree of flexibility in how the VaR is actually calculated. For example, the MCR estimates can be updated more frequently than quarterly, a longer run of data than one trading year can be employed, and the Basel Committee does not prescribe which model should be employed for the calculations. The multiplication factor, which has a minimum value of 3, depends on the regulator’s view of the quality of the bank’s risk management system, and more precisely on the backtesting results of the models. Unsatisfactory results might see an increase in

the multiplication factor of 3, up to a maximum of 4. The regulator performs an assessment of the soundness of the bank's procedure in the following way. Underprediction of losses by VaR models (that is, the days on which the bank's calculated VaR is insufficient to cover the actual realised losses in its trading book) is termed 'exception'. Between zero and four exceptions over the previous 250 days (implying a VaR failure rate of no more than 1.6%) places the bank in the Green Zone; between five and nine (a failure rate between 1.6% and 4%), it is in the Yellow Zone; and when ten or more exceptions (a failure rate higher than 4%) are noted, the bank is in the Red Zone. The multiplication factor is fixed to 3 if the bank is in the Green Zone and increases incrementally with the number of exceptions if it is in the Yellow Zone, while if the firm falls into the Red Zone, it is likely to be no longer permitted to use the internal modelling approach. It will instead be required to revert back to the "building block" approach, which does not include a reduction in the MCRR for diversified books and which will almost certainly yield a much higher capital charge. Having a sound risk measurement procedure is thus of paramount importance to financial institutions. Since the amount of economic capital that a firm holds and the allocation of economic capital has a profound effect on the overall performance of a financial institution, so it is important that all candidate models be thoroughly evaluated.³¹

6.3 Volatility Models

There exist a number of different methods of VaR calculation, which can be classified as being parametric, non-parametric or semi-parametric (Angelidis and Degiannakis, 2007). The parametric method involves the modelling of the entire return distribution and volatility dynamics of the target portfolio. Parametric VaR approach tracks the time-series behaviour of volatility better than historical and simulation-based techniques, and appears to yield slightly superior volatility

³¹ The economic capital held by financial institutions generally exceeds the required amount of regulatory capital, but we use the two terms interchangeably in this study.

forecasts (Jackson *et al.*, 1998). The major representatives of the parametric family are the Generalised Autoregressive Conditional Heteroskedasticity (GARCH) models. The second category, the non-parametric modelling, relies on actual prices without assuming any specific distribution. The semi-parametric family combines parametric and non-parametric models in order to take the most of them.

The basic GARCH (p, q) model is introduced by Engle (1982) and Bollerslev (1986) is given by:

$$\sigma_t^2 = \omega + \sum_{i=1}^q \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^p \beta_i \sigma_{t-i}^2 \equiv \omega + \alpha(L)\varepsilon_t^2 + \beta(L)\sigma_t^2 \quad \text{Eq. (6.2)}$$

where $\alpha(L)$ and $\beta(L)$ are polynomials of order p and q , respectively, expressed in terms of the lag (or backshift) operator, $L^i y_t \equiv y_{t-i}$. Thus, forecasts of volatility are generated as a weighted average of the constant long-run or average variance, ω , past volatility reflecting squared ‘news’ about the return, ε_{t-i}^2 , and past estimates of the conditional variance, σ_{t-i}^2 . As volatility forecasts are increased following a large return of either sign, the GARCH specification captures the well-known volatility clustering effect in financial time series data. In particular, if $\alpha(L) + \beta(L) < 1$, then the process ε_t is covariance stationary and its unconditional variance is equal to

$$\sigma^2 = \omega / [1 - \alpha(L) - \beta(L)] \quad \text{Eq.(6.3)}$$

The simple GARCH (p, q) model has been applied in many studies in order to forecast the risk that the investors face and it has been showed that it generates accurate forecasts. Hansen and Lunde (2005), in an extensive study of volatility models, concluded that the best performing models, out of 330 alternatives, did not provide significantly better volatility forecasts than the GARCH (1, 1) model. In a risk management environment the use of the GARCH (1, 1) is not

always suggested. For example, Billio and Pelizzon (2000) demonstrate that the number of exceptions that have been generated by a GARCH (1, 1) model deviates significantly from the theoretical values.

A special case of the GARCH (p, q) family is the Integrated GARCH or IGARCH (p, q) model, since in empirical applications of the GARCH (p, q) model to daily data is likely to be found that $\alpha(L) + \beta(L) \approx 1$. In IGARCH model the unconditional variance is infinite and a shock on the conditional variance is persistent, which implies that it remains important for all conditional volatility forecasts.

A special case of the IGARCH model is the Exponentially Weighted Moving Average (EWMA), which has been popularised by J.P. Morgan. Under exponential smoothing, the volatility forecast is computed as

$$\sigma_t^2 = \lambda\sigma_{t-1}^2 + (1 - \lambda)\varepsilon_{t-1}^2 \quad \text{Eq. (6.4)}$$

The widely adopted RiskMetrics™ model set $\lambda = 0.94$ for daily data. Although practitioners commonly find that RiskMetrics perform satisfactorily well, there is evidence that it underestimates total risk. In particular, Pafka and Kondor (2001) point out that the success of RiskMetrics is actually the artifact of the choice of the risk measure: the effect of fat tails is minor when one calculates VaR at 95%; however, RiskMetrics underestimates risk when higher significance levels are adopted.

In the simple and symmetric GARCH structure, the variance depends only on the magnitude of ε_t and not on its sign. These models implicitly assume that opposite shocks of equal magnitude incur the same effect upon variance. A significant issue that has arisen in the empirical application of

GARCH models to equity market data concerns the potential for an asymmetric effect of positive and negative shocks upon conditional variance. As noted by Black (1976) and expounded upon further by Christie (1982), a negative relationship is often observed to hold between current variance and the sign of past shocks. Thus, a negative shock ($\varepsilon_t < 0$) increases the conditional variance by a greater amount than an equal positive shock ($\varepsilon_t > 0$). This feature is known as leverage effect, a term that was introduced by Black (1976).

A number of asymmetric GARCH models have therefore been developed to account for the asymmetric response of volatility to shocks or ‘news’. In the arena of VaR, the importance of asymmetry has been noted by several authors. Brooks and Persaud (2003) point out that risk models which do not account for asymmetries in volatility specification, are most likely to generate inaccurate forecasts. Other authors, such as Giot and Laurent (2003) favour models that accommodate at least the asymmetry of the volatility, while Angelidis and Degiannakis (2005) argue that models that parameterise the leverage effect for the conditional variance, forecast accurately the VaR at the 99% confidence level.

Here we consider three most commonly used asymmetric GARCH specifications. The first of these is the Threshold GARCH or TGARCH model of Glosten *et al.* (1993):³²

$$\sigma_t^2 = \omega + \sum_{i=1}^q (\alpha_i \varepsilon_{t-i}^2 + \gamma_i I_{t-i} \varepsilon_{t-i}^2) + \sum_{i=1}^p \beta_i \sigma_{t-i}^2 \quad \text{Eq. (6.5)}$$

where the leverage effect is captured by the dummy variable I_{t-1} , such that $I_{t-1} = 1$ in the event of negative news in the sense that $\varepsilon_{t-1} < 0$, and $I_{t-1} = 0$ in the event of positive news when $\varepsilon_{t-1} > 0$. Thus, in the TGARCH (1, 1) model positive news has an impact of α_1 , and negative news has an

³² The TGARCH model described in the text is sometimes referred to as the GJR model.

impact of $\alpha_1 + \gamma_1$, and hence negative (positive) news has a greater effect on volatility if $\gamma_1 > 0$ ($\gamma_1 < 0$).

The second asymmetric GARCH model is the exponential GARCH, or EGARCH (p, q) model introduced by Nelson (1991) and is given by:

$$\ln \sigma_t^2 = \omega + \sum_{i=1}^q \alpha_i g(z_{t-i}) + \sum_{i=1}^p \beta_i \ln \sigma_{t-i}^2 \equiv \omega + [1 - \varphi(L)]^{-1} [1 + \psi(L)] g(z_{t-i}) \quad \text{Eq. (6.6)}$$

$$g(z_{t-i}) = \theta_1 z_{t-i} + \theta_2 (|z_t| - E|z_t|) \quad \text{Eq. (6.7)}$$

where \ln denotes the natural logarithmic transformation of a variable, and $z_{t-i} = \varepsilon_{t-i} / \sqrt{\sigma_{t-i}^2}$ is the normalised error series. The logarithmic transformation not only ensures that variance will be always positive, but also implies that the leverage effect is exponential, rather than quadratic as in the TGARCH model above. The functional form for $g(z_{t-i})$ accommodates the asymmetric relationship between stock returns and volatility changes associated with the leverage effect by virtue of both a ‘sign effect’, $\theta_1 z_{t-i}$ and a ‘size effect’, $\theta_2 (|z_t| - E|z_t|)$. In the EGARCH (1, 1), negative news has an impact of $(\alpha_1 \theta_1 - \alpha_1 \theta_2)$ on the log of the conditional variance, while positive news has an impact of $(\alpha_1 \theta_1 + \alpha_1 \theta_2)$, and volatility is at a minimum when $\varepsilon_{t-1} = 0$.

The third asymmetric model is the asymmetric power ARCH, or APARCH (p, q) model introduced by Ding *et al.* (1993), where the power parameter on the standard deviation is estimated rather than imposed. The APARCH (p, q) model can be expressed as:

$$\sigma_t^\delta = \omega + \sum_{i=1}^q \alpha_i (|\varepsilon_{t-i}| - \gamma_i \varepsilon_{t-i})^\delta + \sum_{i=1}^p \beta_i \sigma_{t-i}^\delta \quad \text{Eq. (6.8)}$$

where $|\gamma_i| < 1$ and $\delta > 0$. σ is the conditional standard deviation and δ is the power parameter while γ captures any asymmetric effect of positive and negative news upon volatility.

The APARCH model comprises several ARCH extensions as special cases. For example, if $\delta = 2$ and $\gamma_i = 0$, the APARCH model becomes the GARCH model. Giot and Laurent (2003) calculate the VaR number for long and short equity trading positions and proposed the APARCH model with skew Student t conditionally distributed innovations as it had the best overall performance.

Ding *et al.* (1993) note that there has been significant evidence of long memory in volatility of asset returns. In order to model the long memory property in volatility, Baillie *et al.* (1996) extend the IGARCH model to Fractionally Integrated GARCH or FIGARCH (p, d, q) as a means of capturing such persistent dynamics in volatility:

$$\sigma_t^2 = \omega + [1 - \beta(L)]^{-1} + \{1 - [1 - \beta(L)]^{-1}\phi(L)(1 - L)^d\}\varepsilon_t \quad \text{Eq.(6.9)}$$

Davidson (2004) generalises the FIGARCH model to Hyperbolic GARCH or HYGARCH in order to address theoretical limitation associated with the FIGARCH process. In particular, Davidson (2004) shows that in the FIGARCH model, the long memory parameter d behaves counterintuitively given that d approaches zero as the memory of the process increases. The HYGARCH model overcome this deficiency by incorporating the additional parameter $\tau \geq 0$. The conditional variance of the HYGARCH (p, d, q) model is given by:

$$\sigma_t^2 = \omega + [1 - \beta(L)]^{-1} + \{1 - [1 - \beta(L)]^{-1}\phi(L)[1 + \tau(1 - L)^d - \tau]\}\varepsilon_t \quad \text{Eq.(6.10)}$$

The HYGARCH model nests the FIGARCH model if $\tau = 1$, and nests the GARCH model under the restriction $\tau = 0$ (or $d = 0$). When $d = 1$ the parameter becomes an autoregressive root and the

HYGARCH reduces to a stationary GARCH ($\tau < 1$), an IGARCH ($\tau = 1$) or an explosive GARCH ($\tau > 1$).

Bollerslev and Mikkelsen (1996) extend the idea of fractional integration to the EGARCH model, building the FIEGARCH (p, d, q) model. Under this specification, the conditional variance is modelled as:

$$\ln \sigma_t^2 = \omega + \phi(L)^{-1}(1-L)^{-d}[1 + \psi(L)]g(z_{t-i}) \quad \text{Eq.(6.11)}$$

where $g(z_{t-i}) \equiv \theta_1 z_{t-i} + \theta_2 [|z_t| - E|z_t|]$ as in the EGARCH captures both size and sign effect. FIEGARCH therefore captures both volatility asymmetry due to leverage and long memory behaviour as reflected by the very slow mean-reverting hyperbolic decay of shocks to stock returns. It is also worth noting that, unlike the other GARCH models outlined here, by virtue of the logarithmic transformation of the conditional variance in both EGARCH and FIEGARCH model specifications, parameter non-negativity constraints do not have to be satisfied in order for the estimated models to be well defined.

Similarly, the long memory extension of the APARCH model is the FIAPARCH (p, d, q) model built by Tse (1998):

$$\sigma_t^\delta = \omega + \{1 - [1 - \beta(L)]^{-1}\phi(L)(1-L)^d\}(|\varepsilon_t| - \gamma\varepsilon_t)^\delta \quad \text{Eq.(6.12)}$$

Although there is a vast number of ways to parameterise the conditional volatility in an ARCH/GARCH framework, the models considered in this study are the most widely known ones and have been applied in many risk management studies. The GARCH models considered here can be classified into three categories – symmetric (GARCH, IGARCH and the RiskMetrics),

asymmetric (EGARCH, TGARCH and APARCH) and long-memory (FIGARCH, FIEGARCH, FIARPARCH and HYGARCH) models. Symmetric class of models, particularly the RiskMetrics model, is widely adopted by risk professionals due to their simplistic nature and ease of computation. Asymmetric and long-memory class of models are computationally intensive but are advocated by financial economists and econometricians in the academic community. Of particular interest is whether the more complex GARCH models can outperform their less sophisticated counterparts.

6.4 Evaluation of VaR Models

A VaR model is subject to validation or periodic backtesting. The quality of the backtesting results would have a direct impact on the multiplication factor imposed by the regulator. VaR forecasts must neither overestimate nor underestimate the 'true' VaR as, in both cases, the financial institution allocates the wrong amount of capital. In the former case, the firm is required to tie higher than needed amount of regulatory capital in an unprofitable, liquid form, worsening its performance; in the latter, the regulatory capital set aside may not be enough to cover market risk.

In the terminology of the Basel Committee, the under-prediction of VaR is referred as an 'exception'. The simplest method of determining whether a VaR model is correctly specified is to record the number of the exceptions. This method is currently used by the Basel Committee in its three-zone framework described in Section 2. In financial literature there are mainly two methods of model evaluation – the evaluation of the statistical properties of VaR forecasts and the construction of loss functions that measure the distance between the predicted VaR and the actual outcome. In the former method, a series of statistical hypothesis tests are performed in order to test whether the VaR measures coming out from alternative models display the required theoretical properties. The sample coverage $\hat{\alpha}$, which is the proportion of realised trading losses greater than

the VaR estimates (i.e. VaR failure rate) frequently used in many of these statistical procedures. Since regulators impose severe penalties on firms whose models generate more than an acceptable number of exceptions, a failure rate that is higher than the chosen probability level ($\alpha = 1\%$) is clearly undesirable. On the contrary, if a volatility model produces $\hat{\alpha}$ that is consistently lower than α , this model is not preferred either since the implementation of which would result in the over commitment of regulatory capital by the financial institution. We expect that $\hat{\alpha}$ is close to α for a correctly specified VaR estimation method. The smaller the discrepancy between $\hat{\alpha}$ and α , the better the performance is the volatility model. This can be formally tested using the Kupiec test (Kupiec, 1995) which examines the equality of the actual failure rate to the chosen left-hand tail cut-off (i.e. 1%). Under the null hypothesis, $H_0: \hat{\alpha} = \alpha$ where $\hat{\alpha}$ is the actual failure rate on any of the independent trials and α is the failure rate under the null hypothesis, the likelihood ratio test of the null hypothesis is given by:

$$-2 \log[(1 - \alpha)^{n-x} \alpha^x] + 2 \log \left[\left(1 - \frac{x}{n}\right)^{n-x} \left(\frac{x}{n}\right)^x \right]$$

Eq.(6.13)

where n is the sample size and x is the number of failures in the sample. This test has a chi-square distribution with one degree of freedom.

Statistically, using the number of exceptions as the basis for appraising a bank's model requires few strong assumptions. In particular, the primary assumption is that the exception is independent of the outcome of any of the others. In this sense, a VaR model should also be invalidated if it produces exceptions that cluster over time. To ensure this assumption is not violated, we further implement the Dynamic Quantile test proposed by Engle and Manganelli (2004) who suggest that a correctly specified VaR model not only should the exceptions occur at the specified rate but also

the exceptions should be independent and identically distributed.³³ To conduct the DQ test Engle and Manganelli define the sequence:

$$Hit_k = I(r_k < -VaR_k) - \alpha \quad \text{Eq.(6.14)}$$

The sequence assumes the value $(1 - \alpha)$ whenever returns, r_t , are less than the VaR quantile and the value $-\alpha$ otherwise, with the expected value of Hit_k equal to zero. This sequence should then be uncorrelated with past information and have a mean value of zero, in which case there will be no autocorrelation in the hits and there will be the correct fraction of exceptions, this latter property is tested in the Kupiec test, but not the former. To test for autocorrelation in the hit sequence Hit_k is regressed on five lags (days) and the current value of VaR. The DQ test statistic is then computed as:

$$DQ = \hat{\beta}' X' X \hat{\beta} / \alpha(1 - \alpha) \quad \text{Eq.(6.15)}$$

where X is the vector of explanatory variables and $\hat{\beta}$ the OLS estimates. The DQ test is χ^2 distributed with degrees of freedom equal to the number of parameters.

In essence, the Kupiec test is an unconditional test of VaR accuracy while DQ test examines the conditional accuracy of the VaR estimates. As for the power of each test, the Kupiec test rejects a model for both high and low failures whereas DQ test can reject a model that generates either too many or too few clustered violations. The aforementioned statistical techniques will allow us to reduce competing models into a smaller set of adequate models. The main drawback of these statistical procedure is the inability to select the best model when more than one model are

³³ The earlier test by Christoffersen (1998) fulfils the similar purpose, as it jointly examines the conjecture that the total number of VaR exceptions is statistically equal to the expected one and the exceptions are independent.

considered as adequate since these methods are not able to rank the models according to their ability to predict VaR. A utility function of risk manager must be brought into picture to judge statistically the differences among the adequate models. Lopez (1999) develop a quadratic loss function that accommodates the specific concerns of regulators and proposed to measure the accuracy of the VaR forecasts on the basis of the distance between the observed returns and the forecasted VaR values if a violation occurs. The loss function is defined as:

$$\Psi_{t+1} = \begin{cases} 1 + (y_{t+1} - VaR_{t+1|t}^{(p)})^2, & \text{if } y_{t+1} < VaR_{t+1|t}^{(p)} \\ 0, & \text{if } y_{t+1} \geq VaR_{t+1|t}^{(p)} \end{cases} \quad \text{Eq. (6.16)}$$

where y_{t+1} is the realised return. A score of 1 is imposed when an exception occurs, the additional quadratic term ensures that exceptions with greater magnitude are penalised more than those with smaller magnitude. A model is preferred to another if it yields a lower total loss value, defined as the sum of these penalty scores: $\Psi = \sum_{t=1}^T \Psi_t$. Nevertheless, this approach has two drawbacks, First, if the proposed VaR model is not approved by the statistical measures such as the Kupiec test, a model that does not generate any exceptions would be deemed the most adequate as $\Psi=0$. Second, the loss function does not penalise the overestimation of VaR which is also undesirable, so it only partially reflects the utility function of risk managers.

Sarma *et al.* (2003) suggest a two-stage backtesting procedure to overcome the abovementioned shortcomings. Since the loss function is more suited discriminate among competing VaR models than deciding for the adequacy of a model, they perform the Christoffersen (1998) test in the first stage. In the second stage, they proposed the Firm's Loss Function by penalising VaR exceptions as well as imposing a penalty reflecting the cost of capital suffered on other days:

$$\Psi_{t+1} = \begin{cases} (y_{t+1} - VaR_{t+1|t}^{(p)})^2, & \text{if } y_{t+1} < VaR_{t+1|t}^{(p)} \\ -\alpha_c VaR_{t+1|t}^{(p)}, & \text{if } y_{t+1} \geq VaR_{t+1|t}^{(p)}. \end{cases} \quad \text{Eq. (6.17)}$$

where α_c is a measure of cost of capital on the overcommitted economic capital. Under this two-stage backtesting procedure, the risk manager is ensured that the models that have not been rejected in the first stage, forecast VaR more accurately. Furthermore, to evaluate the adequate models in the second stage, Sarma *et al.* (2003) implement the Diebold and Mariano (1995) test. Let $X_t^{(A,B)} = \Psi_t^{(A)} - \Psi_t^{(B)}$, where $\Psi_t^{(A)}$ and $\Psi_t^{(B)}$ are the loss functions of models A and B, respectively. A negative value of $X_t^{(A,B)}$ indicates that Model A is superior to Model B. The Diebold-Mariano (1995) statistic is the t -statistic for a regression of $X_t^{(A,B)}$ on a constant with heteroskedastic and autocorrelated consistent (HAC) standard errors.³⁴ Multiple models comparison cannot be performed using this approach. Angelidis and Degaiannakis (2006) implement Hansen's (2005) Superior Predictive Ability (SPA) criterion in order to evaluate the benchmark model (the best performing one) with all the competing models, simultaneously. The hypothesis of the test is:

$$\begin{aligned} H_0: E(X_t^{(i^*,1)} \dots X_t^{(i^*,M)})' &\leq 0 \\ H_1: E(X_t^{(i^*,1)} \dots X_t^{(i^*,M)})' &> 0 \end{aligned} \quad \text{Eq. (6.18)}$$

where $X_t^{(i^*,i)} = \Psi_t^{(i^*)} - \Psi_t^{(i)}$, i^* denotes the benchmark model, $i = 1, \dots, M$ are the competing models. The null hypothesis that the benchmark model i^* is not outperformed by competing models i , is tested with the statistic:

$$T^{SPA} = \max \frac{M^{1/2} \bar{X}_t}{\sqrt{Var(M^{1/2} \bar{X}_t)}} \quad \text{Eq. (6.19)}$$

³⁴ For more details about HAC standard errors, see White (1980) and Newey and West (1987).

for $i = 1, \dots, M$, where $\bar{X}_i = \frac{1}{T} \sum_{t=1}^T X_t^{(i*,i)}$. $Var(M^{1/2}\bar{X}_i)$ is estimated through a bootstrap procedure (see Hansen, 2005).

For our empirical analysis, we adopt a two-stage evaluation framework that is similar in spirit to Sarma *et al.* (2003). The first stage of model selection process involves testing the statistical accuracy of the models is examined in that they have to satisfy both Kupiec test and DQ test. In the second stage, the models that pass the first stage selection are appraised in terms of their ability of minimising the dispersion between projected VaR return and the realised return – the model yields the lowest MAE and RMSE is selected. This two-stage backtesting procedure will allow us to find the best performing model rather than a small set of adequate models.

MAE measures the absolute distance between the true and forecast VaR returns and RMSE measures the square root of the variance of the forecast error. In the context of VaR evaluation, they are computed as:

$$MAE = \frac{1}{T} \sum_{t=1}^T (\widehat{VaR}_t - VaR_t) \quad \text{Eq. (6.20)}$$

$$RMSE = \sqrt{\frac{1}{T} \sum_{t=1}^T (\widehat{VaR}_t - VaR_t)^2} \quad \text{Eq. (6.21)}$$

where VaR denotes the actual index return while \widehat{VaR} denotes the forecast VaR return. The MAE and RMSE criteria are in essence generic loss functions if we assume the under- and over-estimation of VaR have equal impact on bank's utility. Although assuming asymmetric utility function may be a more plausible approach, specifying the utility function of a bank in

reality is beset by two problems: the cost of capital for the overcommitted capital is often unique to the bank and hard to quantify; the regulatory intervention for the bank vary from one to another. How to differentiate the penalties for VaR exception and overestimation is subject to an element of arbitrariness. As with any application of loss functions, our assumption is vulnerable to mis-specification, but the simplification of the loss function would still serve the purpose of this research. In practice, risk managers can modify the penalty imposed at their own discretion. We choose RMSE as our main criterion should inconsistency between MAE and RMSE arise since RMSE penalises large deviations more heavily than small deviations whereby MAE is indifferent for deviations with different magnitudes.

Finally, we implement Hansen's (2005) SPA test to verify whether the selected best performing model is indeed superior to its competitors. RMSE is again chosen as the loss function for the computation of the SPA test statistics. The estimation package for the SPA tests is MULCOM 1.00 Ox developed by Hansen and Lunde (2007).

6.5 Literature Review

The number of studies dealing with the evaluation of various VaR methodologies has increased substantially since VaR has been adopted by the Bank for International Settlements for determining the MCR against market risk exposure of financial institutions. A common finding emerged from these studies was that the various approaches to VaR modelling differ widely in the accuracy with which they predict the frequency of the occurrence of VaR exceptions. In general, the performance of the models is data sensitive. In most cases, there is not a specific model that outperforms its competitors for all datasets.

Because volatility is a key input to VaR models, the characterisation of asset volatility along with

the assumed distribution of the asset returns is of great importance when implementing and testing VaR models. One stream of studies sought to find the combination of parametric model and distribution assumption that produces the most precise VaR estimates. For example, Gurmat and Harris (2002) propose an exponentially weighted likelihood model which gives better VaR estimates than that of the GARCH model under either the normal or the Student t -distributions. By considering the effect of unconditional skewness and conditionally asymmetric response of volatility in the returns of five Southeast Asian stock market indices and S&P 500, Brooks and Persaud (2003) conclude that models which explicitly allow for such asymmetries either in the return distribution or in the volatility specification lead to more accurate and stable VaR estimates. Giot and Laurent (2003) estimate the daily VaR for stock indices using a skewed Student t -distribution and pointed out that it performed better than the symmetric one, as it reproduced the characteristics of the empirical distribution more accurately. The authors also advocate the APARCH model under a skewed Student t -distribution in the VaR estimation for both long and short positions, since the corresponding failure rates of this combination are very close to the expected ones at all confidence levels. The long-memory extension of the APARCH model under skewed Student t -distribution was proposed by Degiannakis (2004). Angelidis *et al.* (2004) evaluate the performance of three GARCH models in various settings for the calculation of VaR in five world's major stock indices. They concluded that leptokurtic distributions especially the Student t -distribution, are more appropriate than the normal distribution in providing more accurate VaR forecasts. They also found that the quality of VaR forecasts is also dependent on the size of the rolling sample used in estimation. While no volatility model is clearly superior to the others, the EGARCH model and Student t -distribution yields the best combination in most cases based on the proposed quantile loss function. So and Yu (2006) examine the 1% VaR forecasting performance of three GARCH models against the RiskMetrics model for twelve stock market indices and demonstrated that the RiskMetrics model is outperformed by both stationary and fractionally integrated GARCH models. They also observed the asymmetric behaviour that t -error

models give better 1% VaR estimates than normal-error models in long position, but not in short position. Bali and Theodossiou (2007) combine the skewed generalised Student t -distribution with ten GARCH specifications and argued that the TS-GARCH and the EGARCH have the best overall performance.

The earlier research has been less inclusive either in terms of the types of models considered or in the application to a range of international markets of differing degrees of development. McMillan and Speight (2007) evaluate a broader array of GARCH models of modelling VaR in eight Asian emerging stock markets as well as the markets of the US and the UK. Their results lend support to the superiority of VaR estimates generated by asymmetric and long-memory models on both an in-sample and out-of-sample basis. However, this finding should be treated with caution since the VaR estimates are neither backtested by any statistical methods, nor evaluated by the construction of loss functions. More recently, using a selection of thirty-one international stock markets, McMillan and Kambouroudis (2009) assess whether the RiskMetrics model can provide adequate forecasts in a VaR setting in comparison to a range of GARCH models. For the 1% VaR, the RiskMetrics model performs poorly across almost all markets in terms of VaR exception frequency and with respect to both the Kupiec and DQ tests. With respect to the GARCH set of models, they found the GARCH, APARCH and IGARCH models perform the best across the average failure rate, Kupiec and DQ tests for the majority of the markets. Since the normality assumption was imposed on the VaR models, the resultant average VaR failure rates reported in McMillan and Speight (2007) and McMillan and Kambouroudis (2009) are therefore almost always higher than the specified VaR probabilities. Should alternative distributional assumption be used, the results might differ substantially.

Many of the aforementioned studies mainly focused on the search of models whose VaR exceptions possess the desired statistical properties but did not investigate the magnitude of

exceptions or rank the relative performance of the candidate models. Lopez (1999) points towards the inability of unconditional coverage test (e.g. Kupiec test) and conditional coverage test (e.g. Christoffersen and DQ tests) for identifying the best model for VaR measurement. He suggests the use of loss function to provide complementary information about the magnitude of the observed VaR exceptions. Angelidis and Degiannakis (2006) propose to replace VaR with the Expected Shortfall to measure the difference of the loss. Sarma *et al.* (2003) develop a two-stage procedure to determine how a VaR model should be selected. They proposed to bring the utility function of the risk manager to find economically significant difference between VaR models that have the correct conditional coverage (this property was tested using the Christoffersen test and a regression-based test for higher-order and periodic dependence). In the empirical application of the two-stage selection procedure on India NSE-50 Index, the RiskMetrics (with $\lambda = 0.90$) is preferred over fourteen other model specifications (including EWMA, the RiskMetrics, GARCH, and Historical Simulation) for the 1% VaR.

Another strand of research addresses the trade-off between complexity and efficiency of different VaR measures. For example, Brooks and Persaud (2003) demonstrate that the cost of capital is on average 1%–20% higher for the asymmetric models than models in a more simplistic manner, but they conjecture that the additional margin of safety is necessary and makes the additional cost worthwhile. Based on a simulated study, Caporin (2003) illustrate that, even though a long-memory GARCH is the true generator, the EWMA model can still provide satisfactory VaR measures that are in line with the Basel requirements. Such economically efficient models with lower level of complexity may be preferred by financial institutions whose priority is to minimise the amount of regulatory capital held. Despite the compiling evidence, practitioners and academics thus far have not reached a common conclusion for the best performing model, so the choice of a universally accepted model for VaR calculation is far from resolved.

Pan and Zhang (2006) study is perhaps the only one written so far on the topic of competing volatility models for VaR estimations in the context of the Chinese stock index returns. The models they tested include a moving average model, a historical mean model, a random walk model, GARCH model, GJR model, EGARCH model and APARCH model under normal, Student t - and skewed Student t -distributions. The main drawback of their study is that the models considered are confined to asymmetric GARCH models. The present empirical chapter contributes to the very limited literature on volatility models for VaR forecasts in China by further including the long-memory GARCH models for performance evaluation, and doing such will also reveal the possible existence of long-memory in return and volatility of the Chinese stock index returns.

6.6 Data

The analysis undertaken in this study is based on daily closing prices of the three Chinese stock market indices: the Shanghai A-share Index (SH), the Shenzhen A-share Index (SZ), and the Hang Seng Index (HK); additionally, the stock indices from New York Stock Exchange Composite Index (US), Financial Times Stock Exchange All-Share Index (UK), Tokyo Stock Price Index (JP), are also employed as benchmark comparators.

The data obtained from Datastream, run from January 1st 1993 to March 31st 2010. In the empirical analysis, the whole time span is divided into two parts – an in-sample and an out-of-sample. The in-sample is used for initial model parameter estimation. The in-sample has two different lengths. The first one has 261 observations, corresponding to a time period of one year, and runs from January 1st 1998. The designation of this in-sample meets the minimum requirement of Basel Committee that the backtest of VaR models should be performed using the most recent twelve months of data. However, in-sample period exceeding one year is often employed in the literature since small sample size may lead to lack of convergence in the

estimation algorithms for more complex models, particularly asymmetric and long-memory GARCH models. Jackson *et al.* (1998) also report that the use of short data samples worsened the biases in the VaR estimates for parametric models. For this reason, an extended in-sample period of six years starting from January 1st 1993 is also used. Both in-sample periods end on December 31st 1998, leaving the remaining observations for out-of-sample evaluation. The out-of-sample thus covers the period from December 31st 1998 onwards to March 31st 2010. The out-of-sample is set to December 31st 1998 since Basel Committee requires the first formal backtesting of VaR to begin by year-end 1998. The out-of-sample generates a total 2934 one-step ahead VaR forecasts. Since the out-of-sample includes the occurrence of several large scale crashes, such as the dot-com bubble burst, the September 11th terrorist attack, and the 2007-2009 financial crisis, it is interesting to see how VaR behaves under these extreme market events. Consistent with the rolling window approach to VaR evaluation stipulated by the Basel Committee, the in-sample is rolled forward and the model is re-estimated every 60 observations.³⁵ All subsequent analysis is performed on the daily logarithmic returns, which is defined as $r_t = \ln(P_t) - \ln(P_{t-1})$. The summary statistics of index returns are given in Table 6.1.

Table 6.1 Summary Statistics of Daily Stock Index Returns

	SH	SZ	HK	US	UK	JP
Mean	0.00030	0.00036	0.00021	0.00010	0.00006	-0.00006
Maximum	0.09400	0.09240	0.13407	0.11526	0.08811	0.12865
Minimum	-0.09261	-0.08926	-0.13582	-0.10232	-0.08710	-0.10007
Std. Dev.	0.01635	0.01744	0.01767	0.01298	0.01213	0.01404
Skewness	-0.07429	-0.32623	0.15541	-0.30576	-0.20425	-0.20098
Kurtosis	7.60510	6.95548	10.0870	12.9472	9.05065	8.87691
Jarque-Bera	2826.1*	2139.5*	6699.1*	13222.1*	4896.0*	4619.4*

Notes: * indicates the Jarque-Bera normality test is rejected at 5% level of significance.

³⁵ The rolling window procedure is not applied to the RiskMetrics model whose parameters are fixed to 0.06 and 0.94.

All six index return series exhibit the standard property of asset return data that they have “fat-tailed” distributions as indicated by the excess kurtosis than that of a normal distribution which is 3. The Jarque-Bera normality test statistics significantly exceed the critical value which suggests that these return series are far from a normal distribution. All series are negatively skewed except for HK whose returns skew to the right. There is evidence that the unconditional distribution of returns is non-normal and asymmetric. Leptokurtic distribution and unconditional skewness is an arguably important but neglected feature of many asset return series, which if ignored could lead to mis-specified risk management models. These features of data are accounted for when we specify the error-distribution in the mean equation of the volatility models.

6.7 Model Specification and Estimation

We model conditional mean as an ARMA (p, q) process. Hannan-Rissanen (1982) procedure is employed to determine the autoregressive (m) and moving average (n) orders of the ARMA model for the mean equation in the proposed GARCH models. The optimal orders are selected based on the Schwarz’s (1978) Bayesian information criterion (BIC). The optimal in-sample ARMA orders (as shown in Table 6.2) are assumed unchanged for the all subsequent rolling samples.³⁶ The orders in the variance equation is set to (1, 1) for all GARCH family models.

Table 6.2 ARMA (m, n) Orders

(m, n)	SH	SZ	HK	US	UK	JP
1-year in-sample	(0, 0)	(0, 0)	(0, 0)	(0, 0)	(0, 1)	(0, 0)
6-year in-sample	(0, 0)	(0, 0)	(0, 3)	(0, 0)	(0, 1)	(0, 0)

³⁶ In a VaR framework, Angelidis *et al.* (2004) show that complex specification of the conditional mean does not add anything significant to the predictive power of the models.

Previous empirical studies on VaR have shown that models based on the normal distribution usually cannot fully take into account the ‘fat-tail’ and asymmetry of the distributions of the returns (as demonstrated in Table 6.1). To accommodate the excess kurtosis, Bollerslev (1987) proposes the standardised Student t -distribution. Lambert and Laurent (2001) introduce the use of the standardised skewed Student t -distribution to accommodate the observed skewness of financial time series. Student t - and skewed Student t -distributions are widely applied in the estimation and evaluation of VaR. To name but a few, Guermat and Harris (2002), So and Yu (2006) apply the Student t -distribution, Giot and Laurent (2003) use the skewed Student t -distribution, while normal distribution was applied in all studies as a benchmark distribution. In our empirical analysis, the Student t -distribution and skewed Student t -distribution are assumed for the error term ε_t in each model, in addition to the normal distribution.

Model parameters are estimated using the method of maximum likelihood and the estimation package is G@RCH 6.0 Ox developed by Laurent (2009). If a particular model fails to converge, then its VaR estimates will not be reported and analysed. We choose not to pre-select candidate models by their in-sample VaR performance. A good in-sample performance for a model is not a prerequisite for a good out-of-sample performance. As noted by Neftci (2000), the real test of a risk management methodology is out-of-sample performance because the risk manager obtains VaR estimates in real time and must use parameters obtained from an already observed sample in order to evaluate the risks associated with current and future random movements in risk factors. Hence, a more sensible appraisal of VaR models is their performance outside the sample used to estimate the underlying parameters.

Unlike previous studies which examine VaR at both 1% and 5% probability levels, we only compute VaR at 1% probability level to match the regulatory requirement of the Basel Committee. 5% level of significance is adopted for the Kupiec test and DQ test.

According to Nankervis *et al.* (2006), it is usual that VaR is separately computed for the left and right tails of the distribution depending on the position of the risk managers or traders. For traders with a long position, the market risk comes from a drop in the asset price, while traders with a short position lose money when the price increases. Therefore, how good a model is at predicting VaR for long positions is related to its ability to model large negative returns, while its performance regarding the short side of the VaR is based on its ability to take into account large positive returns. For this reason, we compute VaR for both long and short positions.

Finally, due to the daily return limit imposed on both Shanghai and Shenzhen Stock Exchanges (effective on December 16th 1996), the maximum and minimum daily returns of the Shanghai A-share Index and Shenzhen A-share Index cannot exceed $\pm 10\%$ level. Hence, for practical consideration, VaR estimates higher than the daily return limit will be adjusted to $\pm 10\%$. This adjustment is applied to the calculation of MAE and RMSE of the VaR models for Shanghai and Shenzhen Indices.³⁷

6.8 Empirical Results

Due to the enormous size of results generated and the nature of rolling window estimation, parameter estimates for the conditional mean and variance of each candidate model are not reported. Table 6.3 to 6.8 display the first-stage backtesting results for the six stock indices. In each table, $\hat{\alpha}$ represents the VaR failure rate; numbers reported under the column named ‘Kupiec’ and ‘DQ’ are the p -values for the Kupiec test and Dynamic Quantile test, respectively; ‘RM’, ‘G’,

³⁷ Tokyo Stock Exchange also implements a daily price limit system to individual stocks. Since all listed stocks on the JP have their own daily price limits, which are based on their previous day’s closing prices, the aggregate effect at the index level is difficult to quantify.

‘E’, ‘T’, ‘AP’, ‘I’, ‘FI’, ‘FIE’, ‘FIAP’, and ‘HY’ stand for the RiskMetrics, GARCH, EGARCH, TGARCH, APARCH, IGARCH, FIGARCH, FIEGARCH, FIAPARCH, and HYGARCH, respectively; ‘(N)’, ‘(T)’, and ‘(S)’ indicate the model assumes normal, Student *t*- and skewed Student *t*-distribution for the error term; Asterisk indicates Kupiec and Dynamic Quantile tests are both insignificant at 5% level so that the respective model passes the first-stage selection process.

Table 6.3 First-Stage Backtesting Results for SH

1-Year In-Sample Models							
Long	$\hat{\alpha}$	Kupiec	DQ	Short	$\hat{\alpha}$	Kupiec	DQ
RM(N)	0.0222	<0.0001	<0.0001	RM(N)	0.0188	<0.0001	0.0064
RM(T)*	0.0126	0.1720	0.1771	RM(T)*	0.0123	0.2327	0.6276
RM(S)*	0.0109	0.6267	0.0549	RM(S)	0.0143	0.0274	0.1679
G(N)	0.0208	<0.0001	<0.0001	G(N)	0.0164	0.0015	0.0582
G(T)	0.0099	0.9496	0.0243	G(T)*	0.0092	0.6599	0.9580
G(S)*	0.0092	0.6599	0.4474	G(S)*	0.0102	0.9029	0.9488
E(N)	0.0218	<0.0001	<0.0001	E(N)	0.0153	0.0071	0.0089
E(T)*	0.0112	0.5055	0.8125	E(T)*	0.0106	0.7602	0.7125
E(S)	0.0027	<0.0001	<0.0001	E(S)	0.0027	<0.0001	<0.0001
T(T)*	0.0106	0.7602	0.8354	T(T)	0.0109	0.6267	0.0058
T(S)*	0.0095	0.8022	0.7907	T(S)	0.0113	0.5055	0.0099
AP(S)	0.0170	0.0005	0.0179	AP(S)	0.0205	<0.0001	0.0001
I(N)	0.0170	0.0005	<0.0001	I(N)	0.0147	0.0178	0.3811
I(T)*	0.0089	0.5274	0.3606	I(T)*	0.0068	0.0659	0.5303
I(S)*	0.0082	0.3063	0.1871	I(S)*	0.0085	0.4087	0.9299
FI(N)	0.0208	<0.0001	0.0006	FI(N)	0.0174	0.0003	0.0037
FI(T)	0.0068	0.0659	<0.0001	FI(T)	0.0055	0.0068	<0.0001
FI(S)	0.0058	0.0129	<0.0001	FI(S)	0.0072	0.1030	<0.0001
FIE(N)	0.0242	<0.0001	<0.0001	FIE(N)	0.0164	0.0015	<0.0001
FIE(T)*	0.0112	0.5055	0.8125	FIE(T)*	0.0099	0.9496	0.6361
FIE(S)	0.0044	0.0007	0.0019	FIE(S)	0.0058	0.0129	<0.0001
HY(T)*	0.0109	0.6267	0.0628	HY(T)*	0.0099	0.9496	0.6361
HY(S)*	0.0089	0.5274	0.3606	HY(S)*	0.0109	0.6267	0.7297

6-Year In-Sample Models							
Long	$\hat{\alpha}$	Kupiec	DQ	Short	$\hat{\alpha}$	Kupiec	DQ
RM(N)	0.0235	<0.0001	<0.0001	RM(N)	0.0181	<0.0001	0.0075

RM(T)*	0.0109	0.6267	0.0549	RM(T)*	0.0109	0.6267	0.5821
RM(S)*	0.0106	0.7602	0.3613	RM(S)*	0.0123	0.2327	0.6276
G(N)	0.0106	0.7602	0.0376	G(N)*	0.0109	0.6267	0.6908
G(T)	0.0058	0.0129	0.0069	G(T)	0.0048	0.0015	0.0085
G(S)	0.0048	0.0015	0.0085	G(S)	0.0051	0.0033	0.0277
E(N)	0.0099	0.9496	0.0133	E(N)*	0.0109	0.6267	0.0838
E(T)	0.0051	0.0033	0.0277	E(T)	0.0044	0.0007	0.0019
E(S)	0.0037	<0.0001	<0.0001	E(S)	0.0027	<0.0001	<0.0001
T(N)	0.0119	0.3081	0.0165	T(N)	0.0116	0.3990	0.0173
T(T)	0.0051	0.0033	0.0277	T(T)	0.0048	0.0015	0.0085
T(S)	0.0051	0.0033	0.0277	T(S)	0.0058	0.0129	0.1462
AP(N)	0.0123	0.2327	0.0232	AP(N)	0.0113	0.5055	0.0116
AP(T)*	0.0075	0.1542	0.7659	AP(T)	0.0051	0.0033	0.0277
AP(S)	0.0065	0.0403	0.3897	AP(S)	0.0058	0.0129	0.1462
I(N)	0.0102	0.9029	0.0234	I(N)*	0.0116	0.3990	0.6956
I(T)	0.0072	0.1030	0.0301	I(T)	0.0055	0.0068	0.0706
I(S)	0.0061	0.0234	0.0213	I(S)*	0.0068	0.0659	0.5303
FI(N)	0.0211	<0.0001	0.0023	FI(N)	0.0147	0.0178	0.1571
FI(T)*	0.0095	0.8022	0.5249	FI(T)*	0.0082	0.3063	0.8970
FI(S)*	0.0078	0.2215	0.3986	FI(S)*	0.0085	0.4087	0.9299
FIE(N)	0.0150	0.0113	0.0891	FIE(N)	0.0123	0.2327	0.0257
FIE(T)	0.0061	0.0234	0.2558	FIE(T)	0.0055	0.0068	0.0706
FIE(S)	0.0041	0.0003	0.0003	FIE(S)	0.0038	<0.0001	<0.0001
FIAP(N)	0.0228	<0.0001	0.0005	FIAP(N)	0.0170	0.0005	0.0180
FIAP(T)*	0.0089	0.5274	0.6865	FIAP(T)*	0.0082	0.3063	0.5063
FIAP(S)*	0.0082	0.3063	0.5081	FIAP(S)*	0.0082	0.3063	0.5063
HY(N)	0.0235	<0.0001	<0.0001	HY(N)	0.0157	0.0043	0.1147
HY(T)*	0.0068	0.0659	0.1069	HY(T)*	0.0068	0.0659	0.5303
HY(S)	0.0065	0.0403	0.0524	HY(S)*	0.0072	0.1030	0.6598

Table 6.4 First-Stage Backtesting Results for SZ

1-Year In-Sample Models							
Long	$\hat{\alpha}$	Kupiec	DQ	Short	$\hat{\alpha}$	Kupiec	DQ
RM(N)	0.0242	<0.0001	<0.0001	RM(N)	0.0164	0.0015	0.0017
RM(T)	0.0153	0.0071	0.0177	RM(T)*	0.0092	0.6599	0.4606
RM(S)	0.0136	0.0609	0.0121	RM(S)*	0.0123	0.2327	0.1590
G(N)	0.0225	<0.0001	0.0002	G(N)	0.0147	0.0178	0.1833

G(T)	0.0140	0.0413	0.4184	G(T)*	0.0082	0.3063	0.8970
G(S)*	0.0112	0.5055	0.8790	G(S)*	0.0095	0.8022	0.7858
E(N)	0.0208	<0.0001	<0.0001	E(N)	0.0147	0.0178	<0.0001
E(T)*	0.0130	0.1243	0.5863	E(T)*	0.0102	0.9029	0.0992
E(S)	0.0020	<0.0001	<0.0001	E(S)	0.0034	<0.0001	<0.0001
T(T)	0.0140	0.0413	0.3697	T(T)	0.0099	0.9496	<0.0001
T(S)*	0.0109	0.6267	0.9108	T(S)	0.0113	0.5055	<0.0001
I(N)	0.0201	<0.0001	0.0016	I(N)*	0.0113	0.5055	0.6025
I(T)*	0.0119	0.3081	0.7517	I(T)*	0.0072	0.1030	0.6598
I(S)*	0.0109	0.6267	0.9108	I(S)*	0.0078	0.2215	0.3917
FI(T)*	0.0133	0.0879	0.5124	FI(T)*	0.0075	0.1542	0.7659
FI(S)	0.0014	<0.0001	<0.0001	FI(S)	0.0020	<0.0001	<0.0001
FIE(N)	0.0235	<0.0001	0.0005	FIE(N)	0.0147	0.0178	<0.0001
FIE(T)*	0.0126	0.1720	0.6583	FIE(T)*	0.0092	0.6599	0.9580
FIE(S)	0.0020	<0.0001	<0.0001	FIE(S)	0.0031	<0.0001	<0.0001
HY(T)*	0.0133	0.0879	0.5124	HY(T)*	0.0082	0.3063	0.5081

6-Year In-Sample Models

Long	$\hat{\alpha}$	Kupiec	DQ	Short	$\hat{\alpha}$	Kupiec	DQ
RM(N)	0.0279	<0.0001	<0.0001	RM(N)*	0.0126	0.1720	0.1686
RM(T)	0.0150	0.0113	0.0175	RM(T)*	0.0092	0.6599	0.4606
RM(S)	0.0143	0.0274	0.0156	RM(S)*	0.0092	0.6599	0.4606
G(N)	0.0143	0.0274	0.0044	G(N)*	0.0078	0.2215	0.3955
G(T)*	0.0099	0.9496	0.9574	G(T)	0.0065	0.0403	0.3897
G(S)*	0.0089	0.5274	0.9487	G(S)*	0.0072	0.1030	0.6598
E(N)*	0.0136	0.0609	0.2208	E(N)	0.0072	0.1030	0.0326
E(T)*	0.0075	0.1542	0.7659	E(T)	0.0041	0.0003	0.0003
E(S)	0.0014	<0.0001	<0.0001	E(S)	0.0020	<0.0001	<0.0001
T(N)*	0.0119	0.3081	0.6851	T(N)	0.0068	0.0659	0.1061
T(T)*	0.0095	0.8022	0.9605	T(T)	0.0061	0.0234	0.2558
T(S)*	0.0082	0.3063	0.8970	T(S)*	0.0072	0.1030	0.6598
AP(N)*	0.0130	0.1243	0.5883	AP(N)	0.0072	0.1030	0.0069
AP(T)	0.0164	0.0015	0.0004	AP(T)	0.0153	0.0071	<0.0001
AP(S)	0.0136	0.0609	0.0138	AP(S)*	0.0126	0.1720	0.1946
I(N)	0.0153	0.0071	0.0072	I(N)*	0.0078	0.2215	0.3955
I(T)*	0.0109	0.6267	0.9108	I(T)*	0.0068	0.0659	0.5303
I(S)*	0.0099	0.9496	0.9574	I(S)*	0.0068	0.0659	0.5303
FI(N)	0.0228	<0.0001	0.0005	FI(N)*	0.0133	0.0879	0.1775
FI(T)*	0.0130	0.1243	0.5863	FI(T)*	0.0072	0.1030	0.6598

FI(S)*	0.0119	0.3081	0.7860	FI(S)*	0.0075	0.1542	0.7659
FIE(N)	0.0184	<0.0001	0.0345	FIE(N)*	0.0095	0.8022	0.3591
FIE(T)*	0.0089	0.5274	0.9487	FIE(T)	0.0048	0.0015	0.0085
FIE(S)	0.0048	0.0015	0.0085	FIE(S)	0.0034	<0.0001	<0.0001
FIAP(N)	0.0225	<0.0001	0.0004	FIAP(N)	0.0147	0.0178	0.1562
HY(N)	0.0232	<0.0001	0.0006	HY(N)	0.0143	0.0274	0.1666
HY(T)*	0.0116	0.3990	0.8374	HY(T)	0.0065	0.0403	0.3897
HY(S)*	0.0095	0.8022	0.9605	HY(S)*	0.0068	0.0659	0.5303

Table 6.5 First-Stage Backtesting Results for HK

1-Year In-Sample Models							
Model	$\hat{\alpha}$	Kupiec	DQ	Model	$\hat{\alpha}$	Kupiec	DQ
RM(N)	0.0150	0.0113	0.0105	RM(N)	0.0174	0.0003	0.0405
RM(T)*	0.0085	0.4087	0.6040	RM(T)*	0.0092	0.6599	0.9580
RM(S)*	0.0068	0.0659	0.1065	RM(S)*	0.0123	0.2327	0.7257
G(N)	0.0130	0.1243	0.0016	G(N)*	0.0085	0.4087	0.9299
G(T)	0.0085	0.4087	<0.0001	G(T)	0.0038	<0.0001	<0.0001
G(S)	0.0082	0.3063	0.0002	G(S)	0.0038	<0.0001	<0.0001
E(N)*	0.0123	0.2327	0.1628	E(N)	0.0150	0.0113	0.1105
E(T)	0.0041	0.0003	<0.0001	E(T)	0.0041	0.0003	0.0003
E(S)	0.0010	<0.0001	<0.0001	E(S)	<0.0001*	<0.0001	<0.0001
T(N)*	0.0109	0.6267	0.0556	T(N)*	0.0085	0.4087	0.9317
T(T)	0.0487	<0.0001	<0.0001	T(T)	0.0552	<0.0001	<0.0001
T(S)*	0.0085	0.4087	0.1096	T(S)	0.0061	0.0234	0.2558
I(N)	0.0130	0.1243	0.0016	I(N)*	0.0095	0.8022	0.9605
I(T)	0.0082	0.3063	0.0001	I(T)	0.0041	0.0003	0.0003
I(S)	0.0082	0.3063	0.0002	I(S)	0.0041	0.0003	0.0003
FI(T)	0.0099	0.9496	<0.0001	FI(T)*	0.0089	0.5274	0.6827
FI(S)	0.0099	0.9496	<0.0001	FI(S)	0.0055	0.0068	0.0711
FIE(N)	0.0150	0.0113	<0.0001	FIE(N)	0.0181	<0.0001	0.0007
FIE(T)	0.0014	<0.0001	<0.0001	FIE(T)	0.0017	<0.0001	<0.0001
FIE(S)	0.0003	<0.0001	<0.0001	FIE(S)	0.0007	<0.0001	<0.0001
HY(T)	0.0095	0.8022	0.0002	HY(T)	0.0058	0.0129	0.1462
HY(S)	0.0099	0.9496	0.0005	HY(S)	0.0058	0.0129	0.1472

6-Year In-Sample Models							
Long	$\hat{\alpha}$	Kupiec	DQ	Short	$\hat{\alpha}$	Kupiec	DQ
RM(N)	0.0174	0.0003	0.0557	RM(N)*	0.0136	0.0609	0.4394

RM(T)*	0.0116	0.3990	0.1114	RM(T)*	0.0075	0.1542	0.7659
RM(S)*	0.0130	0.1243	0.1738	RM(S)*	0.0068	0.0659	0.5303
G(N)*	0.0133	0.0879	0.0525	G(N)*	0.0116	0.3990	0.8399
G(T)*	0.0085	0.4087	0.1096	G(T)	0.0055	0.0068	0.0706
G(S)*	0.0085	0.4087	0.1096	G(S)	0.0051	0.0033	0.0277
E(N)*	0.0130	0.1243	0.1887	E(N)*	0.0123	0.2327	0.7257
E(T)	0.0061	0.0234	0.0212	E(T)	0.0044	0.0007	0.0019
E(S)	0.0065	0.0403	0.0522	E(S)	0.0041	0.0003	0.0003
T(N)*	0.0123	0.2327	0.6222	T(N)*	0.0116	0.3990	0.8399
T(T)*	0.0082	0.3063	0.2018	T(T)	0.0058	0.0129	0.1462
T(S)*	0.0092	0.6599	0.2452	T(S)	0.0058	0.0129	0.1462
AP(N)*	0.0112	0.5055	0.6014	AP(N)*	0.0102	0.9029	0.9503
AP(T)*	0.0078	0.2215	0.1270	AP(T)	0.0058	0.0129	0.1462
AP(S)*	0.0082	0.3063	0.2018	AP(S)	0.0058	0.0129	0.1462
I(N)*	0.0136	0.0609	0.0597	I(N)*	0.0102	0.9029	0.9488
I(T)*	0.0085	0.4087	0.1096	I(T)	0.0055	0.0068	0.0706
I(S)*	0.0085	0.4087	0.1096	I(S)	0.0051	0.0033	0.0277
FI(N)	0.0147	0.0178	0.0069	FI(N)*	0.0123	0.2327	0.7257
FI(T)*	0.0095	0.8022	0.3232	FI(T)	0.0065	0.0203	0.3897
FI(S)	0.0102	0.9029	0.0323	FI(S)	0.9942	0.0129	0.1462
FIE(N)	0.0143	0.0274	0.1679	FIE(N)*	0.0116	0.3990	0.8374
FIE(T)	0.0058	0.0129	0.1462	FIE(T)	0.0041	0.0003	0.0003
FIE(S)	0.0014	<0.0001	<0.0001	FIE(S)	<0.0001	<0.0001	<0.0001
FIAP(N)	0.0143	0.0274	0.4277	FIAP(N)*	0.0109	0.6267	0.9108
FIAP(T)*	0.0095	0.8022	0.7883	FIAP(T)	0.0061	0.0234	0.2558
FIAP(S)*	0.0102	0.9029	0.8299	FIAP(S)	0.0051	0.0033	0.0277
HY(N)	0.0150	0.0113	0.0080	HY(N)*	0.0126	0.1720	0.6583
HY(T)	0.0102	0.9029	0.0320	HY(T)	0.0055	0.0068	0.0706
HY(S)	0.0109	0.6267	0.0044	HY(S)	0.0048	0.0015	0.0085

Table 6.6 First-Stage Backtesting Results for US

1-Year In-Sample Models							
Model	$\hat{\alpha}$	Kupiec	DQ	Model	$\hat{\alpha}$	Kupiec	DQ
RM(N)	0.0266	<0.0001	<0.0001	RM(N)*	0.0078	0.2215	0.3955
RM(T)	0.0143	0.0274	0.0186	RM(T)	0.0024	<0.0001	<0.0001
RM(S)	0.0099	0.9496	0.0222	RM(S)*	0.0072	0.1030	0.1854
G(N)	0.0198	<0.0001	<0.0001	G(N)*	0.0078	0.2215	0.3986

G(T)*	0.0106	0.7602	0.5343	G(T)	0.0048	0.0015	0.0085
G(S)*	0.0099	0.9496	0.4098	G(S)*	0.0068	0.0659	0.5303
E(N)	0.0222	<0.0001	0.0010	E(N)*	0.0106	0.7602	0.7095
E(T)	0.0147	0.0178	0.1837	E(T)	0.0078	0.2215	0.0017
T(T)	0.0136	0.0609	<0.0001	T(T)	0.0058	0.0129	<0.0001
T(S)	0.0147	0.0178	<0.0001	T(S)	0.0095	0.8022	<0.0001
I(N)*	0.0164	0.0015	0.0211	I(N)	0.0072	0.1030	0.6598
I(T)*	0.0095	0.8022	0.3339	I(T)	0.0024	<0.0001	<0.0001
I(S)*	0.0089	0.5274	0.1810	I(S)	0.0051	0.0033	0.0277
FI(N)	0.0174	0.0003	0.0096	FI(N)*	0.0078	0.2215	0.8442
FI(T)*	0.0099	0.9496	0.4098	FI(T)	0.0048	0.0015	<0.0001
FI(S)*	0.0089	0.5274	0.1810	FI(S)	0.0065	0.0403	0.0037
FIE(N)	0.0157	0.0043	0.0006	FIE(N)	0.0092	0.6599	0.0325
HY(N)	0.0194	<0.0001	0.0007	HY(N)*	0.0078	0.2215	0.1163
HY(T)*	0.0106	0.7602	0.5343	HY(T)	0.0038	<0.0001	<0.0001
HY(S)*	0.0092	0.6599	0.2555	HY(S)	0.0058	0.0129	0.1462

6-Year In-Sample Models

Long	$\hat{\alpha}$	Kupiec	DQ	Short	$\hat{\alpha}$	Kupiec	DQ
RM(N)	0.0242	<0.0001	<0.0001	RM(N)*	0.0095	0.8022	0.5449
RM(T)	0.0126	0.1720	0.0061	RM(T)	0.0034	<0.0001	<0.0001
RM(S)	0.0102	0.9029	0.0361	RM(S)	0.0061	0.0234	0.2558
G(N)	0.0222	<0.0001	<0.0001	G(N)*	0.0082	0.3063	0.5044
G(T)*	0.0106	0.7602	0.0539	G(T)	0.0031	<0.0001	<0.0001
G(S)	0.0099	0.9496	0.0222	G(S)	0.0058	0.0129	0.1462
E(N)	0.0187	<0.0001	0.0284	E(N)	0.0072	0.1030	0.0307
E(T)	0.0160	0.0026	0.1275	E(T)	0.0061	0.0234	0.2590
E(S)	0.0010	<0.0001	<0.0001	E(S)	<0.0001	<0.0001	<0.0001
T(N)	0.0187	<0.0001	0.0131	T(N)*	0.0082	0.3063	0.4965
T(T)*	0.0130	0.1243	0.1836	T(T)	0.0027	<0.0001	<0.0001
T(S)*	0.0112	0.5055	0.6114	T(S)	0.0044	0.0007	<0.0001
AP(N)	0.0092	0.6599	<0.0001	AP(N)	0.0051	0.0033	<0.0001
AP(T)*	0.0119	0.3081	0.1298	AP(T)	0.0031	<0.0001	<0.0001
AP(S)*	0.0099	0.9496	0.3025	AP(S)	0.0041	0.0003	<0.0001
I(N)	0.0205	<0.0001	<0.0001	I(N)*	0.0075	0.1542	0.2852
I(T)	0.0102	0.9029	0.0361	I(T)	0.0031	<0.0001	<0.0001
I(S)*	0.0092	0.6599	0.2555	I(S)	0.0051	0.0033	0.0277
FI(N)	0.0208	<0.0001	0.0004	FI(N)*	0.0082	0.3063	0.5044
FI(T)*	0.0106	0.7602	0.5343	FI(T)	0.0038	<0.0001	<0.0001

FI(S)*	0.0095	0.8022	0.3339	FI(S)	0.0055	0.0068	0.0706
FIE(N)	0.0170	0.0005	0.0254	FIE(N)	0.0044	0.0007	0.0019
FIE(T)	0.0143	0.0274	0.1918	FIE(T)	0.0044	0.0007	0.0019
FIE(S)	0.0007	<0.0001	<0.0001	FIE(S)	<0.0001	<0.0001	<0.0001
HY(N)	0.0211	<0.0001	0.0003	HY(N)*	0.0082	0.3063	0.5044
HY(T)*	0.0095	0.8022	0.3339	HY(T)	0.0027	<0.0001	<0.0001
HY(S)*	0.0089	0.5274	0.1810	HY(S)	0.0044	0.0007	0.0019

Table 6.7 First-Stage Backtesting Results for UK

1-Year In-Sample Models							
Long	$\hat{\alpha}$	Kupiec	DQ	Short	$\hat{\alpha}$	Kupiec	DQ
RM(N)	0.0215	<0.0001	<0.0001	RM(N)*	0.0082	0.3063	0.9012
RM(T)	0.0201	<0.0001	<0.0001	RM(T)*	0.0068	0.0659	0.5355
RM(S)	0.0174	0.0003	0.0003	RM(S)*	0.0102	0.9029	0.9519
G(N)	0.0205	<0.0001	<0.0001	G(N)	0.0055	0.0068	0.0016
G(T)	0.0140	0.0413	0.0139	G(T)	0.0031	<0.0001	<0.0001
G(S)	0.0109	0.6267	0.0007	G(S)	0.0055	0.0068	<0.0001
E(N)	0.0184	<0.0001	0.0156	E(N)	0.0061	0.0234	0.0207
E(T)	0.0177	0.0001	0.0007	E(T)	0.0055	0.0068	0.0016
T(T)	0.0143	0.0274	0.4277	T(T)	0.0031	<0.0001	<0.0001
T(S)*	0.0095	0.8022	0.3232	T(S)	0.0058	0.0129	<0.0001
I(N)	0.0174	0.0003	0.0010	I(N)	0.0041	0.0003	0.0003
I(T)	0.0147	0.0178	0.0157	I(T)	0.0027	<0.0001	<0.0001
I(S)*	0.0106	0.7602	0.6921	I(S)	0.0051	0.0033	0.0281
FI(N)	0.0191	<0.0001	0.0002	FI(N)	0.0055	0.0068	0.0716
FI(T)	0.0157	0.0043	0.0007	FI(T)	0.0041	0.0003	0.0003
FI(S)*	0.0116	0.3990	0.1474	FI(S)	0.0065	0.0403	<0.0001
FIE(N)	0.0140	0.0413	0.4786	FIE(N)	0.0065	0.0403	0.3897
FIE(T)	0.0164	0.0015	0.0003	FIE(T)	0.0048	0.0015	<0.0001
HY(N)	0.0198	<0.0001	<0.0001	HY(N)	0.0055	0.0068	0.0016
HY(T)	0.0153	0.0071	0.0156	HY(T)	0.0034	<0.0001	<0.0001
HY(S)	0.0116	0.3990	0.0022	HY(S)	0.0065	0.0403	<0.0001
6-Year In-Sample Models							
Long	$\hat{\alpha}$	Kupiec	DQ	Short	$\hat{\alpha}$	Kupiec	DQ
RM(N)	0.0242	<0.0001	<0.0001	RM(N)*	0.0095	0.8022	0.5449
RM(T)	0.0126	0.1720	0.0061	RM(T)	0.0034	<0.0001	<0.0001
RM(S)	0.0102	0.9029	0.0361	RM(S)	0.0061	0.0234	0.2558

G(N)	0.0222	0.0061	<0.0001	G(N)*	0.0082	0.3063	0.5044
G(T)*	0.0106	0.7602	0.0539	G(T)	0.0031	<0.0001	<0.0001
G(S)	0.0099	0.9496	0.0222	G(S)	0.0058	0.0129	0.1462
E(N)	0.0167	0.0009	0.1712	E(N)	0.0061	0.0234	0.0211
E(T)	0.0160	0.0026	0.1275	E(T)	0.0065	0.0403	0.3940
T(N)	0.0184	<0.0001	0.0511	T(N)*	0.0072	0.1030	0.1797
T(T)*	0.0136	0.0609	0.5448	T(T)	0.0031	<0.0001	<0.0001
T(S)*	0.0106	0.7602	0.6950	T(S)	0.0044	0.0007	<0.0001
AP(N)	0.0051	0.0033	<0.0001	AP(N)	0.0014	<0.0001	<0.0001
AP(T)*	0.0119	0.3081	0.5950	AP(T)	0.0027	<0.0001	<0.0001
I(N)	0.0198	<0.0001	0.0006	I(N)*	0.0078	0.2215	0.3955
I(T)*	0.0106	0.7602	0.0539	I(T)	0.0034	<0.0001	<0.0001
I(S)	0.0095	0.8022	0.0124	I(S)	0.0058	0.0129	0.1462
FI(N)	0.0208	<0.0001	0.0004	FI(N)*	0.0095	0.8022	0.5403
FI(T)*	0.0099	0.9496	0.4098	FI(T)	0.0041	0.0003	0.0003
FI(S)*	0.0099	0.9496	0.4098	FI(S)	0.0051	0.0033	0.0277
FIE(N)	0.0164	0.0015	0.0211	FIE(N)	0.0044	0.0007	0.0019
FIE(T)	0.0143	0.0274	0.1918	FIE(T)	0.0048	0.0015	0.0085
FIE(S)	0.0007	<0.0001	<0.0001	FIE(S)	<0.0001	<0.0001	<0.0001
HY(N)	0.0194	<0.0001	0.0007	HY(N)*	0.0095	0.8022	0.5403
HY(T)*	0.0099	0.9496	0.4098	HY(T)	0.0034	<0.0001	<0.0001
HY(S)*	0.0089	0.5274	0.1810	HY(S)	0.0044	0.0007	0.0019

Table 6.8 First-Stage Backtesting Results for JP

1-Year In-Sample Models							
Long	$\hat{\alpha}$	Kupiec	DQ	Short	$\hat{\alpha}$	Kupiec	DQ
RM(N)	0.0208	<0.0001	<0.0001	RM(N)*	0.0106	0.7602	0.5460
RM(T)*	0.0109	0.6267	0.7086	RM(T)	0.0055	0.0068	0.0017
RM(S)	0.0136	0.0609	0.0036	RM(S)	0.0044	0.0007	0.0019
G(N)	0.0153	0.0071	0.5303	G(N)*	0.0068	0.0659	0.1975
G(T)*	0.0102	0.9029	0.6563	G(T)	0.0038	<0.0001	<0.0001
G(S)*	0.0102	0.9029	0.5026	G(S)	0.0041	0.0003	0.0003
E(N)	0.0153	0.0071	0.0226	E(N)	0.0078	0.2215	<0.0001
E(T)	0.0024*	<0.0001	<0.0001	E(T)	0.0020*	<0.0001	<0.0001
T(N)	0.0089	0.5274	<0.0001	T(N)	0.0252	<0.0001	<0.0001
T(T)*	0.0106	0.7602	0.5062	T(T)	0.0055	0.0068	<0.0001
T(S)*	0.0119	0.3081	0.6265	T(S)	0.0055	0.0068	<0.0001

I(N)	0.0143	0.0274	0.4220	I(N)	0.0058	0.0129	0.1462
I(T)*	0.0092	0.6599	0.4674	I(T)	0.0038	<0.0001	<0.0001
I(S)*	0.0089	0.5274	0.3796	I(S)	0.0038	<0.0001	<0.0001
FI(N)	0.0157	0.0043	0.1816	FI(N)*	0.0068	0.0659	0.1069
FI(T)*	0.0099	0.9496	0.2924	FI(T)	0.0044	0.0007	<0.0001
FI(S)*	0.0102	0.9029	0.3641	FI(S)	0.0051	0.0033	0.0003
FIE(N)	0.0283	<0.0001	<0.0001	FIE(N)	0.0126	0.1720	0.0070
HY(T)	0.0511	<0.0001	<0.0001	HY(T)	0.0426	<0.0001	<0.0001

6-Year In-Sample Models

Long	$\hat{\alpha}$	Kupiec	DQ	Short	$\hat{\alpha}$	Kupiec	DQ
RM(N)	0.0208	<0.0001	<0.0001	RM(N)*	0.0102	0.9029	0.6590
RM(T)*	0.0123	0.2327	0.1397	RM(T)	0.0048	0.0015	<0.0001
RM(S)*	0.0133	0.0879	0.1930	RM(S)	0.0048	0.0015	<0.0001
G(N)	0.0170	0.0005	0.1834	G(N)*	0.0089	0.5274	0.9487
G(T)*	0.0099	0.9496	0.6083	G(T)	0.0038	<0.0001	<0.0001
G(S)*	0.0109	0.6267	0.7086	G(S)	0.0038	<0.0001	<0.0001
E(N)	0.0153	0.0071	0.2823	E(N)*	0.0085	0.4087	0.6061
E(T)*	0.0130	0.1243	0.6002	E(T)	0.0048	0.0015	<0.0001
E(S)	0.0007	<0.0001	<0.0001	E(S)	0.0003	<0.0001	<0.0001
T(N)	0.0160	0.0026	0.1968	T(N)	0.0085	0.4087	<0.0001
T(T)*	0.0116	0.3990	0.6034	T(T)	0.0055	0.0068	0.0017
T(S)*	0.0112	0.5055	0.5838	T(S)	0.0051	0.0033	0.0003
AP(N)	0.0147	0.0178	0.4273	AP(N)	0.0089	0.5274	<0.0001
AP(T)*	0.0106	0.7602	0.6893	AP(T)	0.0058	0.0129	<0.0001
AP(S)*	0.0109	0.6267	0.7086	AP(S)	0.0058	0.0129	<0.0001
I(N)	0.0150	0.0113	0.3283	I(N)*	0.0075	0.1542	0.7659
I(T)*	0.0092	0.6599	0.4674	I(T)	0.0038	<0.0001	<0.0001
I(S)*	0.0089	0.5274	0.3796	I(S)	0.0038	<0.0001	<0.0001
FI(N)	0.0164	0.0015	0.2631	FI(N)*	0.0085	0.4087	0.9299
FI(T)*	0.0092	0.6599	0.1540	FI(T)	0.0041	0.0003	0.0003
FI(S)*	0.0092	0.6599	0.1540	FI(S)	0.0041	0.0003	0.0003
FIE(N)	0.0167	0.0009	0.2219	FIE(N)	0.0113	0.5055	<0.0001
FIE(T)*	0.0116	0.3990	0.7111	FIE(T)	0.0044	0.0007	<0.0001
FIAP(N)	0.0150	0.0113	0.3822	FIAP(N)	0.0082	0.3063	0.0011
FIAP(T)*	0.0106	0.7602	0.6860	FIAP(T)	0.0051	0.0033	<0.0001
FIAP(S)*	0.0112	0.5055	0.7131	FIAP(S)	0.0051	0.0033	<0.0001
HY(N)	0.0170	0.0005	0.1095	HY(N)*	0.0085	0.4087	0.9299
HY(T)*	0.0102	0.9029	0.5026	HY(T)	0.0038	<0.0001	<0.0001

HY(S)*	0.0106	0.7602	0.5577	HY(S)	0.0038	<0.0001	<0.0001
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As for the effect of the sample size, the use of six-year rolling window facilitates the estimation of more complex models, particularly the APARCH, FIAPARCH, and FIEGARCH models, which would otherwise fail to achieve convergence if estimated using the one-year sample. In addition, the six-year sample produces more adequate models (i.e. models that are insignificant for both Kupiec and DQ tests) than the much smaller one-year sample.

The VaR failure rates produced by each model appear to be very sensitive to the specification of the error distribution. Specifically, the assumption of normality tends to produce higher VaR failure rates than an otherwise similar model assuming Student t - or skewed Student t -distribution, irrespective of window length chosen, long and short positions, and the index considered. For long positions, models assuming normal distribution are frequently rejected by statistical tests since they consistently underestimate VaR. In many cases, models assuming Student t - and skewed Student t -distribution provide better fit to the true VaRs as their failure rates are close enough to 1%. A different picture emerges for the VaR of short positions. Leptokurtic and skewed distributional models again demonstrate superior ability in terms of minimizing the frequency of VaR exceptions, but some fail to satisfy the Kupiec test since their associated failure rates are far below the 1% benchmark so that the null hypothesis of equality is firmly rejected. Furthermore, these models are too conservative since they often produce high level of VaR estimates, which consequently lead to the over-commitment of regulatory capital. On the other hand, models based on the normal distribution are preferred since they alleviate the problem due to the ‘conservativeness’ of the leptokurtic and skewed distributions in short positions. Among the models qualified for the second-stage selection, vast majority of long position models are fitted with either Student t - or skewed Student t -distribution. More specifically, none of the normal distribution based models are found to be adequate in modeling long position VaR estimates for

SH, US, UK and JP, while three and seven normal distributional models are selected in the first stage for SZ and HK respectively. On the short position side, normal distribution based models prevail over leptokurtic distributional models in US, UK, JP and HK, but their dominance is not seen in the two Mainland Chinese stock indices, where Student t - and skewed Student t - models have undisputed lead in the number count of adequate models.

The difference between short and long positions is also observed in that the same model yields lower failure rate for short position than for long position. This may be due to skewed distribution of returns and/or the well-known volatility asymmetry in response to good and bad news (So and Yu, 2006). One would expect asymmetric models to produce homogeneous VaR failure rates for both long and short positions since they allow positive and negative returns to have different impacts on volatility. Nevertheless, there is little evidence that the use of asymmetric GARCH models narrows the asymmetry between short and long positions, although these models are developed to account for the asymmetric response of volatility to shocks. The observed asymmetry between long and short position is very noticeable for the three benchmark comparative indices (i.e. US, UK and JP) while being less pronounced for the three Chinese stock indices, which could suggest the leverage effect may not be as strong in these three relatively less developed markets. Our first-stage backtesting results point towards the marked difference in the modeling of VaR for long and short positions. It also appears that this asymmetry is better accounted by different distributional assumptions rather than asymmetric GARCH models.

Among the models that fail to pass the first stage selection, long-memory models tend to produce very few exceptions out-of-sample. There are even cases where certain long-memory models produce virtually no exception over the entire out-of-sample period. However, when investigating the VaR estimates produced by these models in greater detail, we notice that the forecast VaR returns far exceed the actual returns so that exceptions could hardly occur. Conversely, symmetric

GARCH models (i.e. the GARCH, IGARCH and RiskMetrics models), when incorrectly specified, often produce VaR failure rates that could put the bank in danger of the Yellow Zone, which would have a severe negative impact on the amount of regulatory capital that bank must hold. These models also suffer from autocorrelated VaR exceptions.

Finally, symmetric, asymmetric and long-memory class models all have fair shares in the adequate model group for each stock market index whereas models assuming different error distributions do not necessarily have equal presence among the adequate models. The proposed statistical measures cannot compare different VaR models directly, as a greater p -value of a model does not indicate the superiority of that model among its competitors.

Table 6.9 to 6.14 report the second-stage backtesting results for the six stock indices. In each table, the Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) are reported for each model. The model minimises either MAE and/or RMSE is preferred and the top three best performing models (based on RMSE) are in bold and ranked.

Table 6.9 Second-Stage Backtesting Results for SH

1-Year In-Sample Models							
Long	$\hat{\alpha}$	MAE	RMSE	Short	$\hat{\alpha}$	MAE	RMSE
RM(T)¹	0.0126	0.0406	0.0469	RM(T)³	0.0123	0.0398	0.0460
RM(S)³	0.0109	0.0417	0.0480	G(T)	0.0092	0.0425	0.0485
G(S)	0.0092	0.0437	0.0500	G(S)	0.0102	0.0416	0.0475
E(T)	0.0112	0.0432	0.0491	E(T)	0.0106	0.0426	0.0482
T(T)	0.0106	0.0428	0.0495	I(T)	0.0068	0.0447	0.0508
T(S)	0.0095	0.0438	0.0505	I(S)	0.0085	0.0437	0.0497
I(T)	0.0089	0.0450	0.0515	FIE(T)	0.0099	0.0429	0.0485
I(S)	0.0082	0.0460	0.0524	HY(T)	0.0099	0.0425	0.0484
FIE(T)	0.0112	0.0435	0.0493	HY(S)	0.0109	0.0416	0.0475
HY(T)	0.0109	0.0428	0.0491				
HY(S)	0.0089	0.0437	0.0500				

6-Year In-Sample Models							
Long	$\hat{\alpha}$	MAE	RMSE	Short	$\hat{\alpha}$	MAE	RMSE
RM(T)²	0.0109	0.0413	0.0476	RM(T)	0.0109	0.0406	0.0468
RM(S)	0.0106	0.0422	0.0486	RM(S)²	0.0123	0.0396	0.0459
AP(T)	0.0075	0.0500	0.0564	G(N)	0.0109	0.0408	0.0462
FI(T)	0.0095	0.0434	0.0498	E(N)	0.0109	0.0413	0.0466
FI(S)	0.0078	0.0443	0.0506	I(N)¹	0.0116	0.0405	0.0457
FIAP(T)	0.0089	0.0432	0.0497	I(S)	0.0068	0.0450	0.0506
FIAP(S)	0.0082	0.0440	0.0505	FI(T)	0.0082	0.0432	0.0491
HY(T)	0.0068	0.0456	0.0521	FI(S)	0.0085	0.0423	0.0482
				FIAP(T)	0.0082	0.0428	0.0489
				FIAP(S)	0.0082	0.0420	0.0481
				HY(T)	0.0068	0.0453	0.0514
				HY(S)	0.0072	0.0444	0.0504

Table 6.10 Second-Stage Backtesting Results for SZ

1-Year In-Sample Models							
Long	$\hat{\alpha}$	MAE	RMSE	Short	$\hat{\alpha}$	MAE	RMSE
G(S)	0.0112	0.0469	0.0540	RM(T)	0.0092	0.0421	0.0488
E(T)	0.0130	0.0451	0.0515	RM(S)	0.0123	0.0400	0.0467
T(S)	0.0109	0.0469	0.0541	G(T)	0.0082	0.0444	0.0511
I(T)	0.0119	0.0466	0.0539	G(S)	0.0095	0.0424	0.0490
I(S)	0.0109	0.0485	0.0558	E(T)	0.0102	0.0443	0.0504
FI(T)	0.0133	0.0453	0.0524	I(N)	0.0113	0.0398	0.0463
FIE(T)	0.0126	0.0454	0.0518	I(T)	0.0072	0.0461	0.0528
HY(T)		0.0454	0.0526	I(S)	0.0078	0.0440	0.0507
				FI(T)	0.0075	0.0448	0.0514
				FIE(T)	0.0092	0.0446	0.0507
				HY(T)	0.0082	0.0449	0.0516

6-Year In-Sample Models							
Long	$\hat{\alpha}$	MAE	RMSE	Short	$\hat{\alpha}$	MAE	RMSE
G(T)	0.0099	0.0496	0.0568	RM(N)²	0.0126	0.0394	0.0459
G(S)	0.0089	0.0513	0.0584	RM(T)	0.0092	0.0427	0.0495
E(N)³	0.0136	0.0445	0.0503	RM(S)	0.0092	0.0419	0.0487
E(T)	0.0075	0.0518	0.0578	G(N)	0.0078	0.0435	0.0490
T(N)²	0.0119	0.0441	0.0500	G(S)	0.0072	0.0473	0.0540
T(T)	0.0095	0.0496	0.0568	T(S)	0.0072	0.0471	0.0540

T(S)	0.0082	0.0512	0.0584	AP(S)	0.0126	0.0598	0.0685
AP(N)¹	0.0130	0.0441	0.0500	I(N)	0.0078	0.0432	0.0488
I(T)	0.0109	0.0473	0.0542	I(T)	0.0068	0.0466	0.0531
I(S)	0.0099	0.0487	0.0556	I(S)	0.0068	0.0450	0.0515
FI(T)	0.0130	0.0457	0.0528	FI(N)¹	0.0133	0.0385	0.0444
FI(S)	0.0119	0.0470	0.0542	FI(T)	0.0072	0.0450	0.0517
FIE(T)	0.0089	0.0498	0.0559	FI(S)	0.0075	0.0436	0.0502
HY(T)	0.0116	0.0479	0.0553	FI(N)³	0.0095	0.0405	0.0460
HY(S)	0.0095	0.0495	0.0568	HY(S)	0.0068	0.0457	0.0525

Table 6.11 Second-Stage Backtesting Results for HK

1-Year In-Sample Models							
Long	$\hat{\alpha}$	MAE	RMSE	Short	$\hat{\alpha}$	MAE	RMSE
RM(T)	0.0085	0.0409	0.0483	RM(T)	0.0092	0.0377	0.0455
RM(S)	0.0068	0.0430	0.0504	RM(S)	0.0123	0.0360	0.0438
E(N)	0.0123	0.0366	0.0435	G(N)	0.0085	0.0368	0.0436
T(N)	0.0109	0.0370	0.0437	T(N)	0.0085	0.0364	0.0433
T(S)	0.0085	0.0418	0.0489	I(N)	0.0095	0.0367	0.0438
				FI(T)	0.0089	0.0387	0.0457
6-Year In-Sample Models							
Long	$\hat{\alpha}$	MAE	RMSE	Short	$\hat{\alpha}$	MAE	RMSE
RM(T)	0.0116	0.0381	0.0460	RM(N)	0.0136	0.0353	0.0429
RM(S)	0.0130	0.0372	0.0451	RM(T)	0.0075	0.0388	0.0466
G(N)¹	0.0133	0.0355	0.0425	RM(S)	0.0068	0.0397	0.0475
G(T)	0.0085	0.0403	0.0474	G(N)	0.0116	0.0363	0.0432
G(S)	0.0085	0.0398	0.0469	E(N)	0.0123	0.0370	0.0445
E(N)	0.0130	0.0368	0.0445	T(N)	0.0116	0.0359	0.0428
T(N)²	0.0123	0.0358	0.0428	AP(N)	0.0102	0.0359	0.0428
T(T)	0.0082	0.0402	0.0473	I(N)	0.0102	0.0367	0.0439
T(S)	0.0092	0.0396	0.0468	FI(N)²	0.0123	0.0358	0.0426
AP(N)³	0.0112	0.0359	0.0429	FIE(N)	0.0116	0.0364	0.0432
AP(T)	0.0078	0.0402	0.0473	FIAP(N)¹	0.0109	0.0355	0.0422
AP(S)	0.0082	0.0396	0.0468	HY(N)³	0.0126	0.0359	0.0427
I(N)	0.0136	0.0359	0.0432				
I(T)	0.0085	0.0409	0.0480				
I(S)	0.0085	0.0402	0.0474				
FI(T)	0.0095	0.0390	0.0458				

FIAP(T)	0.0095	0.0395	0.0466	
FIAP(S)	0.0102	0.0387	0.0459	

Table 6.12 Second-Stage Backtesting Results for US

1-Year In-Sample Models							
Long	$\hat{\alpha}$	MAE	RMSE	Short	$\hat{\alpha}$	MAE	RMSE
G(T)	0.0106	0.0291	0.0366	RM(N)	0.0078	0.0269	0.0341
G(S)	0.0099	0.0301	0.0378	RM(S)	0.0072	0.0270	0.0343
I(T)	0.0095	0.0303	0.0378	G(N)	0.0078	0.0275	0.0349
I(S)	0.0089	0.0314	0.0391	G(S)	0.0068	0.0284	0.0357
FI(T)²	0.0099	0.0292	0.0363	E(N)	0.0106	0.0370	0.0949
FI(S)	0.0089	0.0302	0.0375	FI(N)	0.0078	0.0279	0.0350
HY(T)	0.0106	0.0291	0.0364	HY(N)	0.0078	0.0275	0.0349
HY(S)	0.0092	0.0302	0.0376				
6-Year In-Sample Models							
Long	$\hat{\alpha}$	MAE	RMSE	Short	$\hat{\alpha}$	MAE	RMSE
G(T)	0.0106	0.0290	0.0367	RM(N)²	0.0095	0.0264	0.0337
T(T)	0.0130	0.0286	0.0366	G(N)	0.0082	0.0265	0.0339
T(S)	0.0112	0.0297	0.0380	T(N)	0.0082	0.0260	0.0339
AP(T)	0.0119	0.0305	0.0489	I(N)	0.0075	0.0271	0.0345
AP(S)	0.0099	0.0317	0.0515	FI(N)¹	0.0082	0.0266	0.0336
I(S)	0.0092	0.0302	0.0379	HY(N)³	0.0082	0.0267	0.0337
FI(T)¹	0.0106	0.0285	0.0357				
FI(S)	0.0095	0.0295	0.0368				
HY(T)³	0.0095	0.0292	0.0363				
HY(S)	0.0089	0.0300	0.0372				

Table 6.13 Second-Stage Backtesting Results for UK

1-Year In-Sample Models							
Long	$\hat{\alpha}$	MAE	RMSE	Short	$\hat{\alpha}$	MAE	RMSE
I(S)¹	0.0106	0.0283	0.0343	RM(N)²	0.0082	0.0264	0.0325
				RM(T)	0.0068	0.0283	0.0343
				RM(S)¹	0.0102	0.0254	0.0313
6-Year In-Sample Models							
Long	$\hat{\alpha}$	MAE	RMSE	Short	$\hat{\alpha}$	MAE	RMSE
G(T)	0.0106	0.0290	0.0364	RM(N)³	0.0095	0.0264	0.0333

T(T)	0.0136	0.0284	0.0361	G(N)	0.0082	0.0265	0.0335
T(S) ²	0.0106	0.0283	0.0343	T(N)	0.0072	0.0261	0.0336
AP(T)	0.0119	0.0303	0.0488	I(N)	0.0078	0.0271	0.0342
I(T)	0.0106	0.0291	0.0365	FI(N)	0.0095	0.0267	0.0333
FI(T) ³	0.0099	0.0284	0.0354	HY(N)	0.0095	0.0268	0.0333
FI(S)	0.0099	0.0293	0.0364				
HY(T)	0.0099	0.0291	0.0360				
HY(S)	0.0089	0.0298	0.0368				

Table 6.14. Second-Stage Backtesting Results for JP

1-Year In-Sample Models							
Long	$\hat{\alpha}$	MAE	RMSE	Short	$\hat{\alpha}$	MAE	RMSE
RM(T)	0.0109	0.0347	0.0400	RM(N)	0.0106	0.0302	0.0358
G(T) ³	0.0102	0.0340	0.0386	G(N)	0.0068	0.0311	0.0358
G(S)	0.0102	0.0340	0.0387	FI(N)	0.0068	0.0312	0.0360
T(T)	0.0106	0.0340	0.0388				
T(S)	0.0119	0.0342	0.0391				
I(T)	0.0092	0.0361	0.0411				
I(S)	0.0089	0.0361	0.0412				
FI(T)	0.0099	0.0341	0.0386				
FI(S)	0.0102	0.0341	0.0388				
6-Year In-Sample Models							
Long	$\hat{\alpha}$	MAE	RMSE	Short	$\hat{\alpha}$	MAE	RMSE
RM(T)	0.0123	0.0338	0.0393	RM(N)	0.0102	0.0303	0.0359
RM(S)	0.0133	0.0337	0.0391	G(N) ¹	0.0089	0.0303	0.0354
G(T)	0.0099	0.0340	0.0390	E(N) ²	0.0085	0.0307	0.0357
G(S)	0.0109	0.0341	0.0392	I(N)	0.0075	0.0318	0.0372
E(T) ¹	0.0130	0.0331	0.0374	FI(N)	0.0085	0.0309	0.0358
T(T)	0.0116	0.0342	0.0396	HY(N) ³	0.0085	0.0307	0.0357
T(S)	0.0112	0.0344	0.0398				
AP(T)	0.0106	0.0341	0.0393				
AP(S)	0.0109	0.0342	0.0395				
I(T)	0.0092	0.0356	0.0408				
I(S)	0.0089	0.0357	0.0410				
FI(T)	0.0092	0.0343	0.0391				
FI(S)	0.0092	0.0344	0.0393				
FI(T) ²	0.0116	0.0337	0.0380				

FIAP(T)	0.0106	0.0343	0.0395
FIAP(S)	0.0112	0.0345	0.0397
HY(T)	0.0102	0.0340	0.0390
HY(S)	0.0106	0.0341	0.0392

Among the adequate models, the top ranked ones are most likely to be associated with highest failure rates while those with relatively high MAE or RMSE are characterised by lower failure rates. Therefore, one may argue that lower VaR failure rate is achieved at the expense of less precise VaR forecasts, thus greater amount of misallocated economic capital. While all adequate models do prove to be satisfactory for regulatory compliance, risk managers need to strike the balance between the acceptable VaR failure rate and desired accuracy of model output according to the bank's risk preference and utility. There are subtle changes to the model ranking should MAE be used as the main selection criterion. The use of RMSE metric as the main selection criterion reflects our view that under- or over-prediction of VaR by greater magnitude should be penalised more heavily, as it is more severe than having more frequent miscalculation of VaR by smaller margin. Furthermore, a stable VaR would be more appealing on the grounds that a highly variable VaR would make it difficult to assess the riskiness of the financial institution over the long term.

The average MAE or RMSE of the adequate VaR models is substantially higher for the three Chinese stock market indices than the three benchmark comparative indices. The lack of model fitness in the Chinese markets implies the proportion of volatility that is not explained by the model is relatively higher, which may be due to the excessive noise trading or the high density of information arrival in these less developed markets.

In terms of the model popularity, RiskMetrics features prominently across all six indices, while adequate APARCH, FIARPARCH and FIEGARCH models are less common for some indices.

The infrequent appearance of APARCH, FIARARCH and FIEGARCH models may partially due to complexity in the estimation procedure of these models. The success of APARCH model in modelling VaR as documented in many previous studies is not strongly evident in this empirical analysis.

Table 6.15 Summary of the Best Performing Models

Rank	Long Position			Short Position		
	1	2	3	1	2	3
SH	RM(T)*	RM(T)	RM(S)*	I(N)	RM(S)	RM(T)*
SZ	AP(N)	T(N)	E(N)	FI(N)	RM(N)	FIE(N)
HK	G(N)	T(N)	AP(N)	FIAP(N)	FI(N)	HY(N)
US	FI(T)	FI(T)*	HY(T)	FI(N)	RM(N)	HY(N)
UK	I(S)*	T(S)	FIE(T)	RM(S)*	RM(N)*	RM(N)
JP	E(T)	FIE(T)	G(T)*	G(N)	E(N)	HY(N)

Table 6.15 summarises the top three performing VaR models for both long and short positions of the six stock index returns. Models with asterisk are those estimated using the one-year in-sample.

Table 6.16 SPA Test Results

	Long Position		Short Position	
	Benchmark Model	<i>p</i> -value	Benchmark Model	<i>p</i> -value
SH	RM(T)*	0.52 (0.52, 1.00)	RM(S)	0.49 (0.49, 1.00)
SZ	AP(N)	0.84 (0.53, 1.00)	FI(N)	0.51 (0.51, 1.00)
HK	G(N)	0.51 (0.51, 1.00)	FIAP(N)	0.10 (0.10, 0.44)
US	FI(T)	0.64 (0.52, 0.99)	FI(N)	0.52 (0.52, 1.00)
UK	I(S)*	0.78 (0.55, 0.88)	RM(S)*	0.51 (0.51, 1.00)
JP	E(T)	0.51 (0.51, 1.00)	G(N)	0.20 (0.20, 0.64)

Table 6.16 reports the SPA test results for each of the best performing model listed in Table 6.15. Entries are the consistent *p*-values with numbers in the parentheses being the lower and upper

bounds for the p -values.³⁸ A p -value that is higher than 0.05 indicates that the best performing model (the benchmark model) cannot be outperformed by all of the competing models on the basis of the specified loss function, RMSE. The SPA test results suggest that all the benchmark models are superior than their respective alternatives with only one exception – the best performing model for short position in SH, I(N), is outperformed by RM(S).³⁹

As shown in Table 6.15, eight out of thirty-six top performing models are estimated from the one-year sample period. The eight one-year window models comprise seven symmetric models and one long memory model. This finding suggests that the choice of window length is important for the accuracy of the VaR forecast. Larger window is favoured if the banks are to implement more sophisticated GARCH models for the computation of VaR.

The significance of distributional assumption is also highlighted. Normal distribution is favoured overwhelmingly for short positions across all six markets and long positions of SZ and HK. The top performing models for long positions in the remaining four indices assume either Student t - or and skewed Student t -distribution. Models in a more simplistic manner (symmetric models) consistently rank in the top three of the best performing models. In particular, the RiskMetrics model is immensely successful in long and short positions of SH, as well as short positions of UK. However, the success of the RiskMetrics is not repeated in SZ. Quite the contrary, the best performing models for SZ are drastically different from those for SH. This finding is striking given the returns of the two Mainland stock indices are almost perfectly correlated. The class of the top ranked VaR models may also give us a flavour of the specific characteristics of the return

³⁸ The upper bound is the p -value of a conservative test which tacitly assumes that all the competing models are as precisely as good as the benchmark in terms of expected loss. The lower bound is the p -value of a liberal test whose null hypothesis assumes that the models with worse performance than the benchmark are poor models in the limit. See Hansen and Lunde (2007) for more detail.

³⁹ The p -values for model RM(S) are presented in Table 6.16 instead of those for I(N).

pattern in that market: long-memory in volatility seems to be a salient feature of US; asymmetric models are preferred for the long position in SZ while long-memory models perform quite well in generating VaR for short positions in HK; and JP embraces a mixture of model classes.

Although no specific model is found to outperform other alternatives in all six indices, the RiskMetrics model is clearly favoured in many cases. The popularity of the RiskMetrics model in the practitioner community is thus warranted. Based on the empirical results presented, no definitive conclusion can be reached as to the superiority of more advanced models over parsimonious model in terms of their ability to produce more accurate VaR estimates.

6.9 Conclusion

6.9.1 Summary of Results

Value-at-Risk (VaR) is widely used as a tool for measuring market risk exposure of asset portfolios. Alternative VaR implementations are known to yield fairly different VaR forecasts. This empirical chapter compares an extensive collection of univariate GARCH family models in terms of their ability to model daily VaR for both long and short positions of six completely diversified stock index portfolios, using three different distributional assumptions and two rolling window lengths. The relative performance of the proposed models is assessed by means of an out-of-sample two-stage backtesting procedure. In the first stage, the Kupiec test and the Dynamic Quantile test are used to examine the statistical accuracy of the models. In the second stage, the Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) metrics are calculated to distinguish the most accurate model from a number of adequate models. The following conclusions are made based on our empirical results: firstly, the choice of window length is important for getting more accurate VaR forecasts and large rolling window is recommended for

the implementation of more sophisticated parametric models, particularly asymmetric and long-memory models; secondly, the nature of long and short trading calls for different distribution specifications in order to correctly model the left and right tails of the return distribution – Student t - and skewed Student t -distributions are generally preferred for long positions while normal distribution is more appropriate for short positions; thirdly, models fitted with Student t - and skewed Student t - errors have greater ability to achieve lower average failure rates than those fitted with normal errors; for incorrectly specified models, symmetric ones have a tendency to underestimate the true VaR returns while their long memory counterparts prone to systematically overstate VaR estimates; we also observe an inverse relationship between the VaR failure rate and the value of the risk function (i.e. MAE and RMSE), which implies lower frequency of VaR exceptions is often achieved at the expense of unnecessarily high level of economic capital committed; finally, the model producing the most accurate VaR forecasts varies from one market to another. Risk managers are therefore advised to develop VaR models specific to the market or asset class in order to achieve better allocation of economic capital.

6.9.2 Connections with Other Empirical Chapters

At first glance, the present empirical chapter may seem to detach from our previous discussions on stock market integration. Quite the contrary, this chapter complements our empirical investigation. Based on our previous findings, while the Mainland Chinese stock market has become increasingly integrated with the world's major stock markets, there is still room for reaping the benefits of portfolio diversification through investing in the Chinese A-share market. In spite of its ability to provide lucrative returns, the tremendous volatility is another prominent feature of the emerging Chinese stock market. Since early 2006, the market went up five-fold until its peak in October 2007, followed by an equally sharp correction – losing 70% of its value a year later. Although stock markets around the world experienced similar downturn during this period, the

one witnessed in Mainland China was certainly the most extreme. The downside risk of such magnitude should put the QFII participants, who largely conduct risk management practices under the guidance of Basel Accord, on high alert. It is thus of their best interests to have a sound risk monitoring mechanism in place, as failure to do so would put their investments in jeopardy and lead to more stringent capital requirements. Our empirical analysis in this chapter offers a general framework for ranking candidate volatility models and should render assistance to both domestic and international financial institutions which operate under the Basel Accord.

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Chapter 7 – Conclusion

7.1 Summary of Results

Motivated by the recent developments within the Mainland Chinese stock markets, this thesis aims to add knowledge to the literature on international financial integration and risk management by investigating the stock market integration and market risk monitoring practice in the emerging Chinese stock market.

The issue of stock market integration has been previously underexplored in the context of Mainland China, to which researchers have begun to pay attention until recently. The limited existing evidence largely points toward the segmentation of the Mainland Chinese stock markets from the world market. The ongoing stock market liberalisation in Mainland China coupled with the occurrence of the 2007-2009 global financial crisis offers a strong motivation to reassess the degree to which the Chinese stock markets are connected with the world stock market. The knowledge of the extent of integration among stock markets is of vital importance to international investors and regulatory bodies – it informs international investors about the effectiveness of cross-country diversification, and helps regulatory bodies to control the undesirable side effects associated with increasing stock market integration.

We investigate stock market integration in three broad lines of enquiry. *Chapter Three* investigates the state of stock market integration from the perspective of measuring cointegration amongst stock index prices over time. We extend prior research by explicitly taking into account abrupt structural breaks and time-variation in the cointegrating relationship. As expected, the results from these modified cointegration tests are shown to be more informative than the conventional cointegration test. With Gregory and Hansen (1996) residual-based cointegration test, we

document stronger evidence of pair-wise cointegration between the Shanghai market and each of the four developed stock markets by allowing for an abrupt structural break in the long-run equilibrium. The recursive and rolling multivariate cointegration tests indicate that cointegration among the five stock markets is period dependent. This particular finding implies prior studies that conclude the presence or absence of cointegration based on an arbitrary sample period may produce misleading results. Our rolling cointegration analysis suggests the cointegrating relationship was stronger after the 1997 Asian financial crisis and during the 2007-2009 global financial crisis. This is consistent with the contagion hypothesis that stock markets become more integrated during or following market turbulence. There were also substantial periods where cointegration was weak or absent. To balance these results, we conclude by suggesting that the Mainland Chinese stock market is still in the progress of integrating with developed stock markets and foreign investors may still be able to realise the benefit of diversifying their portfolios into the Chinese stock market.

While examining the long-run interdependence among stock markets is prevalent in the literature, the growing connectedness of financial markets has inspired analysis of the short-term transmission mechanism among different stock markets. *Chapter Four* is devoted to an examination of this specific aspect of stock market integration. Using GARCH models to capture the patterns of return and volatility spillover effects among the two Mainland Chinese and four developed stock markets, we document stronger regional spillover effects among the three Chinese stock markets (i.e. stock markets of Shanghai, Shenzhen and Hong Kong). We also find evidence of strengthened spillover effects in the post-QFII period. This suggests the opening-up of the Mainland Chinese stock markets has weakened the short-run benefit of cross-border diversification. Moreover, the leadership of the Hong Kong market over its two Mainland counterparts has deteriorated in the wake of the rising prominence of the Shanghai market. The relative exogeneity of the Shanghai market over the Hong Kong market is somewhat consistent

with the results of the ECM derived based on the pairwise Gregory-Hansen (1996) cointegration between these two markets, in which the Hong Kong market plays a more active role in restoring the long-run equilibrium errors. Put these aside, the extent to which return and volatility of the Mainland Chinese stock markets are influenced by shocks from international national markets remains moderate. Similar conclusion can also be drawn from the Variance Decomposition and the Impulse Response Functions conducted at the end of *Chapter Three*.

Chapter Five investigates how these stock markets interact in terms of return correlation, which is regarded as the key catalyst in portfolio diversification. We compute pair-wise return correlations in their unconditional, realised and conditional forms. To analyse the shifting patterns in the unconditional and realised correlation series, we employ the Bai and Perron (1998, 2003a,b) test in searching for structural breaks within series. The regimes identified by the break point tests are broadly in line with the phases of cointegration indicated by the rolling cointegration analysis. Our empirical results reveal a near perfect correlation between returns of the two Mainland Chinese stock markets, moderate correlations with the US, the UK, and Japan, and a progressively increasing correlation with Hong Kong. In particular, we document a remarkable surge in all types of correlations between Shanghai and each of the four developed markets during the 2007-2009 global financial crisis. This finding, once again, offers support to the contagion hypothesis.

Taken together, the results from the first three empirical chapters are blatantly in agreement that Mainland China's stock markets have become increasingly integrated with several developed stock markets in recent years. The increasing integration shows up in the data in the forms of long- and short-run interdependence as well as index return correlation. The finding of intensified integration during the 2007-2009 global financial crisis corroborates with the contagion hypothesis and suggests the emerging Chinese stock markets have become more receptive to shocks from global financial markets. The robust evidence of contagion effect suggests the

benefits of diversification go down exactly when they are most desirable.

We postulate several reasons toward explaining the increased integration, ranging from the gradual relaxation on capital controls to the cross-listing of domestic stocks. The introduction of the QFII and QDII programs facilitates the equity investment in and out of Mainland China, which paves the way to greater stock market integration. The cross-border investments increase the likelihood of ‘psychological contagion’ between the stock market involved, which offers a plausible explanation to our reported contagion effect. The close linkage between Mainland China and Hong Kong can be attributed to pervasive dual-listings of Mainland Chinese companies on stock markets in both locations.

Nevertheless, the extent of such integration should not be overstated since Mainland Chinese stock markets are yet sufficiently liberalised to permit a stronger form of integration to emerge. Further integration may be halted by the stagnation or reversal of the current liberalisation process initiated by the Chinese regulatory bodies.

Risk management constitutes an integral part of portfolio diversification process and is of heightened importance to investors venturing unfamiliar investment environment. While returns from investing in the lucrative Mainland Chinese stock markets certainly look attractive in the eyes of foreign investors, the risk associated with the investments can never be overlooked. Through a thorough evaluation of alternative GARCH family models in providing accurate market risk forecasts under the VaR framework, we find traditional RiskMetrics outperforming other candidate models in the Shanghai market whereas more complicated asymmetric and long-memory GARCH models are favoured in the relatively smaller Shenzhen market. These results showcase the importance of using heterogeneous volatility models in monitoring portfolio market risk exposure while optimising economic capital for regulatory compliance.

7.2 Relationship with Extant Literature

Pretorius (2002: p.86) divides the stock market integration literature into three categories: the first category is studies that simply examine stock market interrelationships to determine how interdependent a specific group of stock markets are; the second category goes beyond this and examines possible changes in stock market relationships; and studies fall into the third category try to explain why stock markets are interdependent, by either decomposing or modelling stock market interrelationships. This thesis tilts more towards the first two categories and less on the last. Our empirical evidence streams into the abundant and fast growing literature on the integration of emerging stock markets, which generally suggests that the emerging stock markets are in the process of further integrating into the world market.

In comparison to the tangential literature concerning the Mainland Chinese stock market, our empirical results share little ground with the past literature which is predominantly in favour of segmentation, but have much in common with evidence emerged from a handful of more recent studies (for example, Tian, 2007; Sun and Zhang, 2009; and Yi *et al.*, 2010), which would place Mainland Chinese stock market in the middle of the segmentation-integration spectrum. Such increased integration can be attributed to the recent developments within the Mainland Chinese stock market.

7.3 Practical Implications

The knowledge of the state of stock market integration serves the interests of practitioners and stock market regulators. For practitioners like portfolio managers, investment and hedge strategies could be more effective if the pattern of market interactions were better understood. Increasing integration implies portfolio diversification in Mainland Chinese stock markets is of reduced

attractiveness to foreign investors. However, given that the integration between Mainland Chinese stock markets and those of New York, London and Tokyo is far from complete, portfolio managers may still use the Mainland Chinese stock markets as an anchor against equity market investment in those developed markets, especially during the non-crisis periods. The same analogy could also be extended to domestic Chinese investors who are equally eager to broaden their investment horizon overseas.

On the evolution and status of integration, much progress was made during the period from 2006 to 2008. This period saw a wave of high-profile IPOs and flood of foreign funds in the already overheated Mainland Chinese stock markets, both of which had accelerated the build-up of a speculative rational bubble that was also commonly experienced by other major international stock markets. From the perspective of financial regulators, it is more difficult to pursue independent financial policy as the stock market becomes more integrated with other stock markets. The contagion effect during the 2007-2009 global financial crisis clearly has important implication for the Mainland Chinese regulatory bodies who are contemplating whether to further open up its capital markets by revising the current quota for the QFII and QDII programs. The key issue is to maintain a pragmatic approach to further financial liberalisation. The fact that the Mainland Chinese stock markets are no longer isolated from the global and regional shocks also necessitates better policy coordination among these stock markets to preserve greater financial stability. The integrating experience of the Mainland Chinese stock market would also enlighten financial regulators in other emerging countries who want to follow the footprints of the Mainland China in gradually opening up its capital markets.

Risk management is an integral part of portfolio diversification process. VaR is the market risk measurement tool stipulated by the Basel committee. The appraisal of GARCH models in the estimation of VaRs highlights the importance of sample length and distribution assumption in

modelling market risk exposure for both short and long positions in the diversified stock index portfolios. To achieve most efficient allocation of economic capital held by a financial institution, risk practitioners would need tailor-made VaR models to accommodate the equity investment in the emerging Mainland Chinese stock markets. The volatility model ranking procedure proposed therein can be readily generalised to other investment contexts. Furthermore, our pioneering work on the comparative performance of volatility models will also benefit derivative practitioners and prepare them for upcoming derivatives innovations on the Mainland Chinese stock indices.⁴⁰

7.4 Methodological Contributions

The literature of stock market integration has long concerned itself with the methodology of integration measurement. These methodologies rest on the differing definitions of integration, leaving results open to interpretation.

Methodologically, this thesis seeks to advance the discussion of the stock market integration in Mainland China in several ways. We provide a synthesis on the issue by considering a number of popular measures in the extant literature. This, to a large extent, avoids spurious and partial conclusion drawn from a standalone model. In comparison to previous studies concerning the Chinese stock market, our empirical analyses overcome some of the deficiencies inherent in their methodologies.

In terms of model design, we fine-tune the previously employed models by explicitly accounting for structural change, time-variation, and nonlinearity in the observed relationships, where necessary. From an applied perspective, these assumptions would provide a better delineation of the true process of stock market integration. As expected, our empirical results demonstrate that as

⁴⁰ The first Mainland Chinese stock index futures made its debut on April 16th 2010.

we deploy more sophisticated, finely grained approaches, we are able to find stronger evidence of integration.

The novelty of our empirical methods hinges on the recognition that stock market integration is subject to change over time. We sought to address this phenomenon through the use of Gregory and Hansen (1996) and dynamic cointegration tests in the search of potential long-run equilibrium among stock market indices; and the use of Bai and Perron (1998, 2003a, b) method in identifying different phases of correlation structure.

In *Chapter Five*, we build upon the work of Chelley-Steeley (2004, 2005) and consider two additional smooth transition models (namely, exponential and second-order logistic smooth transition models) in explaining the movement of return correlations over time. Although the performance of both models is less than satisfactory, our work paves the way for future adaptation of these models in other contexts.

While more recent studies have attempted to explore the long-memory properties of the Chinese stock market returns (see for example, Yi *et al.*, 2010), little has been done on the long-memory in volatility. Our empirical analyses in *Chapter Six* explicitly take into account of long-memory volatility models, through which the existence of long-memory volatility processes of the Chinese stock index returns is revealed simultaneously.

To ensure our results are free from arbitrary model or sample specifications, we perform our analyses under a number of different settings. For instance, the analyses of cointegration and spillover effects are conducted in local currencies and common currency; different window lengths are adopted for dynamic cointegration method; time-varying conditional correlations are estimated from BEKK- and DCC-GARCH models; VaR estimates are computed under different

sample lengths and distributional assumptions, just to list a few. To ensure robustness, holiday adjusted data is also employed to minimise the impact of non-performing observations. These treatments certainly add an extra degree of clarity to our empirical results and increase the credibility of the inferences drawn from these results.

7.5 Limitations and Directions for Future Research

Due to the nature of our research methodology, the normal limitations associated with the econometric method should be recognised. The empirical results derived therein should be interpreted with caution due to the inevitable statistical bias and other technical limitations. For example, we assume linear cointegrating relationship in the investigation of long-run interdependence. Conceptually, cointegration among series may well take nonlinear forms. Such possibility in the context of stock market integration was formally enquired by Li (2006), whose findings challenge the conclusion of market segmentation in some previous studies that only conduct cointegration analysis in a linear fashion. Moving from linear to nonlinear cointegration, we expect the evidence of integration to be at least as strong as the one obtained from linear cointegration. Should that be the case, the gains from cross-border portfolio diversification would have been overstated under the linearity assumption. The presence of a nonlinear cointegration relationship would imply collective inefficiency among the stock markets in the system in that movements in one market's prices will induce other markets' prices to move in a predictable direction, albeit disproportionately, in the long run (Li, 2006). Since the development of nonlinear cointegration method is still very much in its infancy, there is ample room for future development along this line.

At a higher level, this thesis investigates the state of stock market integration using primarily price-based measures. Consideration of quantity-based measures would supplement our findings

and broaden the perspectives on the issue. Furthermore, much of the effort in the thesis is devoted to examining the presence of interdependence, and investigating the possible changes in such relationship over time, less on explaining the possible causes of such interdependence. Although we have put forward several explanations for the increase in integration, including financial crisis, relaxation of capital control and cross-listings, our approaches are less capable of directly discerning their relatively impacts on the process of integration. A more dedicated study is called for if one wants to uncover the main driving force behind the observed increase in integration. Incorporating other relevant exogenous variables into our models may shed some additional light on the empirical results obtained therein. In any case, this thesis should serve as a reference for research that falls into this category.

Lastly, our investigations on both stock market integration and risk monitoring are confined to broad market index level. We are curious about the possible changes in the level of integration and suitable market risk reporting mechanism at industry and company levels. For example, Chen *et al.* (2011) have made efforts in exploring integration and spillover effects between the Chinese A- and B-shares at both market index and sectoral levels. Their study is motivated by the open-up of B-share market to domestic investors in 2001. Since the introduction of QFII scheme, foreign institutional investors have gradually moved away from the B-share market and deliberately increased their stakes in the more liquid A-share market. This tendency has stimulated more research interest on the interaction of the cross-listed stocks that are simultaneously traded on the Mainland and Hong Kong, or even other international stock markets. The large and persistent price differentials between the dual-listed A- and H-shares have been documented in previous research (see for example, Kalok and Kwok, 2005). The introduction of the QFII and QDII schemes establish a channel for arbitrage that would eventually equalise the prices of the dual-listed A- and H-shares. Whether and to what extent the QFII and QDII schemes have fostered the arbitrage activities between the different trading locations is apparently another interesting

research topic. We leave the pursuit of these questions to future research.

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